CLIMATE CHANGE-INDUCED WATER SHORTAGES: IMPROVING DECISION-MAKING IN AN UNCERTAIN FUTURE

By

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ABSTRACT

An innovative approach to translating probabilistic UKCP09 weather generator information into a usable and replicable risk-based climate change impacts assessment and a basis for robust adaptation planning in the England and Wales water sector is described. Applying metrics of risk in the form of crossing control curves at a reservoir, quantitative assessments of the extent to which a Water Resource Zone (WRZ) can be considered robust to climate change-induced water shortages given the application of adaptations options are made. It is shown in a case study of the North Staffordshire WRZ that in its current set-up, the system cannot be deemed robust to climate change from the 2030s onwards. Applying demand and supply-side adaptation options to the WRZ increases the robustness of the system to varying extents. The approach used shows that it is possible to make decisions on how the WRZ can be made robust to future conditions by identifying key metrics of risk, and applying an acceptable probability of not satisfying that risk in the future. Furthermore, a novel analysis of two sources of uncertainty involved in climate change assessments is produced in terms of water shortage probability for the first time, and two downscaling techniques are assessed.

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NOMENCLATURE

AMOC	Atlantic Meridonial Overturning Circulation
AMP	Asset Management Period
Aquator	Water Resource Model produced by Oxford Scientific Software. 'The Aquator Model' refers specifically to the North Staffordshire Water Resource Zone Model.
AR4	IPCC Assessment Report 4
AR5	IPCC Assessment Report 5
CCRA	Climate Change Risk Assessment
CDF	Cumulative Distribution Function
CF	Change Factor
CFM	Change Factor Method
DF	Demand Factor
DHY	Deep Hayes sub-catchment
DJF	December, January, February (winter)*
DO	Deployable Output
DWT	Drought Warning Trigger^
EARWIG	Environment Agency Rainfall and Weather Impacts Generator
FDC	Flow Duration Curve
GCM	Global Climate Model
HYSIM	HYdrological SIMulator
IPCC	International Panel on Climate Change
IWRM	Integrated Water Resource Management
JJA	June, July, August (summer)*

LoS	Levels of Service[^]
MAM	March, April, May (spring)[*]
Ml/d	Mega litres per day
NSRP	Neyman-Scott Rectangular Pulses
Ofwat	Water industry economic regulator (England and Wales)
OSS	Oxford Scientific Software
PET	Potential Evapotranspiration
PPE	Perturbed Physics Ensemble
RCM	Regional Climate Model
RDM	Robust Decision-Making
SAL	Storage Alert line[^]
SOL	Solomon's Hollow sub-catchment
SON	September, October, November (autumn)[*]
SRES	Special Report on Emissions Scenarios
STW	Severn Trent Water
TAR	IPCC Third Assessment Report
TUB	Temporary Use Ban[^]
UC	Upper Churnet sub-catchment
UKCIP02	UK Climate Impact Projections 2002
UKCP09	UK Climate Projections 2009
UKCP09WG	UK Climate Projections 2009 Weather Generator
UKWIR	UK Water Industry Research
VDC	Volume Duration Curve
WG	Weather Generator
WGM	Weather Generator Method

WGR	Wall Grange sub-catchment
WRMP	Water Resource Management Plan
WRPG	Water Resource Planning Guideline
WRZ	Water Resource Zone
WTW	Water Treatment Works

* On some occasions months are displayed as acronyms other than entire seasons (e.g. JA) or as longer periods (e.g. JJASO). On these occasions a non-standardised descriptor is attached (in these cases late summer, and late summer to autumn, respectively). ‘Spring’, ‘Summer’, ‘Autumn’, and ‘Winter’ refer to ‘MAM’, ‘JJA’, ‘SON’ and ‘DJF’, respectively.

^ The order of severity of water resource management triggers used by STW in the North Staffordshire WRZ is: TUB (most severe), DWT, SAL (least severe)

1 INTRODUCTION

1.1 General

Within all of the uncertainty involved with climate science it is sometimes easy to forget what, beyond significant scientific doubt, we do know: that the relentless pursuit of energy by society is altering the composition of the atmosphere and oceans (Solomon *et al*., 2007; Foster and Ranhmstorf, 2011; IPCC, 2013; Wigley and Santer, 2013). The associated build-up of anthropogenic greenhouse gases in the lower atmosphere, acidification and warming of the oceans, melting of ice caps and destruction of rainforests is changing the hitherto relatively stable Earth system within which society has flourished to the point where the Holocene epoch has been informally split in order to isolate the period of significant human influence on the Earth system, known as the Anthropocene (Crutzen and Steffen, 2003; Lean and Rind, 2008; Stott *et al*., 2010; Christidis *et al*., 2012; Wigley and Santer, 2013).

Over civilised human history, water resources that have been developed across the world have been subject to a relatively stable envelope of variability. Droughts, floods, heatwaves and other extreme events have occurred regularly, often with great loss of life, but until the last four decades the probability of such an event occurring again has remained relatively constant through time (with some regional discrepancies, such as the Medieval Warm Period in the North Atlantic region). This had made water resource management a conceptually straightforward discipline; plan for the future based on what has occurred in the past. Now, however, anthropogenic forcing of the climate system means that the present and future are no longer analogous to the past, and water resource management must exist within a moving window of variability (Milly *et al.*, 2008). That is, the idea of a return period of an extreme event is no longer valid, as the frequency of an event of a certain magnitude is different now to a hundred years ago. In the future, that frequency will continue to change, but the precise nature of that change is impossible to know. Therefore, water resource managers are faced with the prospect of using ensembles of future projections numbering in the thousands to make decisions on sustaining supply. In the UK and other developed nations, this means that maintaining Levels of Service (hereafter referred to as LoS) to customers is now a significantly more challenging task than it once was (Gleick, 2011). This thesis tackles that problem, providing original approaches to facilitating uncertain projections of the future into decision-making.

The work provided here focuses on supplying water resources in the UK for the preservation of company targets and customer’s expectations, but the implications of the research permeate into the fields of development, where robust water resource management under future climate change is vital for the preservation of life.

1.2 Aim and objectives:

The aim of this work is therefore to provide original approaches to include uncertain projections of the future into decision-making by UK water resource managers. In order to achieve this aim the following objectives are required:

Objective 1: Develop a replicable and robust risk-based methodology for utilising UK Climate Projections 2009 (UKCP09) data to inform decision-making, thus increasing the incentive to drive investment in the water sector based on climate change. The approach should provide a viable alternative approach to using UKCP09 information to that currently used by water companies.

Objective 2: Produce an assessment of the impacts of climate change on water shortage risk in a catchment-specific study that is transferable to other regions, areas of risk to the water industry, and sectors.

Objective 3: Use robustness assessment approaches to identify effective adaptive responses to climate change in the Water Resource Zone (WRZ) in a way that is easily communicable and facilitates investment despite uncertainty.

Objective 4: Critically assess the performance of the UKCP09 Weather Generator (WG), discuss how the limitations of that and another downscaling approach, the Change Factor Method (CFM), inhibit the ability of the water industry to react to climate change, and map out the way forward for overcoming those issues.

Objective 5: Assess the relative scales of climate model uncertainty and emissions scenario uncertainty in terms of water shortage probability in the future.

Objective 6: Facilitate the increased acceptance of climate change uncertainty into future water resource planning.

Objective 7: Produce an assessment of the impact of climate change on hydrometeorological variables in the study catchment using a WG approach.

1.3 Project organisation

The project builds upon work previously carried out by the author on climate change impacts on climate change impacts on a reservoir in the south-east of England (Harris *et al.*, 2009). A working relationship was built up with the key stakeholders; Severn Trent Water (STW), Hydrologic and Oxford Scientific Software (OSS), which included frequent dialogue with a number of personnel and important data and models being made available for the research.

The study was organised into 5 major areas; 1) investigation and feasibility studies of various WG approaches and further methodologies for gaining future synthetic weather parameter sequences; 2) WG, hydrological and water resource modelling; 3) development of a risk-based approach to quantifying the probabilities of water shortage events in the future; 4) modelling of future adaptation strategies for robustness assessment purposes; 5) data analysis.

The author has planned and completed all modelling and analysis work, with guidance from HydroLogic, OSS, STW and the PhD supervisors on various aspects of the procedure. The hydrological and water resource models used existed previously and have been kindly made available by Ron Manley and Seven Trent Water, respectively.

Being a non-commercial and university-funded research project, the author has had much control over the methodology and objectives of the project. The project is, however, intended to be of direct commercial usefulness and interest to the water industry, particularly in the production of climate change adaptation reports and facilitating improved long-term water resource planning.

1.4 Structure of thesis

The subsequent chapters of the thesis are structured as such:

Chapter 2 – Literature review

An introduction to the science of climate change and the implications it has for water resources is given. The responses of the England and Wales water sector and the approaches taken by researchers around the world to assess and improve water resource management are summarised. The key uncertainties involved assessments of climate change impacts on water resources, and how they have been quantified, are evaluated. Finally, the techniques used for downscaling climate projections to catchment-scales are reviewed.

Chapter 3- Materials, methods and validation

The study site is introduced, and the terminology and details of the modelling procedures used to reach the stated objectives (Section 1.2) are given. Each stage of the methodology used to downscale climate information in order to ultimately produce water shortage probability metrics is validated against the observed record. Finally, the approaches used to provide a robustness assessment of adaptation options from the dataset of precipitation, flow and potential evapotranspiration (PET) are explained.

Chapter 4 – Uncertainty analysis

A quantification of two uncertainty sources in terms of water shortage probability in the North Staffordshire WRZ is given. Differences between the main methodology for Chapters 6 and 7, and that used to produce the uncertainty assessment, are provided. A more traditional uncertainty assessment, using flows at the sub-catchments, is also shown.

Chapter 5 – Hydroclimatological impact assessment

An assessment of the impact of climate change on precipitation, PET and flow in the North Staffordshire WRZ is presented. Analysis of the results, and a discussion of their practicality for use in industry, is given.

Chapter 6 – Climate change impacts on water resource availability and system robustness

First, the impact of climate change on Tittesworth Reservoir levels is analysed. Then, using LoS as metrics of risk, an assessment of water shortage risk in the North Staffordshire WRZ over the probabilistic range of projections is given, and conclusions are drawn as to the robustness of the current system to potential changes as a result.

Chapter 7 – Robust adaptation

Nine adaptation scenarios for the North Staffordshire WRZ, designed to reduce the impact of climate change, are introduced and tested against the probabilistic range of projections. As in Chapter 6, reservoir levels are analysed first, before a robustness assessment of the changed systems is conducted. Conclusions are drawn as to the effectiveness of the adaptation scenarios, and the advantages of using this approach over previous methodologies are highlighted.

Chapter 8 – Discussion

The extent to which the methodology proposed here facilitates improved use of climate change information in the England and Wales water sector, compared to previous work, is considered. The applicability of the approach for widespread use elsewhere is discussed, as are the implications for climate change on the North Staffordshire WRZ itself. A description of how the concepts explored in this research can be extended to other metrics of risk and sectors is provided. The uncertainties and limitations of the methodology taken are also discussed.

Chapter 9 – Concluding remarks and recommendations for further research

Conclusions are made based on the original objectives (Section 1.2), and a number of recommendations are made for future research.

1.5 Publications

1.5.1 Peer-reviewed journal publications

Harris, C.N.P., Quinn, A.D., Bridgeman, J., 2012. Review: The use of probabilistic weather generator information for climate change adaptation in the UK water sector. Meteorological Applications. DOI: 10.1002/met.1335

Harris, C.N.P., Quinn, A.D., Bridgeman, J., 2013. Quantification of uncertainty sources in a probabilistic climate change assessment of future water shortages. Climatic Change. DOI: 10.1007/s10584-013-0871-8

1.5.2 Conference papers

Harris, C.N.P., Quinn, A.D., Bridgeman, J., 2012. A risk-based approach to augmenting resilience to climate change in the UK water sector. *Water Security, Risk and Society Conference, Oxford University. June 2012*

Harris, C.N.P., Quinn, A.D., Bridgeman, J., 2012. Increasing the resilience of UK water resources using probabilistic climate change information. *International Water Association Young Water Professionals Conference, Corvinius University, Budapest, Hungary. July 2012.*

1.5.3 **Submitted articles under peer-review**

Harris, C.N.P., Quinn, A.D., Bridgeman, J. Climate change-induced water shortages: clear metrics for decision—making despite uncertainty. *Journal of Water Resources Planning and Management*

2 LITERATURE REVIEW

2.1 Climate change

2.1.1 Overview

Observable climate change is occurring across the Earth. Average temperature and ocean heat content is rising globally (Jones *et al.*, 2012; Harris *et al.*, 2013(b); IPCC., 2013), and can be expected to continue to rise within estimates detailed by the International Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (IPCC, 2013) (Figure 2.1) given the validation of climate models in projecting global temperatures up to now (Rahmstorf *et al.*, 2012) (Figure 2.2). For those concerned with the management of natural and built environments that are influenced by the climate, global warming becomes a particularly difficult proposition when increases to climate variability and the associated alterations to extreme events are taken into account (Stakhiv, 2011). Observed and projected increases to the frequency and/or intensity of heatwaves (Coumou and Rahmstorf, 2012; Gosling *et al.*, 2012; Coumou and Robinson, 2013), extreme precipitation (Emori and Brown, 2005; Meehl *et al.*, 2005; Sun *et al.*, 2007; Trenberth *et al.*, 2007; Marengo *et al.*, 2009;Min *et al.*, 2011(a); Jones, 2012; van Pelt *et al.*, 2012), droughts (be they meteorological, hydrological or agricultural) (Dai, 2011; Sen *et al.*, 2012; Lee and Kim, 2013; Zhang and Cai, 2013; Zin *et al.*, 2013), extreme wind events (Pryor *et al*., 2012), sea-level rise and associated coastal inundation events (Church and White, 2011; Schaeffer *et al*., 2012) and flooding (Khazaei *et al*., 2012; Trenberth, 2012; Gersonius *et al*., 2013) are amongst the phenomena that global societies must adapt to now and in the future. For water resource managers, it is the changing nature of droughts and extreme rainfall or storms that stand out as the most prominent concerns

It has been shown repeatedly that a warmer atmosphere equates to greater moisture content, and thus the possibility of more severe precipitation and storm events (Trenberth, 1998; Trenberth *et al*., 2003; Sun *et al*., 2007; Jones, 2012; Shiu *et al*., 2012) and larger areas with sustained dry periods (Dai, 2011; Lee and Kim, 2013). With that in mind, Trenberth (2012) showed how flooding extremes across the world in 2010-11 were only being possible in an anthropogenically-altered world, and further argued that the question of whether a particular extreme event is due to climate change or not is unanswerable and therefore unsatisfactory. Rather, the concept of climate change 'loading the dice' of a climate towards more intense extreme events is more useful (Hansen *et al*., 2012).

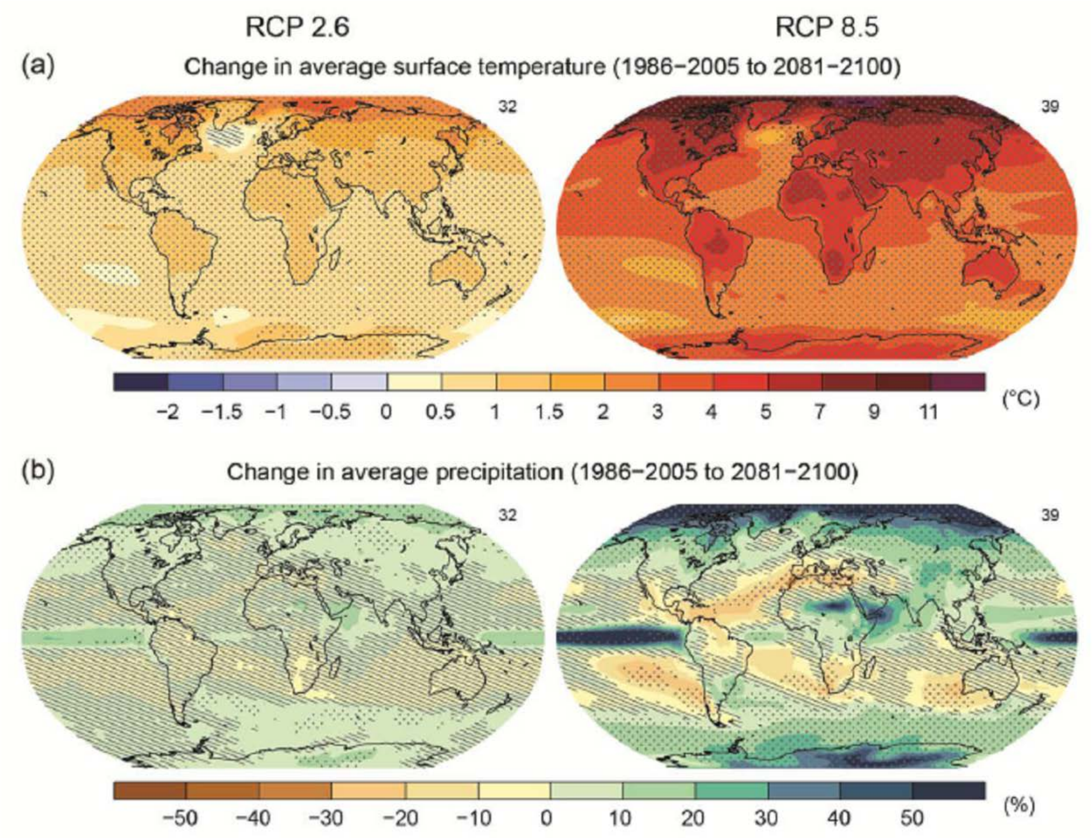


Figure 2.1. Global average temperature (top) and precipitation (bottom) mean projections for the 2081-2100 period compared to 1986-2005 using the Representative Concentration Pathway (RCP) 2.6 and RCP 8.5 projections, which equate informally to 'low' and 'high' emissions scenarios, respectively. Reproduced from IPCC, 2013.

Rather than treating global warming as a linear increase, analyses of climate 'tipping points', such as the release of anthropogenic gases from permafrost and methane hydrates, changes to the Atlantic Meridonial Overturning Circulation (AMOC) and large-scale ice sheet mass loss, have become more common in the global climate change research effort (Keller *et al*., 2008; Good *et al*., 2011). Such impacts are those that have the potential for catastrophic effects on global society, but are extremely difficult to model and estimate due to the lack of any natural analogues in human history. The prospect of such 'catastrophes' widens the uncertainty involved with future climate change and degrades confidence in the models used to describe future climates that are unable to include non-linear processes, but also significantly inflates the need to react to climate change and produce effective mitigation and adaptation policies on global scales. Such futures have gained more attention in the research community given the breakdown of the frameworks put into place to mitigate climate change such as the Kyoto Protocol (Prins and Rayner, 2007), making a surface atmosphere 4°C or more warmer than the pre-industrial world a very realistic prospect (New *et al.*, 2011) and created a movement towards 'when' rather than 'if' the 4°C threshold will be triggered (Betts *et al.*, 2011).

2.1.2 **Observations and projections of global climate change**

Across various metrics of climate change, observations from recent years have agreed well with projections from ensembles of climate models or shown significantly more evidence of global warming than the models estimated. Hansen *et al.* (2012) show that global temperatures have risen in each of the last five decades, with more extreme high anomalies and less low anomalies (Figure 2.3), and Rahmstorf *et al.* (2012) show that that observed global temperatures are increasing in close agreement with the best-estimate projections from the IPCC Third Assessment Report (TAR) and the Fourth Assessment Report (AR4) (Giorgi *et al.*, 2001; Solomon *et al.*, 2007) (Figure 2.4). In their research, which updates similar findings from Rahmstorf *et al.* (2007), it is found that temperature data adjusted for solar variations, volcanic aerosols and El Nino Southern Oscillation (ENSO) using multi-correlation analysis (Lean and Rind, 2008;

2009; Foster and Rahmstorf, 2011) shows a 12 month running temperature mean in the centre of the AR4 projection range as of 2011. Furthermore, less complex early projections of global mean temperature such as those conducted by Hansen *et al*. (1988) are shown to have predicted observed warming well, and in recent years even better than the more complex models used in AR4 (Allen *et al*., 2013), showing that global climate models (GCMs) are proving fundamentally effective at reproducing global temperatures.

Recent observations of other ‘fingerprints’ of climate change relevant to water resource management are found to be in-line with, or above, GCM projection ranges (Anderson and Bows, 2011); Periods of increased precipitation intensity (Sun *et al*., 2007), storm intensity (Coumou and Rahmstorf, 2012), long-standing drought periods (Dai, 2011; Zhang *et al*., 2012) and extreme heat events (Coumou and Rahmstorf, 2012; Gosling *et al*., 2012; Huang *et al*., 2013) are seen in observed records and modelled under future conditions globally (IPCC., 2013). The evidence for each is based on a combination of observed trends, climate modelling and physical reasoning (Coumou and Rahmstorf, 2012), with the more ‘direct’ fingerprints of global warming such as increased extreme heat events showing the clearest trends (Gosling *et al*., 2011; Coumou and Robinson, 2013).

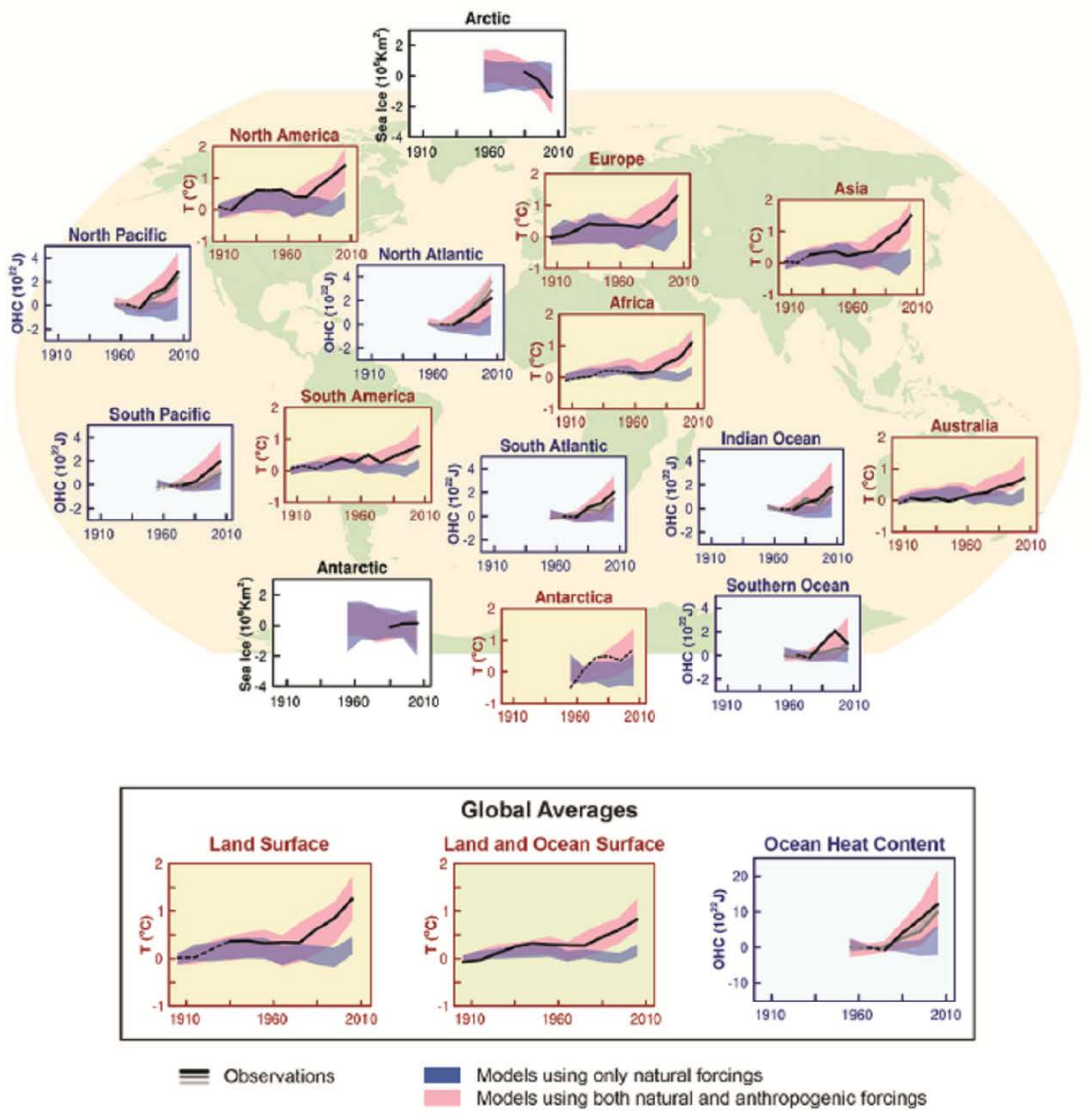


Figure 2.2. Observed anomalies of global temperature, ocean heat content and sea ice extent relative to 1880-1919, 1960-1980 and 1979-1999, respectively. Model estimates from the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the same periods are overlain, showing the input from anthropogenic and natural forcings. Reproduced from IPCC, 2013.

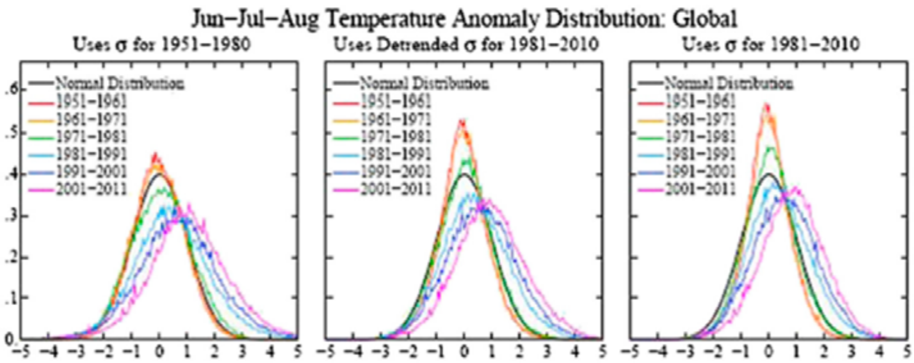


Figure 2.3. Frequency of occurrence (y-axis) of local temperature anomalies (relative to 1951-1980 mean) divided by local standard deviation (x-axis). Three choices of standard deviation are use, with each showing shifting decadal global temperature distributions over the period 1950-2009. Reproduced from Hansen et al., 2012.

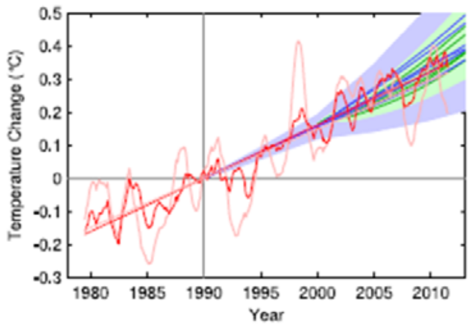


Figure 2.4. Projections and observed temperature analysis . Pink line is unadjusted (raw), red line is adjusted for short-term variations due to solar variability, volcanoes and ENSO. 12 month running averages are shown as well as linear trend lines, compared to the scenarios of the IPCC (blue range = TAR, green = AR4). Reproduced from Rahmstorf et al., 2012.

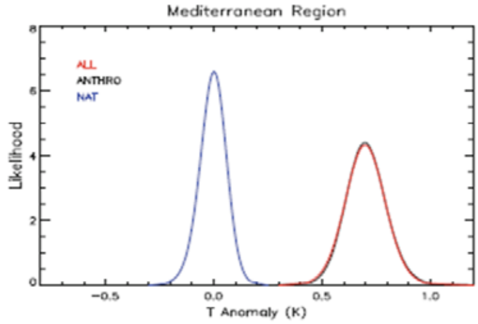


Figure 2.5. PDFs of 2000-2009 temperature anomalies in the Mediterranean region attributed to anthropogenic forcings (black), natural forcings (blue) and all forcings (red), using two GCMs. Reproduced from Christidis et al., 2012).

Christidis *et al*. (2012) showed using two GCMs that temperature anomalies for 2000-2009 from a 1961-1990 baseline can be attributed to anthropogenic forcings in all regions of the world (Figure 2.5). Furthermore, Wigley and Santer (2013) found the AR4 statement that the 'increase in global average temperature since the mid twentieth century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations' is an understatement when quantified, calculating a 93% probability that the greenhouse gas component of warming is greater than the entire observed trend (i.e. not just greater than 'most' of the observed warming).

Future projections of precipitation change have reduced confidence compared to those for temperature, but IPCC Assessment Report 5 (AR5) was able to make *likely* (>66% likelihood) projections for most regions of the world, which are summarised in Figure 2.1 (IPCC, 2013). This anthropogenic destabilisation of the climate increases the vulnerability of freshwater resources across much of Earth primarily as a result of societies, infrastructure and agriculture being exposed to climates they were not developed within, built or designed for, with wide-ranging consequences for humanity and ecosystems (Bates *et al*., 2008; Vaze and Teng, 2011; Sanderson *et al*., 2011). Shiu *et al*. (2012) showed using atmospheric models that there is an approximate 100% increase in the intensity of the annual top 10% precipitation events, and a 20% decrease in light and moderate rainfall events with 1°C of average warming. The authors went on to show that coupled climate models were not able to account for alterations to atmospheric convection due to coarse spatial resolution, thus suggesting that increases in extreme rainfall events are under-estimated by GCMs, a phenomenon that should be taken into account in research regarding drought or flood events. In a practical application of the Clausius Clapeyron relationship (that saturation water vapour pressure increases approximately exponentially with temperature), Trenberth *et al*. (2007) showed that there is an observed 7% increase in atmospheric water vapour per 1ºc of warming, resulting in a shift towards a greater proportion of precipitation falling as rainfall in intense events globally. These findings corroborate with further research in the area by Min *et al*. (2011(a)) and van Pelt *et al*. (2012).

2.1.3 **Observations and projections of climate change in the UK**

Using ENSEMBLES regional climate change projections (van der Linden and Mitchell, 2009), Heinrich and Gobliet (2012) showed that the signage of future rainfall projections as a result climate change in the UK are less clear than in much of the rest of Europe. The trend of average summer rainfall is especially unclear, although any deviation from the historical mean is unlikely to be large by the 2040s. Spring and autumn are found to be equally uncertain, but increases in mean rainfall are found across the range of projections for winter. However, temperature increases are projected across all of the climate model range for every season, thus increasing Potential Evapotranspiration (PET) rates. Interannual variability is found to be likely to increase in the UK, both for temperature and precipitation, with more frequent and intense wet events projected to occur. Heinrich and Gobliet (2012) show that the extreme south and north of Europe have very defined climate change projections and associated risks, whilst the central latitudes show far more uncertainty and less acute risk. In each case, it should be stressed that the mean model projection is stated here, so the range of uncertain results from the ENSEMBLES models used are not taken into account. The lack of clarity over the signage of summer precipitation changes in the UK is also seen in the UK Climate Change Projections 2009 (UKCP09) (Murphy *et al*., 2009), which are used in this research project, but wetter winters are projected across >90% of the probabilistic range for most of the UK (Figure 2.6).

Precipitation trends seen in the England and Wales observed dataset indicate an increase in seasonality, with wetter winters and drier summers. Spring and autumn periods show no trend. Summer average rainfall amount has dropped by ~40mm over the three months of June, July and August (JJA) between 1951 and 2010, whilst winter average rainfall has increased by ~10mm over the three months of December, January and February (DJF) (Simpson and Jones, 2012). These changes vary regionally, and so an assessment of trends for the catchment is a useful precursor to any climate change impact assessment. The seasonal rainfall record for the Upper Churnet (UC) catchment in Staffordshire, UK, where this research project focuses, is shown as an example (Figure 2.7). It can be seen that there is no observable trend through the observed record in any season. Average rainfall in the catchment is substantially greater than the England and Wales average (Simpson and Jones, 2012). Despite the lack of a trend in average rainfall, there are more frequent local arid conditions, as indicated using the 12-month Standardised Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano, 2009) (Appendix C). Rainfall intensity has increased across much of the UK from the middle of the 20th century to the present, with a greater contribution of total rainfall coming from the most extreme events (Maraun *et al.*, 2008; Jones *et al.*, 2013).

Assessments of outputs from the UKCP09 data showed that the trends for climate variables in the UK were broadly similar to those expressed in the UK Water Industry

Research (UKWIR) assessment in 2006, with some minor differences and a larger spread of results (von Christierson *et al*., 2009). As projections are created for longer time horizons (e.g. 2080), the climate signal becomes clearer and overpowers natural variability (von Christierson *et al*., 2009). Over the next 30 years or so different emissions scenarios do not produce notably different projections due to the dominance of natural variability and greenhouse gas loading already in the atmosphere from past emissions (Wilby and Harris, 2006). The UKCP09 data (Figure 2.6) and other climate modelling studies (such as Bates *et al*., 2008; Maraun *et al*., 2008; Heinrich and Gobiet, 2012; von Christierson *et al*., 2012; Rahiz and New, 2013) project the following for the UK:

- All areas warm, particularly in the summer, with projected mean temperature increases for the 2080s ranging from 2.2 to 6.8°C in the south of England. This creates an increase in PET which affects surface water resources, and a demand increase as temperatures rise.
- Higher sea-surface temperatures (SSTs) in the Atlantic will increase the severity of winter storms
- With the increase in mean temperatures comes a substantial increase in peak temperature summer days, with substantial heterogeneity dependent on location.
- Nearly all simulations suggest that winter rainfall will increase by the 2080s as the seasonality of UK rainfall is accentuated in many regions (Figure 2.6). The extent of this increase is highly uncertain. Winter refill is essential to water resources, but this precipitation is only effective if sufficient infrastructure is in place to put it to use. The

effect is highly regional, with evidence to suggest that the south and west are set to become predominantly drier in the summer whilst the north and east will become predominantly wetter in the winter.

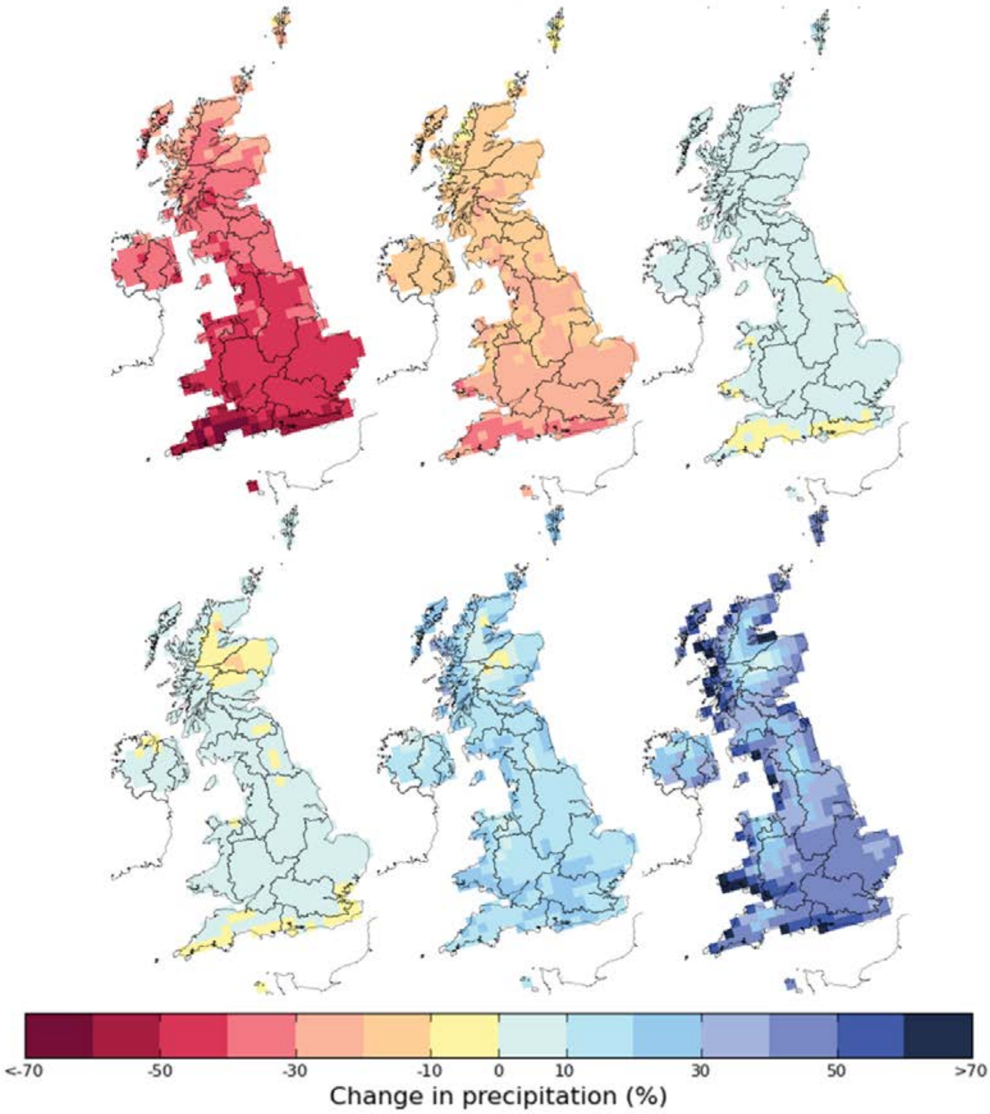


Figure 2.6. Percentages changes in summer (top) and winter (bottom) precipitation in the 2080s compared to the 1961-1990 baseline using the medium (SRES A1B) emissions scenario. Left: 10% probability level (very unlikely to be less than); middle: 50% probability level (central estimate); right: 90% probability level (very unlikely to be more than). (© 2009 UK Climate Projections)

- Most of the simulation range suggests that summer precipitation decreases (Figure 2.6), with an unchanged or slight increase in mean annual rainfall in much of the UK. Decreased summer precipitation will reduce runoff and increase the demand for water use during peak months.

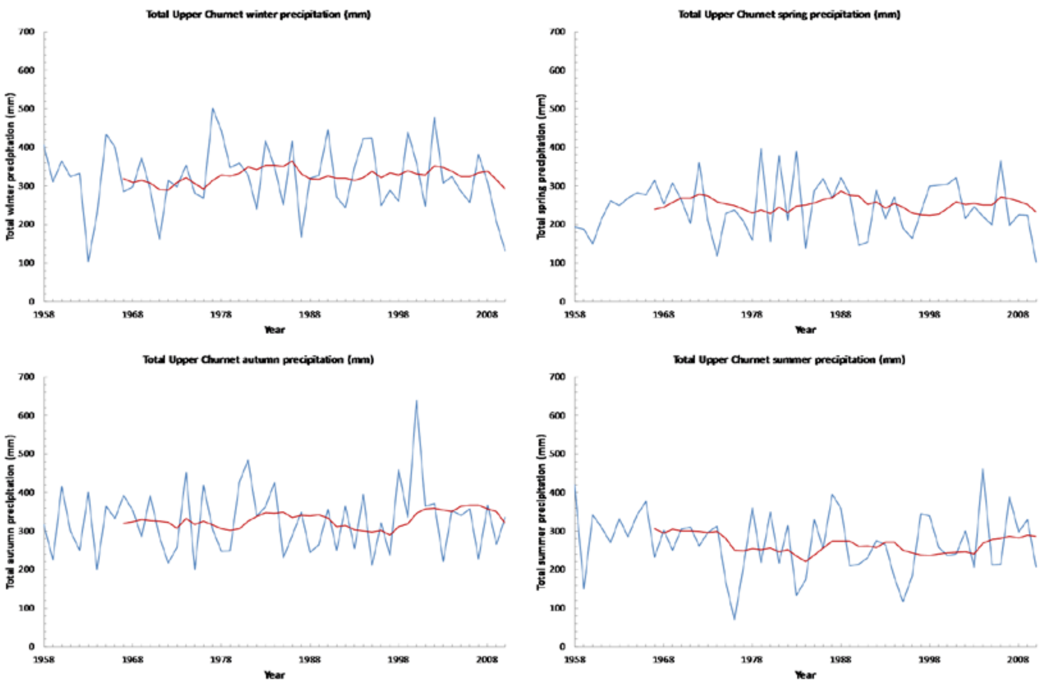


Figure 2.7. Observed seasonal rainfall at Upper Churnet, Staffordshire. Clockwise from top left: winter, spring, summer, autumn.

- Projected future summer rainfall reductions and winter rainfall increases are particularly evident in the south. Scotland in particular is likely to see less change to summer averages. The greatest mean summer temperature increases are projected in the south and east of England, although the largest increases to peak summer temperatures are in Scotland.

- England and Wales will become more susceptible to long dry periods of various intensities, whilst Scotland and Northern Ireland are likely to see less aridity.

The effect of these changes to temperature and precipitation on flows and water storage in the UK are discussed in Section 2.2.4.

2.2 The effects of climate change on water resource shortage

2.2.1 **Overview**

Extreme dry events represent a huge challenge to natural resource managers. Periods on the edge of past experience force decisions to be made outside out of normal management plans, leading to inherently ad-hoc responses and therefore increasing the scope for maladaptation (Gallant *et al.*, 2012). As climate change increases the extremity of dry events, those events that are on the edge of what is seen in the instrumental record become more common and hitherto unprecedented events occur with no procedural framework existing for how to deal with them, exacerbating the problem. Enhancing capabilities for responding to such events requires eschewing reliance on the instrumental record and looking towards using representations of future weather sequences for planning purposes (Milly *et al.*, 2008). That is, the past is no longer a suitable analogue for the future.

Unfortunately it is the case that our most reliable knowledge on how the climate will change in the future lies in variables that are not of paramount importance to decision-making on water resources, such as mean rainfall changes rather than extreme low or high events (Stakhiv, 2011). It appears then, that effectively planning for future climate change impacts on water resources suffers from the twin difficulties of the instrumental record not supplying the necessary range of events to plan against, and the projections of the future struggling to describe the extreme meteorological events within a changed climate at high resolution for water resource management purposes (Harris *et al.*, 2012).

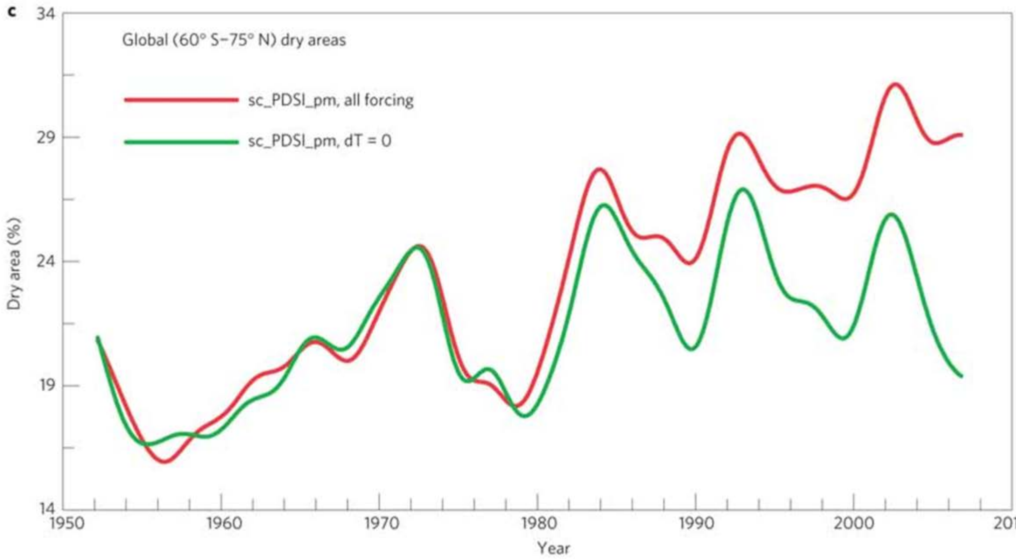


Figure 2.8. Smoothed time series of drought area as a percentage of global land area based on the Palmer Drought Severity Index (PDSI) with (red line) and without (green line) the observed warming. A drought area is defined locally as a PDSI value below the twentieth percentile of the 1951-1979 period. Reproduced from Dai, 2012.

2.2.2 **Observed global impacts**

Decadal-scale drought periods have occurred frequently over the last millennium across the planet, with anomalous SSTs generally the cause (e.g. La Nina-like anomalies creating drought in North America, El Nino conditions leading to drought in east China). Local feedbacks elongate and strengthen drought episodes (Dai, 2011). Global aridity has risen significantly since the 1970s, in line with many other fingerprints of climate change, although significant regional differences exist dependent on climate type and physical catchment structure (Figure 2.8) (Dai, 2011; Dai, 2012; van Lanen *et al*., 2013). Observational records and climate projections have shown that climate change has lead to the alteration of the large-scale hydrological cycle, including increased atmospheric moisture demands and changes to circulation patterns that, alongside the usual pattern of SST anomalies, has created more major multi-seasonal instances of drought (Bates *et al.*, 2008). Most GCMs show a general picture of decreased daily precipitation frequency and increased precipitation intensity in the future, signifying more intense and extreme precipitation events (Sun *et al.*, 2007), which is in-line with recent observations (Coumou and Rahmstorf, 2012). As a result, GCMs indicate an increase in aridity in vast areas of the world over the coming century with more widespread severe droughts and soil moisture reductions (Dai, 2011; Lee and Kim, 2013).

Studies focussing on detecting trends in observed runoff records on various scales are numerous, and many of them are framed within analysing the effect of climate change. All major river systems have analyses of historical trends associated with them, and basins with extreme and recent drought events or glacier loss have had particularly large amounts of research afforded them (e.g. the Murray-Darling basin in Australia and the upper Brahmaputra in the Himalayas) (Gallant *et al.*, 2012; Kirby *et al.*, 2013; Mukhopadhyay, 2013). As well as the catchment-specific assessments (Abdul Aziz and Burn, 2006; Chen *et al.*, 2007; Lorenzo-Lacruz *et al.*, 2010; Xu *et al.*, 2010; Zhang *et al.*, 2012; Gao *et al.*, 2013; Wang *et al.*, 2013; Yong *et al.*, 2013), other studies focus on providing overviews of continental or global trends (Bates *et al.*, 2008; Mahe *et al.*, 2013) or assess historical flood and/or drought events (Lehner *et al.*, 2006; Dai, 2011; Lee and Kim, 2013).

Bates *et al*. (2008), a technical review of climate change and water as part of the AR4 report, showed how anthropogenic changes to the hydrological cycle have created an increased vulnerability of freshwater resources in many studies of catchments across the world, with wide-ranging consequences for humanity and ecosystems (Figure 2.9). However, many studies at a catchment level have shown varying results when separating climate change impacts from human interventions such as economic development, soil and water conservation and water projects (e.g. Chen *et al*., 2013; Gao *et al*., 2013). Only two-thirds of the world has reliable streamflow gauge records, making a complete picture of global flow changes problematic (Bates *et al*., 2008). Palaeoclimatological techniques for extending streamflow records have proved useful in some areas (Wise, 2010; Starheim *et al*., 2013), but with specific conditions needed for the preservation of proxy climate information this is not a universal solution.

Broadly speaking, changes to observed runoff in the Anthropocene differ greatly across regions, with high latitudes and large parts of USA seeing increases, and West Africa, southern Europe and southern South America seeing decreases. Crucially, there is good evidence to suggest that timings of river flows are being altered by climate change across the world, particularly in areas with a high percentage of precipitation falling as snow (Bates *et al*., 2008).

Despite the regionalisation of climate change effects on streamflow, recent catchment-scale investigations into observed runoff sequences are finding the fingerprints of climate change in many areas of the world. Recent research by Wang *et al*. (2013)

showed that anthropogenic forcing was the main driving factor behind the decline in runoff in three Chinese river catchments. An extensive study by Mahe *et al*. (2013) found that river runoff across the major African rivers has been changed by climatic change to precipitation since the 1970s, despite the modification of watercourses by other means such as dams and increased agriculture. Xu *et al.* (2010) conducted an assessment of headstream runoff in the Tarim River basin, Asia, which is heavily dependent on glaciers, showing that increased temperatures have significantly increased glacial melt and associated runoff since 1994 in all rivers of the area, effectively accelerating the hydrological cycle. Barua *et al*. (2013) described how decreased rainfall trends across the Yaara River catchment, Australia, throughout the year from 1953 to 2006 have contributed to the extreme droughts of recent decades in Victoria.

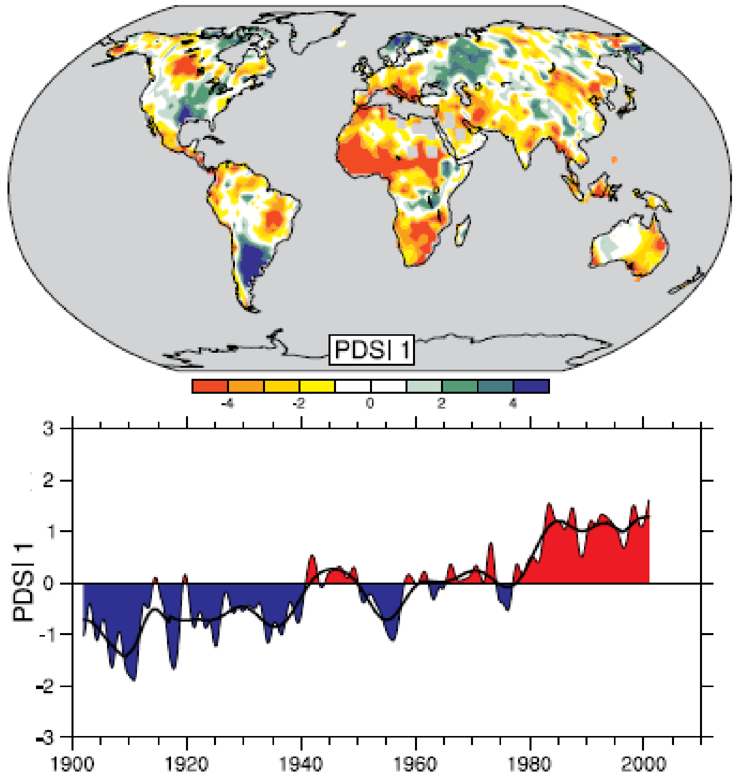
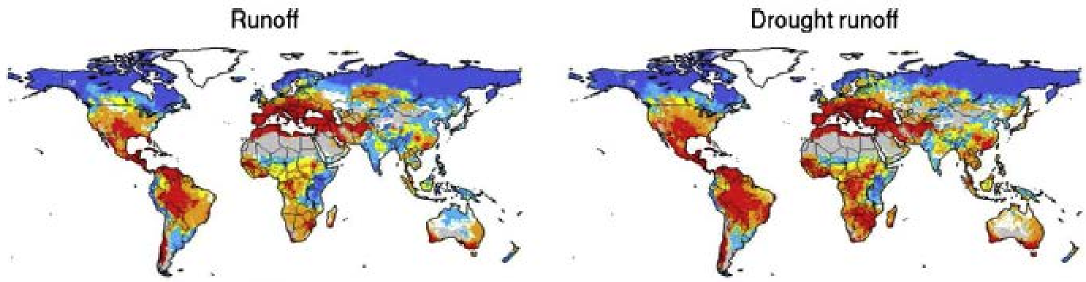


Figure 2.9. Spatial pattern of global Palmer Drought Severity Index (PDSI) change from 1900-2002, and the sign and strength of the global pattern over time. Positive anomalies in the lower panel (red) correspond with drier conditions in the upper panel (negative PDSIs) (reproduced from Bates et al., 2008).



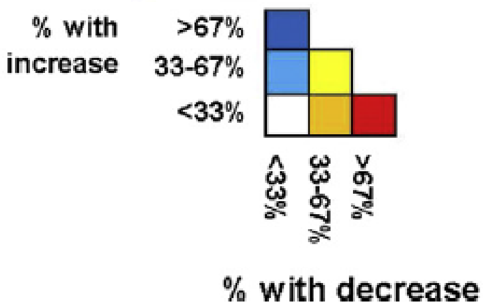


Figure 2.10. Consistency in hydrologic indictor change across an ensemble of 21 GCMs. Global projected runoff and drought runoff in the 2050s (reproduced from Arnell and Gosling, 2013).

2.2.3 **Projected global impacts**

A substantial amount of research has been carried out on projecting how freshwater will be impacted by climate change across the globe, sometimes as a follow-on from assessments of historical trends (Lehner *et al.*, 2006; Fowler and Kilsby, 2007; Vaze *et al.*, 2011; He *et al.*, 2013; Liu *et al.*, 2013; Smiatek *et al.*, 2013) and sometimes as standalone impact assessments (Ng *et al.*, 2010; Ali *et al.*, 2012; Shrestha *et al.*, 2012; Majone *et al.*, 2012; Safeeq and Fares, 2012). Much work has looked at individual catchments and focussed on runoff as the key indicator of change (Evans and Schreider, 2002; Wilby and Harris, 2006; Fowler and Kilsby, 2007; Minville *et al.*, 2008; Cloke *et al.*, 2010; Taye *et al.*, 2011; Vaze *et al.*, 2011; Shrestha *et al.*, 2012; Bennett *et al.*, 2012; von Christierson *et al.*, 2012; Kim and Chung, 2012; Majone *et al.*, 2012; Prudhomme *et al.*, 2012; Safeeq and Fares, 2012; Sulis *et al.*, 2012; He *et al.*, 2013; Liu *et al.*, 2013; Smiatek *et al.*, 2013), whilst others have looked at continental or global runoff (Laurent and Cai, 2007; Todd *et al.*, 2010; Fung *et al.*, 2011; Heinrich and Gobiet, 2012; Schneider *et al.*, 2013; Sperna Weiland *et al.*, 2012; Arnell and Gosling, 2013), regional or global aridity (Dai, 2011; Rahiz and New, 2013), water balances of aquifers and groundwater assessments (Murphy *et al.*, 2004; Scibek and Allen, 2006; Herrera-Pantoja and Hiscock, 2008; Holman *et al.*, 2009; Ng *et al.*, 2010; Jackson *et al.*, 2011; Stoll *et al.*, 2011; Oude Essink *et al.*, 2012; Ali *et al.*, 2012), individual bodies of water (Sahoo *et al.*, 2013) or changes to flood and/or drought events (Leander *et al.*, 2005; Lehner *et al.*, 2006; Ducharne *et al.*, 2010; Khazaei *et al.*, 2012; Sulis *et al.*, 2012; Kidmose *et al.*, 2013).

Using global-scale low resolution hydrological models linked to ensemble GCM data, Sperna Weiland *et al*. (2012) showed that much of southern Europe, Africa and Australia are likely to have reduced average discharge in the 2080s, and most major catchments will be subject to greater extreme high and low flows. Discharges from basins in the high northern latitudes are likely to be substantially increased (Arnell and Gosling, 2013). However, large disagreement between the different GCMs within ensembles exist, and there are only very small areas of the world's surface where all ensemble members project significant change in the same direction of the mean (Laurent and Cai, 2007; Sperna Weiland *et al*., 2012). Furthermore, the research by Sperna Weiland *et al*. (2012) does not take into account the IPCC Special Report Emissions Scenarios (SRES) scenario uncertainty or non-climatic factors (population change, land-use change etc.), both of which substantially increase future discharge uncertainty in many areas (Praskievicz and Chang, 2009).

Figure 2.10 shows projections for mean runoff and runoff during drought periods in the 2050s produced by Arnell and Gosling (2013). It can be seen that runoff is severely reduced over some very large areas (such as northern South America), and increased in others (such as north-eastern Eurasia and north-western North America). Projections for Europe suggest that seasonality of runoff will become more pronounced by the 2050s. This is in-line with research by Heinrich and Gobiet (2012) (Figure 2.11). Similarly, Schneider *et al*. (2013) showed that low flow magnitude is projected to decrease by 30% or more in many major southern European rivers, with little or uncertain change in central, western and Eastern Europe and increased low flows in Northern Europe. The authors further concluded that ecosystem services will be compromised as species' natural environments change in south and north Europe.

Fung *et al*. (2011) reflects the growing pessimism in our ability to mitigate greenhouse emissions successfully (as a result of high profile global climate deal failures such as Conference of Parties (COP)-15 and the Kyoto Protocol) by looking at how a 4°C average temperature rise compares to the common political target of a 2°C rise in a study on global water stress. The authors found that large increases to water stress in the low-to-mid northern latitudes and most of the southern hemisphere are caused primarily by climate change in a +4°C world, whilst population and population density change are the key factors in a +2°C world (Figure 2.12). The changes to runoff show similar trends to the findings by Arnell and Gosling (2013) (Figure 2.10).

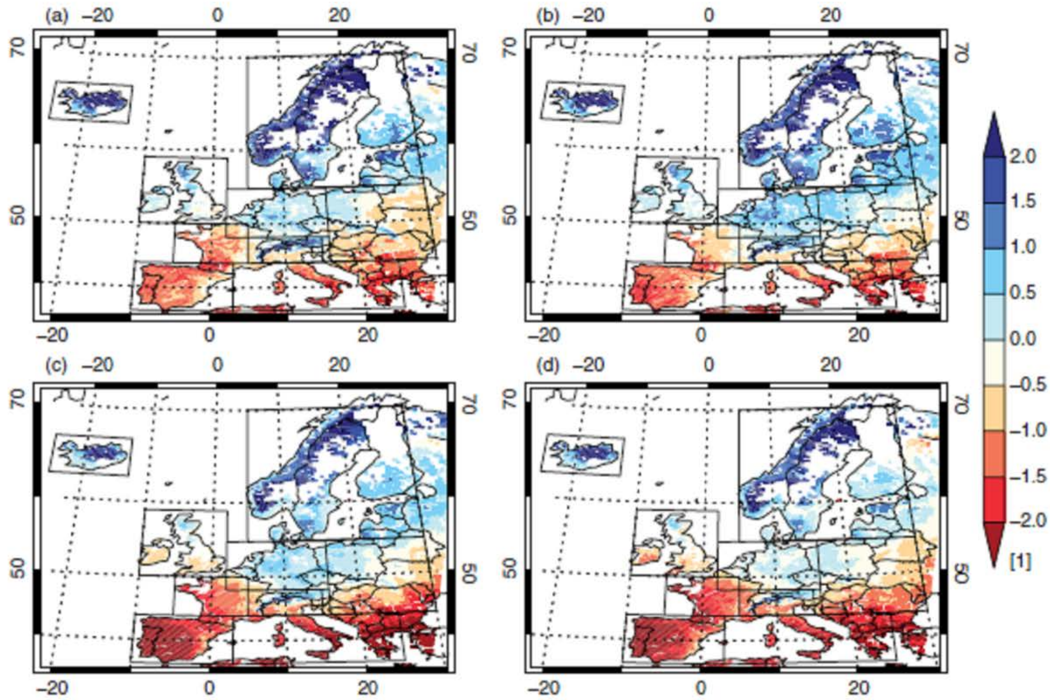


Figure 2.11. Palmer Drought Severity Index (PDSI) change in the 2021-2050 period from baseline conditions (1961-1990) in Europe central estimate. White represents areas with missing soil moisture data or infeasibility of the calculation procedure. (a) = DJF, (b) = MAM, (c) = JJA, (d) = SON. Reproduced from Heinrich and Gobiet, 2012

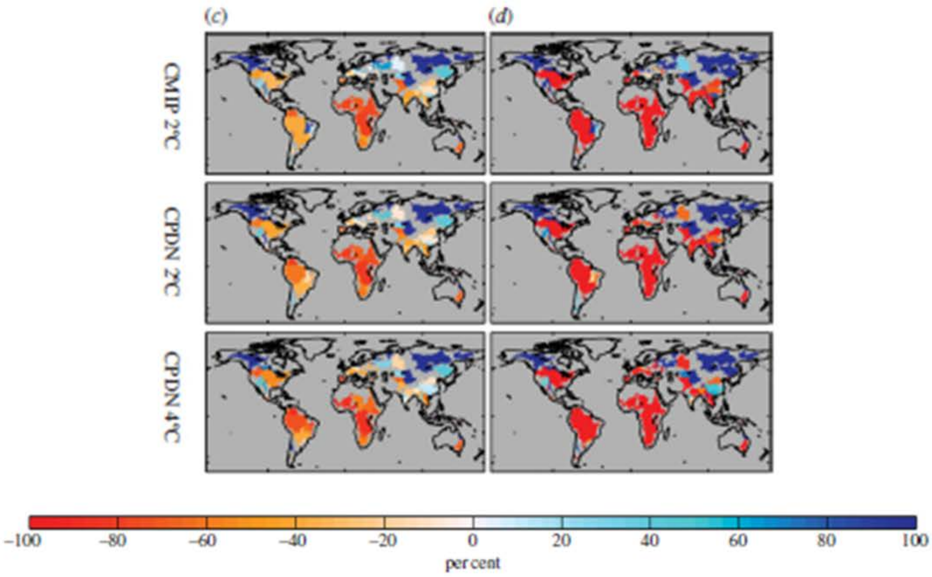


Figure 2.12. Global water stress in the 2080s under 2°C and 4°C global temperature rises. Left: ensemble average change in water stress. Right: model consensus on the direction of water stress. Water stress is defined as the ratio of annual surface runoff to population. CMIP and CPDN refer to different GCM ensembles used by the authors (CMIP only contains one member that reaches 4°C warming, and thus is only used to model 2°C change). Reproduced from Fung et al., 2011.

Examples of hydroclimatological assessments at the catchment level, particularly in areas highlighted in global assessments above as vulnerable, are numerous. In California, He *et al*. (2013) shows that large uncertainties in annual streamflow change is dependent on a variety of temperature rises and precipitation changes, without using specific GCMs. This is an unusual approach which simplifies the climate information, but enabled the authors to show that a shift to progressively earlier peak flow timing with increased temperatures was evident. An increased dichotomy of flow seasonality was also projected. Lauri *et al*. (2012) carried out a catchment-scale analysis of 2030s flows of the Mekong River in Vietnam, finding that there is no definitive trend in the sign of change in either the wet or dry season solely due to climate change forcing, and that projected discharges are more affected by planned reservoir operations. Taye *et al*. (2011) used an ensemble of GCM simulations to project 2050s flows in the Nile Basin. The authors found that increases in peak flows for the Nyando sub-catchment in the 2050s were projected across the model range, with unclear trends for the Laka Tana sub-catchment. Little change to extreme low flow was projected.

2.2.4 **Effects of climate change on the England and Wales water sector**

With the future climate changed from that of today, the water industry will be forced to operate in a more testing environment if Levels of Service (LoS) and environmental standards are to be maintained (Water UK, 2008; Chartered Institute of Water and Environmental Management (CIWEM), 2011). Infrastructure that is strained today may fail under future climates, current water resource management methods may not suffice, and the prediction of demand may have to be adapted. The primary impact of changes to temperature, precipitation and evapotranspiration on the water industry is in the changes to available water quantity. The infrastructure with which the water we rely on is managed, controlled, stored and transported is based on a historical pattern of river flows that is now changing, and can therefore be considered unfit for purpose unless proved otherwise (Gleick, 2011). Furthermore, warmer, drier summers will increase demand and irrigation requirements due to increased evapotranspiration, putting further pressure on the system (Gill and Wood, 2000; Paton *et al*., 2013; Brown *et al*., 2013).

Changes in climatic variables will affect all raw water resources. Surface water reservoirs will have a reduced yield if incoming flows are decreased. Sensitivity of surface reservoirs to climatic changes increases as yield increases as a proportion of average flow, and as storage decreases as a proportion of annual flow. Therefore small, isolated, rain-fed reservoirs with no groundwater element are at particular risk of increased drought, whereas large or inter-connected reservoirs are at less risk (Cole *et al*., 1991; Gill and Wood, 2000; Harris *et al*., 2009). Sustainability may be affected if the sediment yields of inflowing rivers change (Gill and Wood, 2000). The reliability of groundwater abstraction points will be reduced as a result of increased evapotranspiration rates decreasing aquifer recharge. Summer river flows are projected to decrease in much of the UK (Figure 2.13), reducing the potential for direct river abstraction, which is regarded as the most sensitive water supply source to climatic change (Arnell, 1998).

Large variations in hydroclimatological change are projected across the UK, with greater drying and peak temperatures in south east England than elsewhere (Prudhomme *et al*., 2012; von Christierson *et al*., 2012; Rahiz and New, 2013), leading to an increase in extreme drought frequency (Figure 2.15). Extensive research on flows in the UK has been carried out in the recent past, often based on the UKCP09 datasets. Von Christierson *et al*. (2012) studied catchments across the UK in the 2020s, finding that mean annual flow is likely to decrease in much of England except western areas, whilst flows are likely to increase in Scotland and Northern Ireland, with no significant trend in Wales (Figure 2.13). In terms of seasonality, Prudhomme *et al*. (2012) showed using the 11 regional climate models (RCM) ensemble included within the UKCP09 suite of tools that by the 2050s summer flows are extremely likely to be reduced in much of, if not all, the UK, whilst flows are increased across much of the model range in the winter (Figure 2.14).

The key climate threats to water companies vary spatially, with reduced raw water availability, decreased water quality and inundation of assets crucial to Severn Trent Water (STW), sea level rise important to Anglian Water, and flooding caused by increased storm water overpowering sewer capacity threatening United Utilities, South West Water and other western companies (Anglian Water, 2011; Severn Trent Water, 2011(a); South West Water, 2011; United Utilities, 2011). These projected impacts are in line with the expected exacerbation of the meteorological divide in the UK, with south-eastern areas susceptible to increased drought frequency and intensity through reduced river flows and prolonged dry days, whilst north-western areas are at risk of more extreme winter rainfall events, less-reduced or even higher average river flows and associated flooding events (Murphy *et al*., 2009; von Christierson *et al*., 2012).

It has long been asserted that water stress will intensify globally with anthropogenic warming (Trenberth *et al*., 2003), however global-scale studies into climate change impacts on water resources show that in relation to many areas of the world the UK will have relatively minor changes to water stress (Fung *et al*., 2011; Heinrich and Gobiet, 2012; Arnell and Gosling, 2013). This is no cause for complacency, as within the UK physical impacts and the adaptive capacity of humans will vary (Smith *et al*., 2001), creating areas of relatively high impact and stress. For example, a recent study by Rahiz and New (2013) showed that in a majority of England and Wales, persistent droughts (3/6 months) are projected to become more severe and frequent throughout the 21st century, particularly in the south. Drought intensity is projected to reduce in the north of England and Scotland (Figure 2.15). The south-east is particularly at risk of future water shortage as a result of the high water demands of London and the large reductions in flows (<50% to <70%) in some summer months by the 2070s in the River Medway (Cloke *et al*., 2010). Crucially, *all* projections from the UKCP09 subset used by the authors projected decreased summer flows in the catchment.

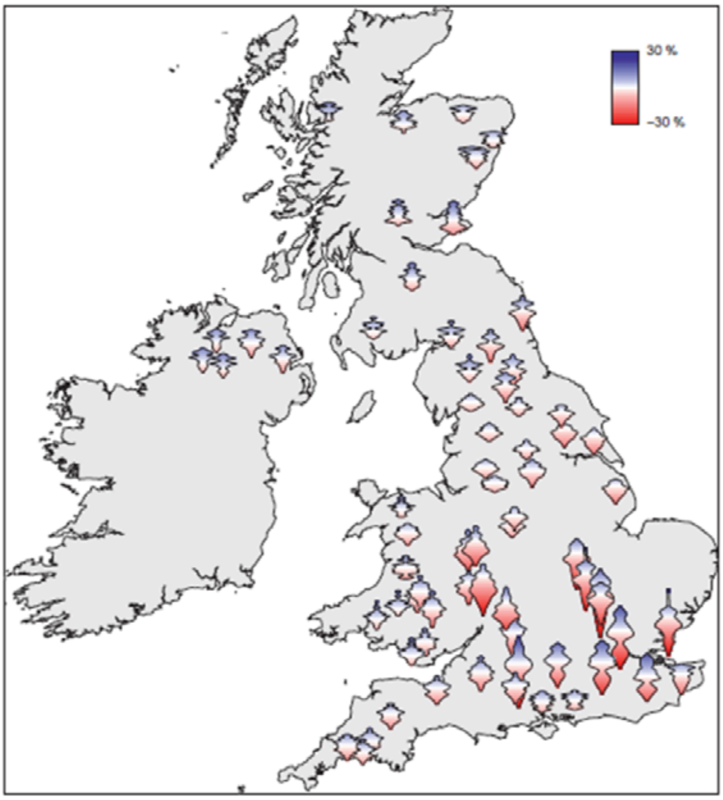


Figure 2.13. Changes in mean annual flow (%) for the 2020s across the UK using UKCP09 climate change forcing. Blue and red colours indicate the position of the distribution with respect to zero change. Reproduced from von Christierson et al., 2012.

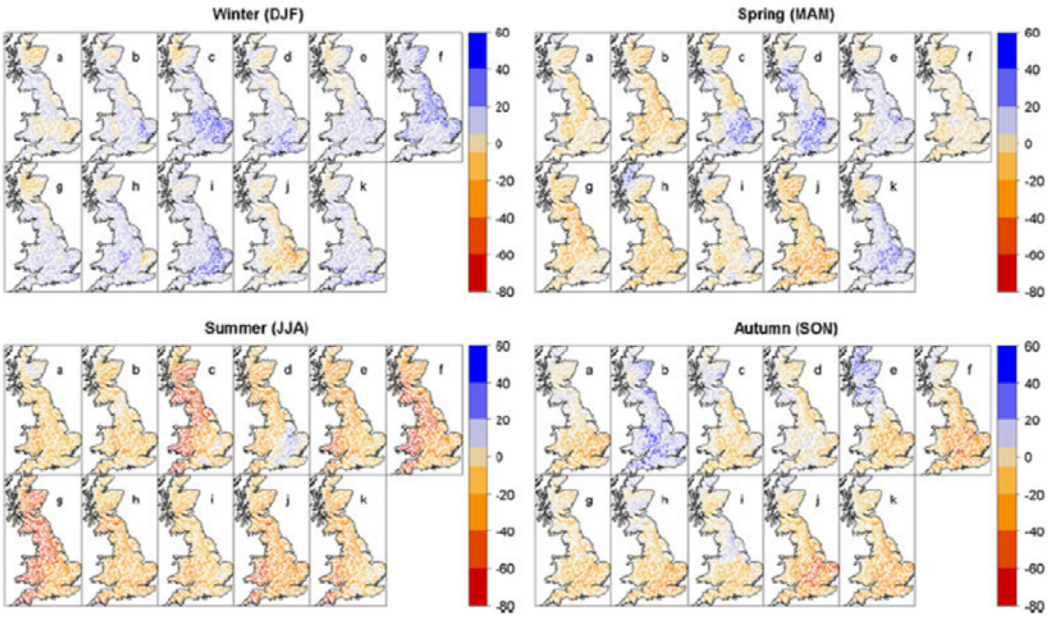


Figure 2.14. Percentage change in mean seasonal flow for the 2050s, simulated using a n 11-RCM ensemble from UKCP09 (b-k), and an unperturbed simulation (a), and the hydrological model CERF (Young, 2006). Reproduced from Prudhomme et al., 2012.

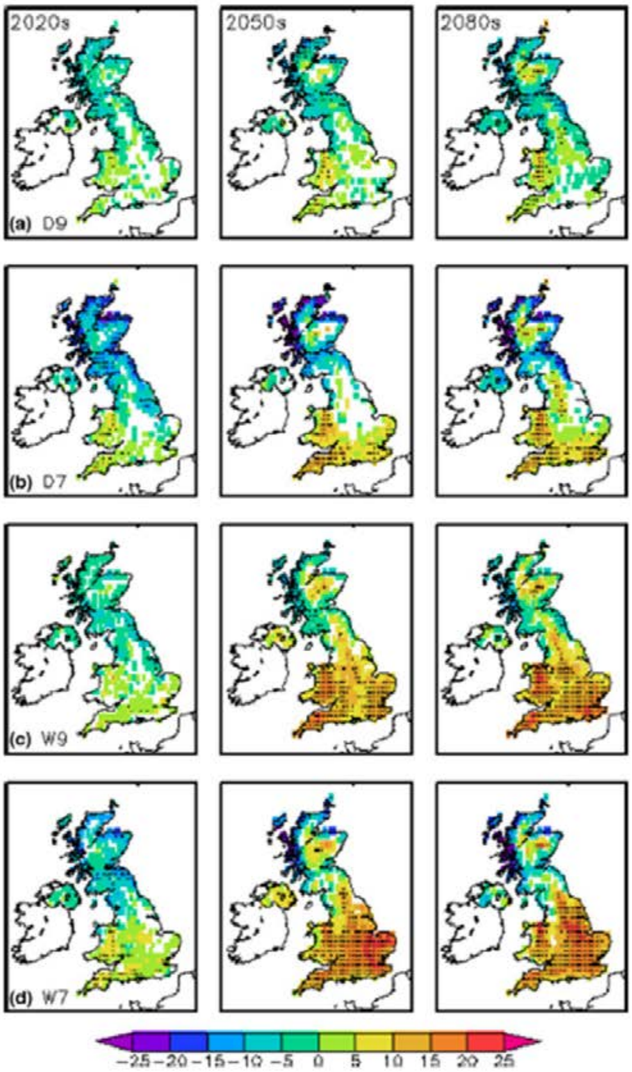


Figure 2.15. Frequency of drought months in the 2020s, 2050s and 2080s compared to the 1980s. Colour bar shows number of drought months per 30 years. Colour denotes agreement on signage of change between 7 of 11 RCMs, black stippling denotes agreement on signage of change between 9 of 11 RCMs. D9 = dry season extreme drought, D7 = dry season moderate drought, W9 = wet season extreme drought, W7 = wet season moderate drought. Reproduced from Rahiz and New, 2013.

By collating the output from the nationwide Climate Change Risk Assessments (CCRAs), required of water companies by the 2008 Climate Change Act, Wade *et al.* (2013) outlined how water supply-demand deficits are projected to change by the 2050s across the UK (Figure 2.16), showing particular pressure on water resources in the south-east of England. Wade *et al*. (2013) also point out the urgent need to balance environmental water requirements with water demand, and suggest that sharing water resources across and within sectors and company boundaries may be necessary, despite the potentially high costs.

2.2.5 **Integrated assessment of water security**

The issues and challenges detailed above relate primarily to water availability alone, but challenges remain in bringing climate change research within integrated water resource management (IWRM) approaches, rather than isolating it as a separate issue. Multiple issues, stakeholders and scales of system behaviours need to be considered when managing water resources. Population change (often driven by immigration/emigration and reduced mortality), land-use change and urbanisation, industrial and energy pressures, demographic change, altered construction patterns and the maintenance of ecosystem services are just some of the factors which influence water supply and quality (Birrell *et al*., 2005; Berger *et al*., 2006; Lehner *et al*., 2006; Croke *et al*., 2007; Hill, 2010; Haasnoot *et al*., 2012; Brown *et al*., 2013; Howells *et al*,. 2013).

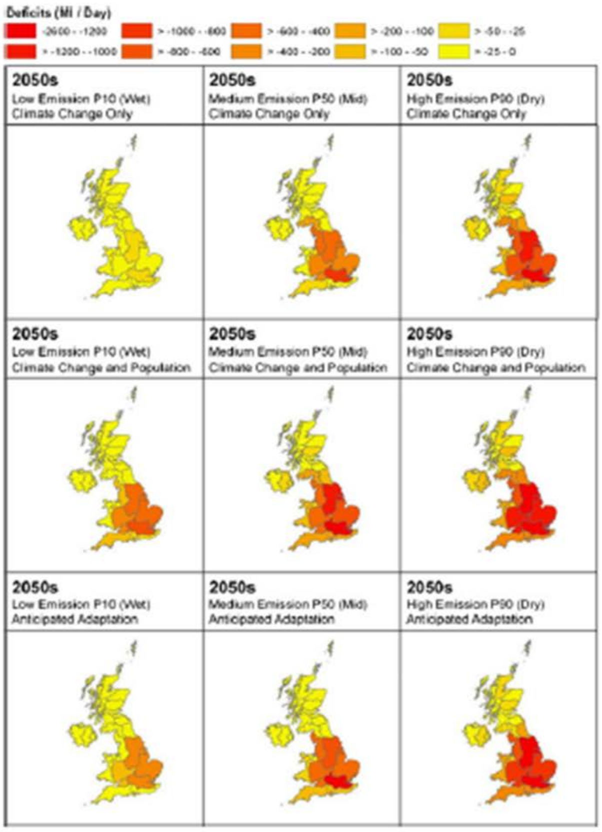


Figure 2.16. Water supply-demand deficit (Ml/D) by river basin region using dry/med/wet UKCP09 scenarios. Climate change only, climate change and population and 'anticipated adaptation' (mostly in the form of demand reduction) are shown for comparison. Reproduced from Wade et al., 2013.

Integrated models driven by climate change scenarios represent useful tools for studying conjunctive use within water resource management areas. One such model produced by Hanson *et al*. (2012), provides a projection of one feasible transient climate projection in California for the 21st century. The study highlights the importance of linking climate models with integrated groundwater-surface water models and agricultural models in order to analyze transitions between different water resource sources in the future (Figure 2.17). An example of the 'side-effects' of climate change impacts on flows in the area is the heightened use of groundwater to mitigate the onset of drought leading to increased land subsidence and reduced water for riparian habitat. Howells *et al*. (2013)

recently introduced a new resource assessment tool for taking into account climate change, land-use, energy and water (CLEWS) when making policy decisions. CLEWS aims to reduce instances of inconsistent strategies across these sectors leading to inefficient use of resources, and has been shown to be effective in a case study of water use in Mauritius.

Wang *et al*. (2013) showed that in many major catchments in China increased irrigation was more important to streamflow and water resource availability than climate variability, clarifying that local factors should be taken into account when making assessments. Kim and Chung (2012) applied a simple spatial downscaling approach in a study of climate change and land-use change on flows in South Korea, finding that climate change had a detrimental effect on adaptation strategies to improve water quality and increase low flows, whilst urbanization increased the effectiveness of the adaptation strategies for both metrics. The research by Kim and Chung (2012) highlights the importance of integrating urbanization/land-use and climate change pressures into modelling endeavours.

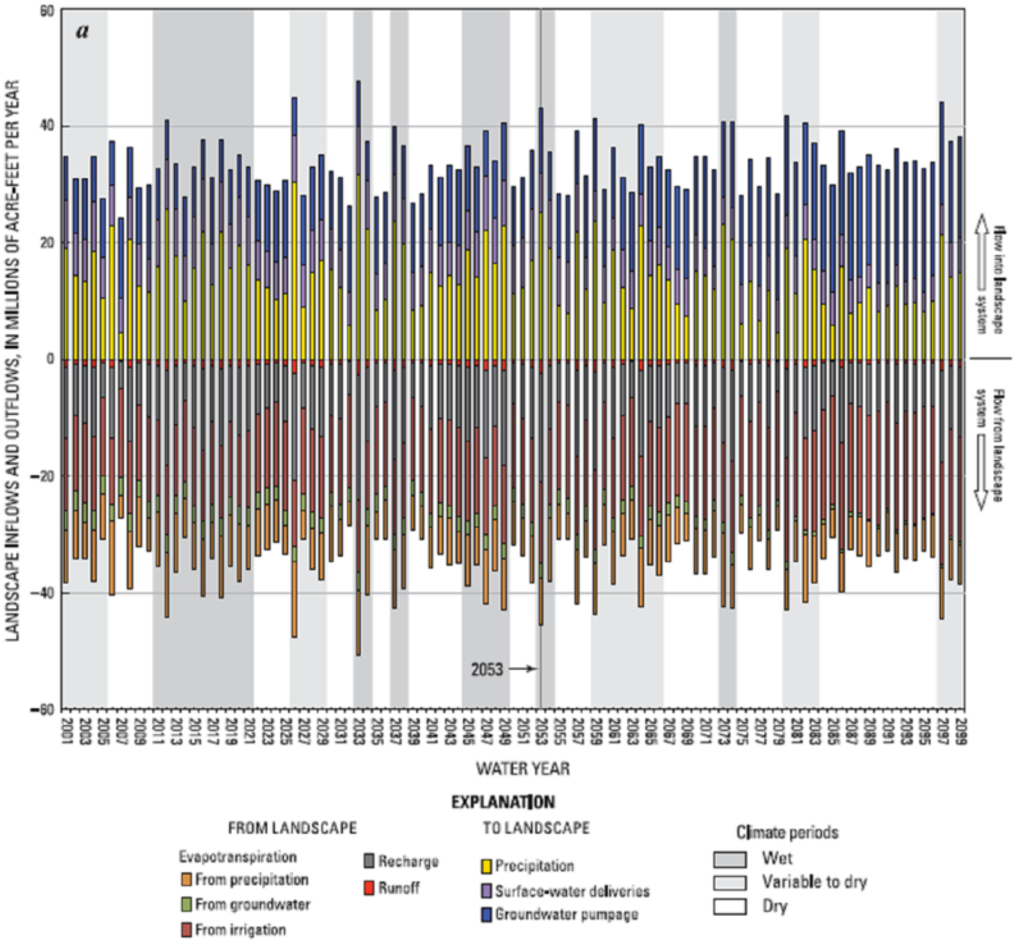


Figure 2.17. Future hydrologic budgets simulated by a Californian water resource system model resulting from a transient climate scenario. Reproduced from Hanson et al., 2012.

Taken together, these studies show that whilst water resource supply and demand models provide useful overviews of the broad range of possible climate futures, integrated studies taking into account further climate change-induced water resource stressors should be considered in decision-making.

2.3 Climate change and adaptation in the England and Wales Water Sector

2.3.1 **Overview of adaptation**

It is becoming increasingly clear that adaptation is necessary if humanity is to successfully manage and overcome the risks posed by climate change given the inadequate multilateral response concerning the mitigation of greenhouse gas emissions (Krysanova *et al*., 2010; Prins *et al*., 2010; New *et al*., 2011; Smith *et al*., 2011; Dow *et al*., 2013). This adaptation is especially necessary in industries where key resources are directly impacted by climatic conditions, such as the water sector (Hall and Murphy, 2012). Adaptation itself covers a broad range of measures and approaches on highly divergent scales which can vary from having few discernible environmental or financial drawbacks, such as smart metering of a utility service for better efficiency, to those fraught with risk and open to moral questioning, such as large-scale geo-engineering of the atmosphere (Bala, 2009; Fox and Chapman, 2011).

Approaches to building climate change information into decision-making structures generally suffer from one of two contrasting problems; they are either simple to implement but lack the ability to deal with all of the potential future situations that arise, or they allow for flexible and comprehensive assessments of adaptations under a broad scope of feasible future scenarios but inherently become too complex (Jones and Preston, 2011). There is now a greater clarity in terms of the direction in which climate change adaptation should be moving in the UK (primarily as a result of UKCP09 and the guidance to water companies promoting the use of probabilistic information (see

Section 2.3.2)), but the development of practical decision-making approaches and the incorporation of uncertainty in order to promote ‘low-regrets’ decisions has been slow to arise (Jones and Preston, 2011; Arnell, 2011(b); Wade *et al*., 2013).

The first key milestone towards more effective climate change adaptation in the water sector is a detachment from predict-and-manage approaches, where an expected future is described by a model and effective adaptation measures are selected based on that. Beyond this, more complex and integrated risk management includes wide ranges of risks and uncertainties can be produced (Jones and Preston, 2011).

Adaptation strategies across all sectors must be developed that are as robust and ‘no-regrets’ as possible, even given a large range of plausible futures (Dessai *et al*., 2009). Effective management, aided by better tools to make beneficial adaptation decisions, is regarded as more important to increasing water supply resilience than the ongoing improvement of climate modelling and technologies involved (Howard *et al*., 2010; Gober, 2013). However, despite substantial literature on the clear need for adaptation of water supply infrastructure in the face of modelled climatic changes over the 21st century, the extent to which it has been meaningfully carried out in developed nations is surprisingly minimal, with large regional and sectoral variances (Krysanova *et al*., 2010; Ford *et al*., 2011). Climate-related disasters and national legislation remain the key drivers for adaptation, whilst uncertainty in climate projections, lack of finance and poor cooperation are oft-quoted barriers to the implantation of adaptation approaches (Krysanova *et al*., 2010). On a global scale, mitigation can be considered the best form of adaptation as the reduction of greenhouse emissions carries few negative effects and combats the anthropogenic climate change cause rather than dampening the severity of its effects (Bartlett *et al*., 2009). However, global scale mitigation efforts have proved problematic at best (Prins *et al*., 2010), so the burden to maintain services despite climate change often lies with individual organisations.

Much is made of the risks and threats associated with climate change, but often the opportunities that it provides are overlooked. In many sectors, the uncertainty involved with climate change acts as a stimulus to alter outdated decision-making processes that assume stationarity in the climate. Changing such a core process within an organisation (such as long-term water resource planning or national health strategies) is daunting, but the added depth of understanding that can be gained from analysing processes across uncertain futures can actually produce many benefits to an organisation, chiefly in increasing system resilience (Hall *et al*., 2012(a))

2.3.2 **Past and current consideration of climate change in the England and Wales water sector**

Climate change adaptation planning for water resources in the UK has existed since the mid 1990s, with the current situation based upon the gradual build-up of hydroclimatological change knowledge over the previous two decades (Arnell, 2011(b)). However, only in the last decade have specific guidelines for *how* to incorporate climate change into England and Wales water resource planning been developed (Environment Agency, 2003). The UK Climate Impacts 2002 (UKCIP02) projections, which incorporated the SRES (Nakicenovic *et al.*, 2000), became the standard cross-sectoral approach for climate change impact assessments in the UK (Hulme *et al.*, 2002). As a result, a more standardised consideration of climate change was taken across the water companies. However, despite projected deployable output (DO)[1] reductions of up to 10-12% by 2030 in some water resource zones (WRZs), climate change was deemed less significant that many other drivers by companies. This resulted in there being no extra investment to address climate change in the final determination of prices for The Third Periodic Review[2] (Ofwat, 2004), and therefore little in the way of climate change adaptation occurred (Arnell, 2011(b)).

The delay of the UKCP09 projections from the original planned release in 2008 meant that they were too late for inclusion in The Fourth Periodic Review of 2009, so an interim approach utilising outputs from an ensemble of GCMs used in the IPCC AR4 report was included instead (UKWIR, 2006). The Water Resource Planning Guidelines

[1] Deployable output is the output of a group of sources and/or bulk supplies when a number of constraints (environment, license, pumping plant / well / aquifer properties, raw water mains / aquifers, transfer and/or output main, treatment, water quality) are applied. The term is the core metric upon which water resource management in England and Wales is based, but is given less prominence in this research due to its reduced usability when 'deep' climate change uncertainty is introduced, and the argument that it is abstract and not easily communicable.

[2] Investment made by the UK water industry is defined by 5-year Asset Management Plan (AMP) cycles, at the beginning of which the regulator OFWAT sets prices that water companies can charge customers in a process known as the 'periodic review'. This price-setting determines the amount of money that the water companies can spend over the AMP cycle until the next review. At the time of writing, the UK water industry is within AMP5, with AMP6 set to begin in 2015.

(WRPGs) for the Fourth Periodic Review (Environment Agency, 2007) were more precise than the previous generations, stating that the “mid” estimates of climate impact should be included in estimates of DO, whilst the range of “wet” and “dry” estimates should be included in headroom calculations[3]. This increased complexity in the methodology was matched by explicit requirements to include climate change in company plans for the 2009-2014 Asset Management Period (AMP) (Ofwat, 2008). In contrast to the previous Water Resource Management Plan (WRMPs), climate change was found to be the largest source of effect on projected water supply, and a proposed spending of £1.5 billion on climate change was announced as a result (Ofwat, 2009). However, these investments were delayed until the release and analysis of UKCP09 in June 2009 (Arnell, 2011(b)). Immediately after the release it became evident that finding practical methods for including the probabilistic UKCP09 in UK water resource management would be challenging.

The Climate Change Act 2008 set a requirement for the assessment of the risks climate poses to the water industry over the 21st century, which culminated in the 1st CCRAs (2012) prepared by companies across the UK. Wade *et al*. (2013) analysed the CCRAs, and described the key approaches used by companies to involve probabilistic information in their management plans. The CCRAs identified a variety of risks across

[3] ‘Headroom’ is a term used within the water industry that relates to the provision of extra water availability to account for uncertainties in projections. It is defined by Ofwat as “the minimum buffer that a prudent water company should allow between supply and demand to cater for specified uncertainties (except for those due to outages) in the overall supply and demand balance”

the water companies, but water availability and potential climate change-induced shortage was a recurring theme and accounted for a majority of the research carried out. This is as a result of projections showing increased dichotomy of seasonal rainfall in much of the UK, potential increases to drought magnitude and frequency, and widespread temperature-induced PET increases (Murphy *et al*., 2009; Burke *et al*., 2010; Rahiz and New, 2013; Wade *et al*., 2013). The CCRAs have been useful to provide underpinning knowledge for the National Adaptation Plan, which is currently being developed by the UK and devolved Governments (Wales, Scotland and North Ireland) across 11 sectors (Wade *et al*., 2013).

The new Draft WRMPs (2013), which have been re-submitted by water companies after consultation for final publication in 2014, build on the CCRAs to take UKCP09 into account by sub-sampling the range of projections and including it as headroom in the DO calculations (Severn Trent Water, 2013; Thames Water, 2013). These reports assign mostly qualitative determinations of risk to operations, and little or no use of weather generator (WG) information. There is also a continuation of the prominence afforded to central estimates from previous work using UKWIR 1997, UKCIP02 and UKWIR 2006 approaches, which has been shown to increase the potential for over-confidence in future water supply estimates, potentially leading to maladaptation (Harris *et al*., 2013(a)).

Despite the issues relating to the use of climate change information in the water industry detailed above, water companies have spent considerable resources assessing and appraising potential adaptation options using risk-based approaches over the course of AMP5 (2009-2014). STW's CCRA (Severn Trent Water, 2011(a)) describes 33 options for maintaining water supply under stressed future conditions, as well as an approach for ranking them (based on flexibility, sustainability, equity, cost, acceptability, effectiveness, timing, coherence and robustness). However, it is not possible to fully include climate change uncertainty in this type of assessment, as assigning one value to 'effectiveness' of an option is not viable when the extent to which water is able to be supplied across a probabilistic range of futures will not be consistent. This shows that although climate change adaptation is being taken into account, the decision-making structures utilised in the water industry are not set-up to get the optimal information from uncertain data on future conditions (Stakhiv, 2011).

Although water companies in England and Wales consider both supply and demand side water resource supply options in a 'twin-track' approach, there is a clear preference shown by decision-makers to focus on the supply side due to uncertainties and a lack of confidence in the effectiveness of demand side options such as leakage reduction and smart-metering (Charlton and Arnell, 2011). In the WRZs where climate change has been identified as an important driver of change, it is generally the development of new resources that gains favour in the option appraisal system, primarily as the gains made by demand-side measures are considered to be inconsequential compared to the climate change impact. This has been found to be largely due to the least-cost capacity expansion optimisation analysis approaches used, with other techniques such as robust decision-making (RDM) suggesting demand-side measures to be of more consequence (Matrosov *et al*., 2013).

2.3.3 **Barriers to progress**

There are many barriers that hamper the incorporation of uncertain climate change information into decision-making in the England and Wales water sector. The alteration of practice represents a paradigm shift in the way decision-making in the industry works, with a move away from deterministic approaches which assume one sequence of flow can be used as the basis of a management plan towards a 'messier' view of the future in which deep uncertainties provide a plethora of different and equally probable future states (Hall and Murphy, 2012). Water sector decision making, rooted in predict-then-manage approaches and optimization models that assume key features of a system can be predicted, is more suited to a challenging but certain future than an easy but uncertain one. Moving away from these methods is vital should robust assessments of climate change information be taken up, but the difficulty of achieving that cannot be underestimated.

Generic and specific barriers

Arnell and Charlton (2009) divided the major barriers that limit the extent to which climate change is taken into account in water resource decision-making as into 'generic' and 'specific' barriers. The generic barriers concern those that reduce practitioner's ability to apply to the adaptation challenge itself (such as defining the need for adaptation and evaluating what adaptation options are available), whilst the specific barriers relate to individual options (such as physical or financial limitations of an option). It is easy to see how uncertainty in climate change projections substantially increases the generic barriers; the need for adaptation cannot be defined completely, although ranges of the feasible need for adaptation can be constructed, for example. However, the extent to which different adaptation options are affected by this uncertainty is variable, and so it should be possible to identify options that are beneficial to water resource availability regardless of the future that becomes reality (or at least to a pre-determined level of acceptable risk (Hall *et al.*, 2012(b)). Furthermore, some adaptation options are constrained by the current institutional framework more than others, and there is significant divergence between how different stakeholder groups rate various options and the metrics they would employ to do so (e.g. an ecological pressure group compared to the executives of a water company).

Engle (2012), in a study of water resource management bridges and barriers in southern USA, found that several general barriers were prevalent to water resource managers; particularly 'trust, confidence and scepticism' (doubting the validity, or importance, of climate change), 'political' (water conflicts, lobbying efforts by industries) and 'perception and cognitive' (not driven to act until a drought is an emergency). Specific barriers were less forthcoming, although financial restrictions were deemed important to water resource managers.

Uncertainty as a limiting factor

Despite the indications of increased water stress for much of the UK, the concept of climate change struggles to catalyze action in the water resources sector, where dealing with uncertainties when making high cost decisions creates inertia (Stakhiv, 2011). Decision-making approaches in the industry have traditionally been based on deterministic approaches, with the historic dataset normally seen as an envelope of variability within which the future will also lie. Over-reliance on a single simulation can lead to maladaptation, as decision-makers would be given no indication of where the size of the impacts produced by the research lay in relation to other climate models or emissions scenarios. However, it is still often seen in industry as an advantage to have a single representation of the future, as from a planning perspective a certain but difficult future is often preferable to an uncertain future with relatively small impacts. This accounts for the reluctance to move towards probabilistic and risk-based perceptions of the future in many industries where stationarity and deterministic projections of the future have been the norm. With probabilistic information, the data available to planners can be seen as being accurate but not precise, whereas deterministic approaches are extremely precise but unlikely to be accurate (Figure 2.18), resulting in false positives or false negatives. 'Predict-and-provide' approaches cannot prevail when precise information is not available (Dessai *et al*., 2009). As a result, significant conceptual challenges remain before more robust water resource management that uses uncertainty as an 'asset' to the decision-making process must be overcome (Arnell, 2011(b)).

Shifting perceptions of risk

For such a movement away from 'predict-and-provide' to occur in the water industry, the perceptions of risk held by resource managers must change. STW state in their CCRA that a decrease to the 50^{th} percentile water supply confidence level is appropriate from 2035 onwards as a result of "longer term uncertainties around issues such as climate change and water quality" which make avoiding expenditure on "long-term schemes that prove unnecessary" viable (Severn Trent Water, 2011(a)). This suggests that the default position is to assume that the risk of over-mitigation or over-adaptation is more worthy of attention that the potential for low-probability, high risk catastrophes, which is at odds with much academic research into climate change impacts (Gerst *et al*., 2013).

Timescales

Although the 5-year AMP cycles employed within the UK water sector since privatisation in 1989 have been successful in driving improved water quality and environmental standards, they are not best suited for incorporating climate change into planning decisions. It is unlikely that climate change would be a primary concern within any one AMP cycle due to their short time-span, so the gradual build-up of climate-related water stress continues largely unopposed by adaptation measures. In that respect, increased water shortage periods due to climate change represents a 'chronic problem' to the water industry; the short-term pressures and risks which the industry is used to dealing with are not apparent, but the long-term threat is substantial. Longer 25-year planning horizons are also in use, and are the basis of company WRMPs, but with the allocation of funds based on the 5-year cycle, the importance of the longer periods is diminished. The shortcomings of AMP cycles are highlighted by a STW stakeholder workshop in 2012, where upon being asked “When planning ahead, how quickly should we take action to reduce risks posed by long-term changes to our weather?” only 3% of those present suggested that it was reasonable to adapt in the next five years, despite 97.1% stating that climate change posed ‘significant’ or ‘very significant’ risks to the company (Severn Trent Water, 2012(a)).

2.4 Uncertainty

2.4.1 Climate uncertainty

Uncertainties involved with climate change can be divided into three broad categories; 1: Understanding of Earth system processes (i.e. epistemic uncertainty) and climate sensitivity (which also includes our ability to reproduce that understanding in models). 2: Future anthropogenic emissions or scenarios of socio-economic future states, and; 3: Deep uncertainty, or non-linear climate change. In climate change impact assessments, non-linear events are rarely taken into account due to the difficulties in modelling such complexities. These three areas of uncertainty are expanded upon below.

1. Our ability to quantify the magnitude, pattern and potential impacts of the changes humanity is inflicting on the Earth is limited by the fundamental incompleteness of our understanding of the climate system, anthropogenic climate change and climate sensitivity. This epistemic uncertainty manifests itself as disagreement between climate models and is a part of any climate change-based impact assessment (Dessai and Hulme, 2004). Selecting the most fit-for-purpose approach when conducting a climate change-based impact assessment and applying it correctly drives down the epistemic uncertainty involved in a study as much as possible. However, the naturally-stochastic nature of the Earth system and the influence of human behaviour means that significant uncertainty will always be involved in a future climate change impact study regardless of the quality and relevance of the climate change

information provided (Gawith *et al*., 2009). It should be remembered though, that uncertainty is an inherent part of decision-making in environmental and social phenomena (Dessai *et al*., 2009) and should not be seen as a vehicle for inaction (see Section 2.4.4).

2. The development of scenarios to describe plausible futures, or storylines, of human society and how they affect the amount of anthropogenic influence there will be on the climate has a long history and makes up an important section of any climate change impact assessment (Leggett *et al*., 1992; Nakicenovic *et al*., 2000; Hulme *et al*., 2002; Arnell, 2004). Since Nakicenovic (2000), the future narratives from the Special Report: Emissions Scenarios (SRES) have become the *de facto* set of scenarios used in global climate change research, and are built into many downscaling tools (including UKCIP02 and UKCP09 (Hulme *et al*., 2002) and the Environment Agency Rainfall and Weather Impacts Generator (EARWIG) (Kilsby *et al*., 2007) and the UKCP09 weather generator (UKCP09WG) (Jones *et al*., 2009)). The SRES scenarios are based on demographic change, social and economic development and the rate and direction of technological change (Nakicenovic *et al*., 2000). Other approaches for developing scenarios specifically for water resource management that take into account climate change have also been developed (Dong *et al*., 2013). The SRES have been replaced in the IPCC AR5 by a new set of scenarios; the Representative Concentration Pathways (RCPs), which are based on the total radiative forcing in 2000 compared to 1750 (IPCC, 2013).

3. Climate change is being realised as the ultimate example of what Rittel and Webber (1974) termed a ‘wicked problem’; something that is difficult to define, has interdependencies that are multi-causal, addressing which leads to unforeseen consequences, is not stable, has no clear solution, is socially complex, does not sit conveniently within the responsibility of any one organisation, involves changing behaviour and suffers from chronic policy failure. Lazarus (2008) and Levin *et al*. (2012) cemented this by suggesting that climate change should be upgraded to a class of its own, or a ‘super’ wicked problem, as a result of having further characteristics such as hyperbolic discounting. Considering the difficulty in dealing with other wicked problems in the water sector, such as the unsustainable state of the Sacramento-San Joaquin Delta where rising sea levels, land subsidence, earthquakes, floods and declining native ecosystems resulted in a descent into competing stakeholder narratives and deadlocked progression as a result of conflicting concerns (Lund, 2012), it is not surprising that progress towards dealing with climate change has been slow. However, it seems that research-based organisations and universities are better placed provide solutions to wicked problems than water companies thanks to a lack of partisan support for one particular discourse (Cash *et al*., 2003), assuming no affiliation.

Non-linear climate impacts, such as the slowdown of AMOC, rapid ice sheet loss, and accelerated carbon release from permafrost and ocean hydrates, add complexity and uncertainty to any climate change assessment as they are extremely difficult to model given that there are no natural analogues for their occurrence (Good *et al*., 2011). The extent of this difficultly in modelling is highlighted by the lack of sea-ice dynamics in sea level rise (SLR) estimates in the IPCC AR5 report (IPCC, 2013). Recent research into structured expert judgement offers a route towards applying expert informed modelling to a problem that cannot be properly modelled by traditional means. This allows for deeply uncertain aspects of climate modelling such as the cryosphere to be included in projections of the future, when in conventional modelling they would have to be ignored (Bamber and Aspinall, 2013; Cooke, 2013).

2.4.2 **Progression from single-simulation to probabilistic impact assessments**

It is clear that assuming stationarity is no longer valid when making decisions on future resource planning (Milly *et al*., 2008), and nor is utilising precise yet potentially highly inaccurate deterministic projections of climate change that lead to overly-confident predictions of future hydrological conditions (Dessai *et al*., 2009; Gosling *et al*., 2012; Harris *et al*., 2012), given the wide range of uncertainties detailed above. Ensembles of GCMs from modelling centres across the world give a better understanding of the uncertainties involved with hydroclimatological assessments and have been used extensively (Shrestha *et al*., 2012; Ott *et al*., 2013; Zhang and Cai, 2013) but their ad-hoc nature means the representation of the entire parameter space they give is unclear. As a result, it is difficult to have confidence that GCM ensembles account for an extensive range of feasible future climates (Gosling *et al*., 2012). It is also difficult to rank or give weighting to different models within an ensemble based on performance, so a ‘best-guess’ equal weighting is normally offered (Knutti *et al*., 2010; Mearns *et al*., 2012). As a result different approaches have been developed, with probabilistic projections of climate change from perturbed physics ensembles (PPEs) such as the

United Kingdom Climate Projections (UKCP09) (Murphy *et al.*, 2009) emerging as an alternative means of projecting future conditions for use in impact assessments in the UK. The UKCP09 methodology involves using different parameter errors which result from imprecise knowledge of what the actual parameter values should be, and applying those errors to one model (HadCM3) in order to create potentially infinite variations of the same model (Murphy *et al.*, 2009).

Probabilistic information can be considered accurate, rather than precise; that is, there is a broad range of plausible futures that should be taken into account, rather than one precise possible future from somewhere on a distribution that may, or may not, be the reality of the future (Dessai *et al.*, 2009). Assuming a precise piece of information (such as using a single or small ensemble of GCM projections) is definitely a true representation of the future can lead to maladaptation, as that particular projection may be *entirely* incorrect (Figure 2.18). Such approaches are still used actively (e.g. von Lany *et al.*, 2013) despite a long period of recommendations otherwise from academia (e.g. Dessai and Hulme, 2004).

Probabilistic assessments of climate change impacts on water provision can be used to provide the information required for robust decision making (Groves and Lempert, 2007; Dessai *et al.*, 2009; Lempert and Groves, 2010)), where the performance of different water resource planning strategies are tested against a set of future hydroclimatological and/or socio-economic scenarios across the range of uncertainty (see Section 2.5). However, the vast array of potential futures provided by probabilistic means does not lend itself to more traditional deterministic/predict-then-manage decision-making approaches used in the water industry, leading to the uncertainty being seen as a barrier to decision-making rather than an opportunity (Section 2.4.4)

Precise projections of the future are still made within water industry output, such as "By 2035 we are projecting a 144Mega-litres per day (Ml/d) loss of DO due to climate change" (Severn Trent Water, 2010, p. 44). Given the uncertainties involved with climate change, a statement like this cannot be made with any confidence, showing that a paradigm shift in the way water resource management is approached is required (Stakhiv, 2011; Hall and Murphy, 2012).

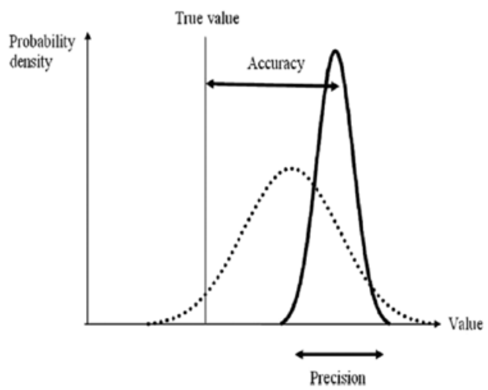


Figure 2.18. Hypothetical example of two future projections, showing the difference between precision and accuracy. In this case, the precise projection (akin to a limited set of projections, or even one projection) is shown to be inaccurate, whilst the wider PDF (akin to a probabilistic range of projections or large ensemble of projections) is shown to be accurate, if imprecise. Reproduced from Dessai et al., 2009.

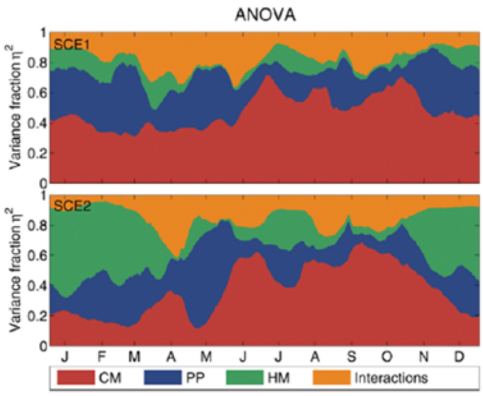


Figure 2.19. Variance decomposition of the uncertainty sources in projections of mean runoff at Diepoldsau, Switzerland, for the 2030s (top) and 2080 (bottom). CM = Climate Model (ensemble of 8 GCMs), PP = Post-Processing (bias-correction and delta change), HM = Hydrological Model (HBV and Prevah). GCM uncertainty is seen to be the dominant source of uncertainty in the summer and autumn of the 2030 and 2080s, but is less dominant in the more remote time-horizon in other months, where the hydrological model choice produces more uncertainty. Reproduced from Bosshard et al., 2013

2.4.3 **Sources of uncertainty in hydroclimatological studies**

Considering uncertainty in hydroclimatological assessments is crucial, as failure to do so results in overly confident predictions of the future. The main sources of uncertainty in such analyses are: future greenhouse gas emissions and other socio-economic scenarios (such as natural carbon sink destruction); climate model selection (either from an ensemble of GCMs/RCMs or PPE range if probabilistic data from one GCM is used, as in UKCP09); downscaling procedure; hydrological model parameterization, approach taken to calculate PET, natural climate system variability, and other changes to the local environment (i.e. global change). Of these, climate model structure, downscaling and natural climate system variability fall within epistemic uncertainty (group 1 in Section 2.4.1), greenhouse gas emissions in group 2, whilst the others relate to difficulties specific to hydroclimatological assessment. Uncertainty group 3, deep uncertainty and non-linear change, is generally not included in such a study due to difficulties in effectively modelling such events. As a result, using even using the fullest available range of a probabilistic array of projections provides “only a certain kind of confidence” that uncertainty is properly taken into account (Stainforth *et al*., 2007).

Research into quantifying uncertainty sources in hydroclimatological studies ranges from looking at one source (Kay and Davies, 2008; Kingston *et al*., 2009; Mehrotra and Sharma, 2009; Bormann, 2011; Chen *et al*., 2011; Deser *et al*., 2012; Velazquez *et al*l., 2013), comparing two sources against each other (Minville *et al*., 2008; Ducharne *et al*., 2010; Lawrence and Haddeland, 2011; Najafi *et al*., 2011; Taye *et al*., 2011; Teng *et al*., 2012; Harris *et al*., 2013(a)), to considering a large range of sources (Kay *et al*., 2009; Prudhomme and Davies, 2009; Xu *et al*., 2011; Dobler *et al*., 2012; Bosshard *et al*., 2013; Paton *et al*., 2013). Uncertainty assessments from other areas impacted by climate change, such as heat mortality and building construction (Tian and de Wilde, 2011; Gosling *et al*., 2012), often use similar techniques. Although each study is catchment specific, much of the body of research finds the choice of climate model (or PPE range) to be the largest source of uncertainty (Minville *et al*., 2008; Kay *et al*., 2009; Prudhomme and Davies 2009; Ducharne *et al*., 2010; Najafi *et al*., 2011; Taye *et al*., 2011; Dobler *et al*.,2012; Teng *et al*., 2012; Bosshard *et al*., 2013), but this finding is not universal (Lawrence and Haddeland, 2011). The uncertainty of extreme events is often influenced more by the downscaling, or post-processing, technique (Dobler *et al*., 2012; Bosshard *et al*., 2013), and the dominance of uncertainty sources can change over seasons and through time (Bosshard *et al*., 2013) (Figure 2.19)

In can be argued that much of the recent research into using water shortage or system reliability metrics for robustness assessments using large numbers of feasible climate futures limits the usefulness of basing uncertainty assessments on flows, and that assessments should ‘skip’ that step and directly assess the metric used by water resource managers (such as Hall *et al*., 2012(a); Harris *et al*., 2013(a); Matrosov *et al*., 2013; Paton *et al*., 2013). In an example of such an approach, Paton *et al*. (2013) found that by extending the uncertainty analysis beyond flows to take into account water resource management in South Australia, demand became the largest uncertainty source (Figure 2.20).

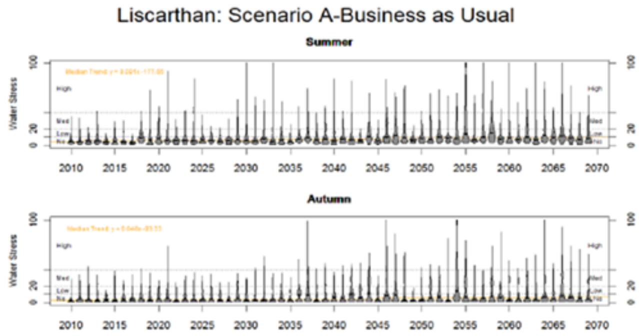
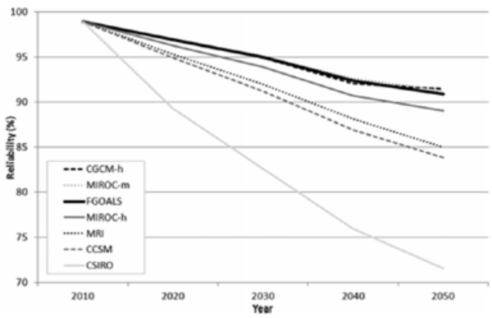


Figure 2.20. Two approaches to assessing water resource robustness. Above: Use-to-resource ratio analysis of abstraction points over a transient climate change projection in Liscarthan, Ireland. Low, medium and high water stress categories are identified. Right: Changes to median reliability (defined as a probability of system failure over the course of a simulation) of Adelaide's southern water supply system for different GCMs. Reproduced from Hall and Murphy, 2012, and Paton et al., 2013, respectively.



2.4.4 **Uncertainty: a vehicle for inaction?**

Given the uncertainty discussed above, the challenge for the water industry is to transform this from a barrier restricting adaptation to an opportunity With the historical preference for precise information against which to make decisions in the water industry, the uncertainty involved with climate change is generally still seen as a hindrance, as shown in these passages from the recent CCRAs:

> *"[the] uncertainties associated with UK Climate Impacts Projections (UKCIP) forecasts and the associated impact on sewerage and water networks may make the definition of effective adaptation measures problematic. In making the case for future investment there needs to be a sound evidence base to justify the benefit of potential investment"* (United Utilities, 2011)

"If new projections are not available we will have to use UKCP09 and acknowledge the level of uncertainty. It is likely that this will make it more difficult to put together a sound business case to secure funding for adaptation options" (Severn Trent Water, 2011(a))

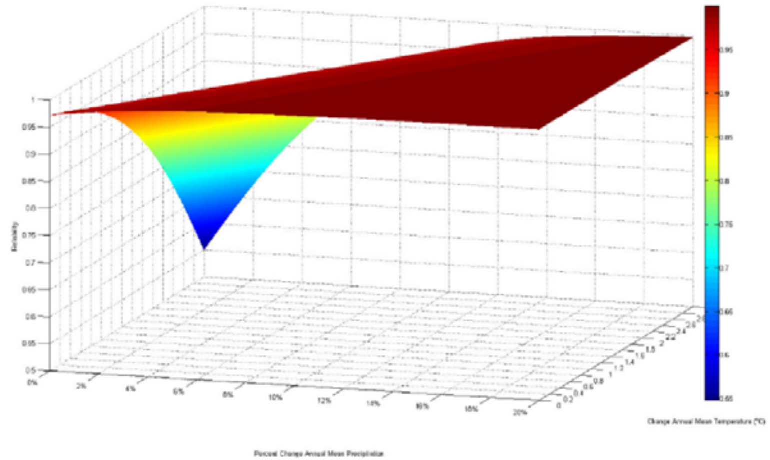
Both of these statements suggest that the uncertainty involved with UKCP09 is something that should be used with reluctance, and then express a hope that any further improvements in any further UKCIP projections would reduce that range of uncertainty. This shows that in the water sector climate change is seen as a science problem which must be solved (by reducing uncertainties and further downscaling of climate data) before action should be taken (Gober, 2013). However, quite the opposite is true; as our knowledge of the climate system increases we become aware of factors that were previously not accounted for or were even not recognized at all, such as the effects of aerosols on clouds (Trenberth, 2010).

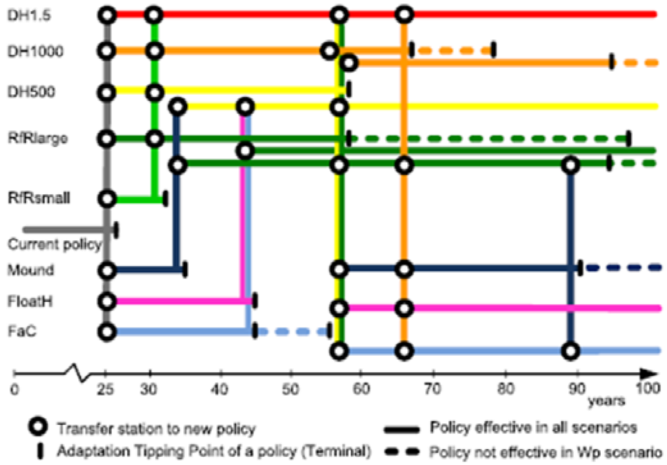
To see an improvement as an increase in precision rather than accuracy shows that water companies struggle to acknowledge that ranges of potential futures would be useful should a change in approach to decision-making on climate change be taken. This explains why attempts to use probabilistic information with decision-making structures designed for individual time series have proved troublesome. In contrast, it is becoming increasingly clear within research that uncertainty involved with climate change projections can be beneficial to the water sector by facilitating exploratory modelling in order to explore the potential success, or otherwise, of various potential adaptation schemes (Hall and Murphy, 2011; Hall *et al*., 2012(a); Matrosov *et al*., 2013). Therefore, translating this to industry applications is a key challenge, and is a broad aim of this thesis (See Section 1.2, Objectives 1 and 6).

A shift needs to take place from focussing attention on reducing, clarifying and representing climatic uncertainty to facilitating the use of uncertainty in a practical sense (Gober, 2013). A number of researchers have led this movement by promoting innovative routes to easing the movement towards decision-making with highly uncertain datasets. Brown *et al*. (2012) showed in a case study of an urban water supply system in Boston, USA, that by understanding the conditions that are of most threat to a system using a climate response function (reservoir reliability) in relation to two variables (precipitation and temperature) it was possible to assess what future climatic conditions will stress a system and work towards adapting to those conditions. This process inverts the usual ‘top-down’ approach to climate change impacts assessment, which begins with a range of climate futures from GCMs supplying the climate scenarios within which the system may exist in the future, to instead use a ‘bottom-up’ approach that discovers the climate hazards that are important to water supply first, detail the exact climate state that triggers that hazard, and then calculate the probability of that climate state occurring using a range of GCM iterations. This is designed to maximize the utility of climate information in water-resource decision-making, and lends itself to probabilistic projections such as UKCP09 (Figure 2.21)

In a case study of the River Waal by Haasnoot *et al*. (2012), a roadmap approach is taken to show where different policy options for overcoming flooding risk become effective (or otherwise) across a range of scenarios. This 'pathways' approach relies on transient climate change information, rather than the stationary 'time-slices' produced by UKCP09. By looking at threats and opportunities as they arise over time, Haasnoot *et al*. (2012) suggest that the dynamic aspect of adaptation that is missed by many long-term water resource management studies can be included. The idea of a 'sell-by date' of a particular policy option is introduced, at which point a transfer to one of a series of other policy options is triggered (Figure 2.21). Gersonius *et al*. (2013) extended this thinking to flood management under climate change-forced futures, resulting in a 'sawtooth' chart explaining the triggering of adaptation measures only when certain conditions are met (Figure 2.22)

Lopez *et al*. (2009) aimed to show how PPEs could be made more accessible to water resource planners if they are presented in the right way and the merits of management options are easily comparable. By describing the PPE range as a fraction of the models in which demand has failed to be met in the case study region in south-west UK, the research shows that large arrays of future projections could be communicated clearly, and the effectiveness of various adaptation decisions on a key metric (in this case meeting demand) could be seen simply using a water resource management model (Figure 2.21). However, the project does little to describe how the ranges of risk that were found can be used in a practical decision-making sense. It is this risk-based approach to using PPE information and water resource models that this research project looks to explore and expand.





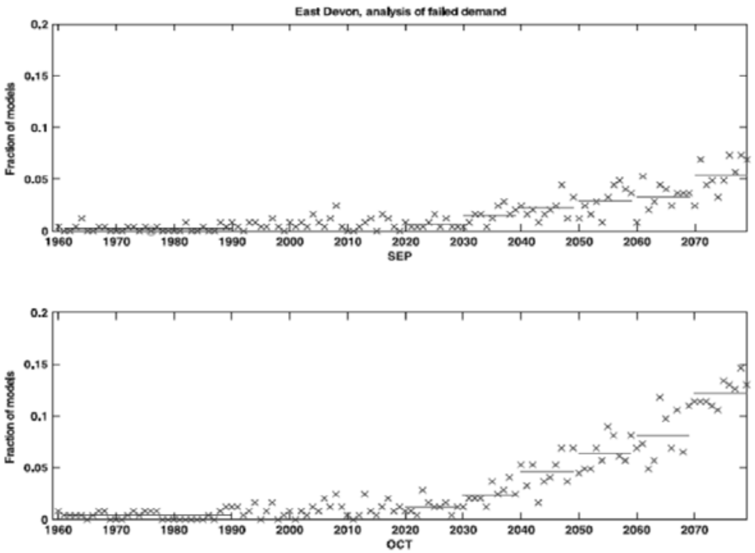


Figure 2.21. Results from three studies showing practical output for water resource management from uncertain climate information.

Top left: Reservoir reliability (defined as probability of modelled system failure) as a climate response function of departures from current mean temperature (°C) and precipitation (mm yr^{-1}). Reproduced from Brown et al., 2012.

Top right: Adaptation pathway map for flood management based on the sell-by-date of policy options. Several different routes are indicated, that would be triggered when climate conditions reach an adaptation tipping point (shown as transfer stations) in the transient climate scenario. Each of the parameters on the left represents an adaptation portfolio. Reproduced from Haasnoot et al., 2012.

Bottom left: Fraction of a range of models that fail to supply September (top) and October (bottom) demand in future time horizons. Horizontal lines represent means over 1960-1989 and the corresponding decades after 2020. Reproduced from Lopez et al., 2009.

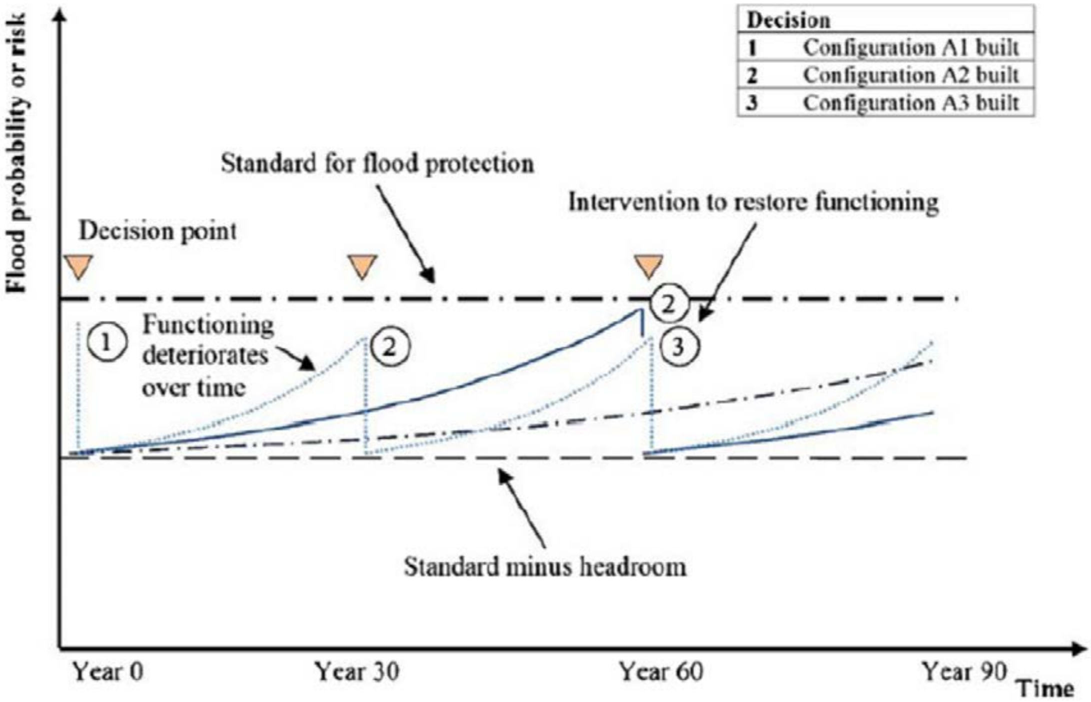


Figure 2.22. 'Sawtooth' chart explaining the process for flexible adaptation of flood management infrastructure under a range of plausible climate futures. Reproduced from Gersonius et al., 2013.

2.5 New approaches to climate change decision-making in the water sector

2.5.1 Climate change risk in the water sector

Risk assessments of climate change in the UK water sector are well-developed, primarily due to the obligations imposed on companies by the 2008 Climate Change Act (e.g. Severn Trent Water, 2011(a); Severn Trent Water, 2012(b)), to the extent that the opening questions of any climate change risk assessment, as defined by Jones and Preston (2011) are well-versed:

1. Is climate change a problem?

2. What are the potential impacts of climate change?

Having been considered across the UK water industry, the answers to these questions vary regionally, although all water providers have some climate change risks and all, to some extent, identify less secure water resources as an impact. With that in mind, this project assumes that climate change, and water shortage in particular, is a problem to water companies, and therefore moves on to answer the next logical questions-

3. How do we effectively adapt to climate change?

4. Which adaptation options are the most effective?

This effectively means that scoping exercises and risk *identification* are complete, and that the work of this project and others in a similar research sphere are focused on producing original and effective means for employing risk *analysis* (where consequences and likelihood are established) and risk *evaluation* (where adaptation/mitigation approaches are prioritised). In doing so, the foundations for the actual risk *management* (where the selected measures are applied) and the monitoring and review of those applications, are lain (Jones and Preston, 2011).

Risk assessment in the water industry has tended to be top-down, or prescriptive, and so has been most suitable for risk identification and scoping. This process has been useful in determining key risks (i.e. question 2 above), particularly within frameworks such as the CCRAs, but it is important to now move away from such approaches toward bottom-up, or diagnostic, techniques, where a resource manager is able to identify several critical paths in order to calculate a range of possible outcomes (quantified in terms of cost, resource reliability, environmental impact or other metrics), thus providing more robust answers to questions 3 and 4 identified by Jones and Preston (2011).

Risk of water shortage is of course not the full representation of water security risk as a result of climate change due to other factors such as water quality, sewerage, flooding events, sludge removal, inundation of water treatment works (WTWs), failure of power supply and storm damage to assets. Ideally, assessments of risk to a company, catchment or sector should be viewed in terms of vulnerability as a whole, rather than focussing on climate change (Jones and Preston, 2011), but this is in practice not easy to achieve, especially with legislation to explicitly assess climate change being enforced on water companies in England and Wales.

2.5.2 **Metrics of risk**

The understanding of threats to water supply in the UK has historically been based around the concept of DO. Values of DO have then been compared to a 'dry year', the difference between which becomes known as 'headroom', acting as a buffer between supply and demand, accounting for uncertainty. The DO is therefore the maximum amount of water available to the region in question during a pre-determined dry period, and any dry period of severity greater than the 'dry year' will cause water use restrictions to be put in place. In terms of climate change impact assessment using uncertain information, DO is unsuitable because it relies on stationarity and an arbitrarily selected dry period upon which to base the calculations, and the terms involved are abstract quantities and thus hard to validate against simulated future sequences. Determining climate change risks requires not only identifying hazards, but also identifying performance indicators and thresholds that enable thorough 'risk discovery' (Brown *et al*., 2012). DO does not serve as a suitable indicator, so better practice would be to define periods of water stress in terms of outcomes such as a water shortage or resultant water restriction (Hall *et al*., 2012(a)). Using such risk metrics makes it easier not only to assess the effect of various stressors or policy decisions upon a system, but for non-experts (and therefore customers) to understand and conceive the state of water resources. This is particularly important given that water company plans must be made available to the public.

As a result, the use of thresholds that denote passing below company LoS of a certain severity has been highlighted as a useful metric for conducting hydroclimatological risk assessments (Hall *et al*., 2012(a); Hall and Borgomeo, 2013). In many areas, those thresholds are manifested as a control curves at a major reservoir. Indeed, information on the breaking of those thresholds in the instrumental record is available already, and can therefore act as a baseline against which to assess future changes to water shortage risk. These pre-determined values for each WRZ would be representative of an unwanted outcome- a water shortage of a certain severity. The range of futures given by the UKCP09 projections can be transformed into a distribution of probabilities of failure to meet a LoS each year for a particular time-slice in the future, which is similar to the approach suggested by Hall *et al*. (2012(a)) (Figure 2.23).

This method results in a statistically robust understanding of the water shortage risks to a supply system in the future, that is, the probability of a particular system 'failing' at a given point in the future. These values can also be compared to a baseline value of water shortage to communicate climate change threat. The determination of an acceptable level of risk is important when analysing the output of such an approach. There would, for example, be little merit in investing in adaptation measures that completely eradicate the possibility of water shortages in the most extreme drought of the driest future scenario. It would stand to reason that the acceptable level of risk for a particular area or sub catchment would remain temporally constant, necessitating a gradual increase in investment to adapt to increasing climate change threats over time.

LoS is only one example of a metric suitable for climate change impact assessment. Other approaches for describing water resource security under future climates include the notion of 'reliability', where the extent of time a system is deemed to be within a state that can be termed as a failure is assessed, resulting in a percentage value (Paton *et al*., 2013) (Figure 2.20). Nazemi *et al*. (2013) use the term system 'infeasibility', which is the proportion of the simulations that stop before a complete run (Figure 2.24). Simply taking inflow to be representative of water resource security is also still common in research (e.g. Smiatek *et al*., 2013). These metrics are particularly useful for studies where the datasets are particularly big (in the orders of tens of thousands of simulations, rather than hundreds) and more in depth assessment of each run is not feasible. Respectively, they allow for an assessment of two parameters at a time in terms of 'infeasibility' or 'reliability', such as shift in peak flow and changes to annual flow compared to a baseline level (Nazemi *et al*., 2013); a comparison of different uncertainty sources such as GCM model, water demand and emissions scenarios across a large range of simulations (Paton *et al*., 2013); and the description of a hydrological model for a data sparse, hydrogeologically complex region of the world (Smiatek *et al*., 2013).

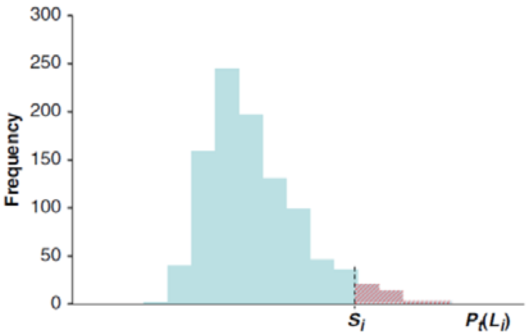


Figure 2.23. Hypothetical histogram of simulated probabilities ($P_t(L_i)$)of water shortage of severity L_i being imposed in a year t. The number of simulations satisfying a target maximum probability S_i enables the robustness of a system to be assessed. Reproduced from Hall et al., 2012(a).

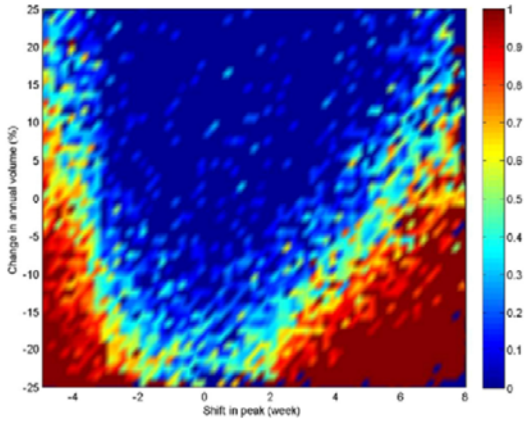


Figure 2.24. System infeasibility under climate change in southern Alberta in relation to shifts in timing of peak flow and changes to annual flow. System infeasibility is defined as the proportion of simulations that stop before a run is completed. Reproduced from Nazemi et al., 2013.

2.5.3 **Robustness assessment and robust decision-making**

It is becoming increasingly apparent that the requirement for water resource systems to exhibit flexibility, which increases adaptive capacity, in the face of uncertain climate change is vital if water supply is to be regarded as secure in the future (Adger *et al.*, 2011). The rationale behind this is twofold:

1. There is a desire to eliminate the possibility of gross maladaptation, where unwise and potentially expensive measures are put in place on the guidance of a single (or perhaps a small number of) climate change projection(s) (e.g. von Lany *et al.*, 2013). Poor adaptation and mitigation could have impacts that match or even exceed the direct effects of climate change (Turner *et al.*, 2010). Policy approaches that focus on short-term benefits and technological fixes fail to address the multiple and interacting factors affecting the resilience of a system (Adger *et al*., 2011).

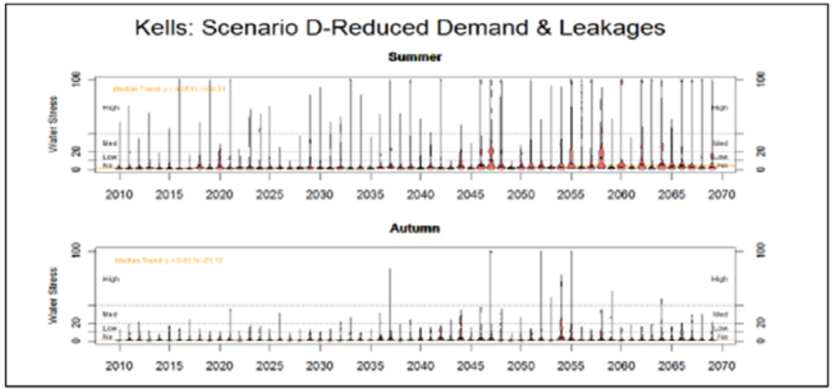
2. As the range of climate change uncertainty has broadened it is becoming ever-more useful to the water industry to identify approaches that exhibit a benefit to water resource management across a wide uncertainty range.

Theoretically, the outcome of achieving these two goals is a 'no-regrets' portfolio of adaptation approaches that lead to a water supply system that is fully robust to the range of potential future climates that may influence it. In reality, the notion of fully 'no-regrets' water infrastructure interventions is unlikely, but in-depth exploration of uncertainty using modelling approaches can at least enable water resource managers to successfully prioritise selections based on all the available information.

RDM is a term that relates to a set of methods and tools developed over the last decade (particularly since Lempert *et al*., 2006) to support decision-making and policy analysis when ambiguity is large and inevitable (Kunreuther *et al.*, 2013). Describing deep uncertainty using probability distributions enables a RDM process to evaluate large sets of strategies for a climatically-influenced system. Optimality is ignored in an RDM process, with the robustness of the system deemed of more use to a decision-maker (that is, a design that is not optimal under any individual future scenario or projection may chosen over one that is optimal in one plausible future, but is not as robust across a range of futures) (Kunreuther *et al.*, 2013). RDM requires the selection of thresholds, such as those defined for water resources in section 2.5.2, against which policies fail or succeed. Therefore, the selection of thresholds that are suitable to stakeholders is vital in order for the analysis to be useful (Liu *et al*., 2008).

Robustness assessments can be considered a catch-all term for the range of approaches proposed for transforming uncertain climate change information into risk *evaluation*, where adaptation measures are prioritised based on their ability to reduce risk to one or more metrics in the risk *analysis* process. They are differentiated from full RDM as they do not necessarily require all of the stages of a full RDM investigation (e.g. identifying the climate conditions that are problematic to a water resource supply system through modelling, rather than using a risk assessment) but retain the core objective of working towards robustness rather than optimality (Kunreuther *et al*., 2013). In terms of water resource management, climate change adaptation strategies that have already been highlighted as feasible can be compared to analyse how well they perform under each scenario. The success of each strategy is then defined against the pre-determined threshold(s) which reflect a key objective for maintaining a service (water supply, water quality, environmental flow indicators (EFI), overflow spill frequency, aridity etc.). The process of identifying these thresholds in England and Wales is already largely complete (Wade *et al*., 2013). Employing a robustness assessment approach allows water resource planners to use the future projections to identify weaknesses in water resource management or adaptation strategies. With that knowledge, each potential adaptation measure can be rigorously explored before being implemented and sensible decisions on how to augment resilience despite the uncertainties involved can be made (Groves *et al*., 2008).

A number of studies that can be considered robustness assessments have been completed recently (Figure 2.25). It can be seen that outputs from these studies are varied but the underlying approaches have been shown to work and can be considered an improvement for planning and designing water resource infrastructure on previous techniques. However, the rules and evaluation principles for project justification must also be changed to work in tandem with the new approaches.



Alternatives	Management Options	Years of Implementation 2000	2020	2040	2060	2080	2100
Alt. 1	CON	1.00	0.99	0.96	0.89	0.83	0.78
	CON + MAR	1.00	0.99	0.99	0.96	0.90	0.83
Alt. 2	CON	1.00	1.00	0.96	0.89	0.83	0.78
	CON + MAR	1.00	1.00	0.99	0.96	0.90	0.86
	CON + MAR + WMO	1.00	1.00	1.00	0.99	0.96	0.91
Alt. 3	GWC(15)	0.97	0.89	0.83	0.78	0.74	0.59
	GWC(15) + GWC(20)	0.97	1.00	1.00	0.99	0.92	0.91
Alt. 4	GWC(20)	1.00	1.00	1.00	0.99	0.96	0.91
	GWC(20) + WMO	1.00	1.00	1.00	0.99	1.00	0.97
Alt. 5	CON	1.00	0.99	0.96	0.89	0.83	0.78
	CON + MAR	1.00	0.99	0.99	0.96	0.90	0.83
	CON + MAR + WMO	1.00	0.99	0.99	0.99	0.96	0.91
	CON + MAR + WMO + GWC(5)	1.00	0.99	0.99	0.99	1.00	1.00

Notes: Additional management options in the column of management options are implemented when current options are unable to meet the system reliability of 97% in the ESPA (e.g., only CON was applied in Alt. 1 until 2020, and MAR in addition to CON was applied to meet the target, which is the system reliability of 97%). The shaded areas indicate system reliability that is higher than 97% (0.97), which has been defined as an acceptable level.

Option	RDM	EBSD
South London Aquifer Recharge Schemes (SLARS)	No	Yes
Upper Thames Reservoir (UTR)	No	Yes
Severn Water Transfer (SWT)	Yes	No
Mains replacement (MAINS)	Yes (all WRZs)	In the LDN WRZ
Active leakage control (ALC)	No	Three l levels in LDN level 1 and 2 in SWOX 14 levels in SOUTH ALC options in CENT, RZ4 and RZ5
Metering (MET)	Compulsory metering (all WRZs)	Targeted compulsory metering in the LDN WRZ and change of occupancy metering in SWOX
Seasonal Tariffs (SETA)	Yes (all WRZs)	No
Water efficiency (EFI)	Yes (all WRZs)	LDN, SWOX, SOUTH, CENT and RZ5 WRZs

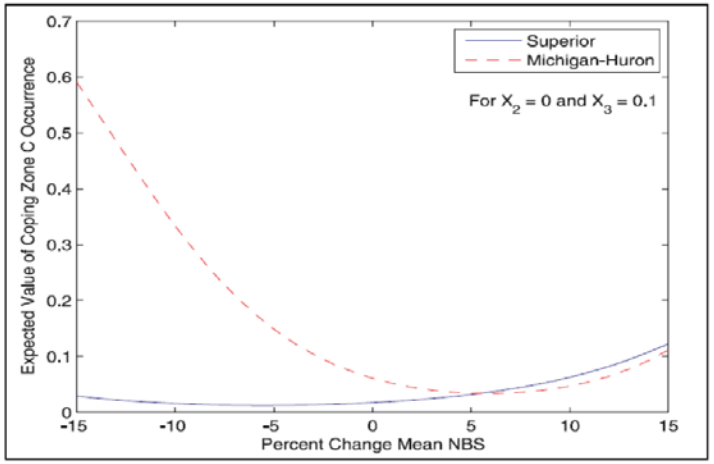


Figure 2.25 Outputs from recent robustness assessments / RDM approaches. Top left: Effectiveness of a scenario (reduced demand and leakages) against a water stress metric using a transient climate scenario in Kells, Ireland. Other scenarios are tested against the same projections to assess effectiveness. Top right: Various management options tested against a system reliability metric over the course of the 21st century in Snake Plain, USA. Bottom right: Coping zone robustness metrics used to assess how net basin supply (NBS) affects various stakeholders using two lakes in North America. Robustness of Lake Superior is primarily affected by increases to NBS, while Lake Michigan-Huron is primarily affected by reduced NBS. Bottom left: Summary of demand and supply-side management options recommended by an RDM approach and an economic optimisation approach (EBSD) in south-eastern UK. RDM recommends demand-side management more than EBSD. Reproduced from Hall and Murphy (2012), Ryu et al (2012), Moody and Brown (2012) and Matrosov et al., 2012, respectively.

2.6 Climate change data sources and downscaling

2.6.1 Overview

Global-scale modelling endeavours are useful to drive climate change policy and give overviews of large-scale hydrological changes (see Todd *et al.*, 2010 and Sanderson *et al.*, 2011; Arnell and Gosling, 2013; Schneider *et al.*, 2013). However, there is a spatial disparity between what GCMs can offer, and what water resource managers require to make decisions on water infrastructure and policy (Buytaert *et al.*, 2010); therefore downscaling coarse GCM information to a higher spatial resolution is necessary for most hydroclimatological assessments (Varis *et al.*, 2004; Hashmi *et al.*, 2009). Diaz-Nieto and Wilby (2005) suggest that there is a place in research for both, with the coarser-resolution dynamical downscaling approach used for 'broad-brush' level assessments of vulnerability, and downscaling techniques delving deeper to explore detailed impacts deriving from sequencing and persistence of daily events at finer resolutions, normally once vulnerable water resources have been identified.

There are many different approaches to downscaling coarse resolution GCM information for use in hydrological impact studies, and various review papers have shown the strengths and weaknesses of each (Xu *et al.*, 2005; Fowler *et al.*, 2007; Maraun *et al.*, 2010). In general, techniques for downscaling can be classed as either dynamical or statistical. Dynamical downscaling can be considered an extension of coarse-gridded GCM modelling on a higher-resolution RCM (Wilby and Wigley, 2000). RCMs take smaller-scale features within the GCM grid into account, but are extremely computationally demanding and require further processing to provide daily information. Statistical downscaling methods combine empirical understanding to address the differences between GCM data and meteorological records. The key drawback with statistical downscaling methods is that there is an assumption that any relationships that existed in the past will continue to do so in the future. Stochastic weather generation is related to statistical downscaling, and involves the manipulation of a conventional WG (used to produce realistic weather sequences of the past or present) with corresponding parameters in a GCM to produce local future time series. WGs are a computationally inexpensive downscaling technique, but struggle to reproduce low-frequency events such as multi-seasonal drought, although progress is being made towards this (Table 2.1) (Fowler *et al*., 2007; Qian *et al*., 2010).

Table 2.1. Advantages and limitations of statistical and dynamical downscaling approaches (reproduced from Fowler *et al.*, 2007).

	Statistical downscaling	Dynamical downscaling
Advantages	• Comparatively cheap and computationally efficient • Can provide point-scale climatic variables from GCM-scale output • Can be used to derive variables not available from RCMs • Easily transferable to other regions • Based on standard and accepted statistical procedures • Able to directly incorporate observations into method	• Produces responses based on physically consistent processes • Produces finer resolution information from GCM-scale output that can resolve atmospheric processes on a smaller scale
Disadvantages	• Require long and reliable observed historical data series for calibration • Dependent upon choice of predictors • Non-stationarity in the predictor-predictand relationship • Climate system feedbacks not included • Dependent on GCM boundary forcing; affected by biases in underlying GCM • Domain size, climatic region and season affects downscaling skill	• Computationally intensive • Limited number of scenario ensembles available • Strongly dependent on GCM boundary forcing

Most hydrological impact assessments require time series of weather variables (chiefly precipitation and PET) on a daily time-step (Kilsby *et al*., 2007). The most readily available source of this information is the instrumental record, so hydroclimatological studies have often been based around ‘scaling up’ previous flood and drought events using average monthly change factors (CFs) from GCMs or RCMs (Scibek and Allen, 2006; Boukhris *et al*., 2008); a technique often referred to as the change factor method (CFM) (Jackson *et al*., 2011). This process does not allow for changes to climatic variability and is dependent on long instrumental records, with underestimations of future hydrological extremes if such a record is unavailable (Semenov and Barrow, 1997; Holman *et al*., 2009). The CFM also assumes that the climate of the past is analogous to the climate of the future (or even present), which in terms of variability and seasonality it is not, as shown by various future projections (Solomon *et al*., 2007; von Christierson *et al*., 2012; Shiu *et al*., 2012; Jones *et al*., 2013).

Given the myriad of available climate model downscaling techniques, each with their own particular strengths and limitations, selecting the correct method to use depends on the application (Wilby *et al*., 2009). The detail and spatial resolution that is suitable when assessing the impact of climate change on water resources will vary from catchment to catchment based on perceived risk (Todd *et al*., 2010; Hall *et al*., 2012(a)). Greater depth of analysis should be afforded to areas with high proposed investment in adaptation of the water resource system than to those where no investment is planned (Hall *et al*., 2012(a)). The majority of this sub-chapter relates to WGs, as that is the downscaling approach used in this research project to produce climate futures.

2.6.2 **Weather generators: origins and history**

WGs are a form of statistical downscaling of coarse climatic data from GCMs where statistical relationships between large-scale climatic variables and small-scale hydrometeorological variables are searched for. Essentially stochastic models, WGs take into account randomness and can therefore create a distribution of possible estimates of a particular weather climatic parameter on a daily or sub-daily time-step (Boukhris *et al.*, 2008). The traditional WG approach involves a collection of models that estimate site-specific weather parameters and uses these to derive variables. They have been commonly used to provide inputs into biophysical models (such as hydrological models), as well as in combination with GCMs and RCMs to produce synthetic weather series representative of climate change scenarios. The use of WGs to study future resource vulnerability is a relatively recent development following their original deployment in filling in missing instrumental data and performing quality control on datasets. They have been used to great effect in water engineering design as a means for producing infinitely long synthetic weather sequences from finite records (Wilks and Wilby, 1999)

Up until the early 1980s weather generation had focussed on rainfall, but it had long been known that for more practical applications further weather variables would need to be reproduced (Wilks and Wilby, 1999). Richardson (1981) represents the first attempt at reproducing further weather variables, and the term ‘weather generator’ (or ‘WGEN) is first referred to in Richardson and White (1984) and has been in use ever since. After

Srikanthan and McMahon (1999), it is widely recognised that the Newman-Scott Rectangular Processes (NSRP) model (Cowpertwait, 1991) represents the clustered nature of rainfall more accurately than Markov chains. Newer WGs such as the EARWIG (Kilsby *et al*., 2007) and UKCP09WG (Jones *et al*., 2009) use this technique in their design, enabling them to reproduce higher order rainfall statistics more accurately than simpler techniques.

The rainfall model still forms the basis of the WG design that has led to the UKCP09WG, with the other variables being generated after the rainfall statistics have been derived. The skill of such a WG is determined by validating this baseline synthetic weather sequence against the instrumental record (e.g. Min *et al*., 2011(b)). The other weather variables (generally daily mean temperature, daily temperature range, vapour pressure and sunshine duration) are then normalized by subtracting the mean and dividing by the daily standard deviation for each half month of the year (Jones *et al*., 2009). PET can then be calculated using a variety of methods (see Bormann, 2011, for a study of PET calculation sensitivity in future studies). Finally, maximum/minimum temperatures, relative humidity and direct/diffuse radiation are calculated. Uncertainties increase as the process continues (i.e. rainfall statistics are the most certain, calculated variables less-so). All future WG studies make the assumption that there is a consistency between statistical relationships between climatic parameters in the present (or past) and future. A schematic of EARWIG, produced by Kilsby *et al*. (2007), which has a similar structure to UKCP09WG, is shown in Figure 2.26 (Kilsby *et al*., 2007 Fig 4). Other WG methodologies, which have a similar goal but radically different approaches, have been produced in tandem with the strand of models detailed above (e.g. Lars-WG (Semenov and Barrow, 1997) and Weagets (Chen *et al*., 2010)). A full analysis of all WG approaches is beyond the scale of this thesis, but can be found in Wilks *et al*. (2012a;b) and weather type models are discussed in Alliot *et al*. (2014).

2.6.3 **Weather generators: current technologies and remaining barriers**

A number of key advances in recent years have increased the rate of use and effectiveness of WGs for hydroclimatological impact assessments. These include:

'Science hidden' weather generators

The process of creating daily future weather sequences using a WG now requires no manual data input, prior knowledge of climate modelling or the need to develop local-scale WGs from scratch as was previously necessary (Varis *et al*., 2004). Such 'science-hidden' tools (Fowler *et al*., 2007) allow non-specialist end users to effectively use the WG approach, facilitating more widespread uptake in industry (Diaz-Nieto and Wilby, 2004) (e.g. the use of UKCP09WG by the water industry (Severn Trent Water, 2011(a))). This approach does however make a WG less flexible; without the ability to take the model apart for further development by third parties, end users can be hamstrung by the omission of a particular variable. 'Science-hidden' WGs often utilise a map-based interface (e.g. EARWIG, UKCP09).

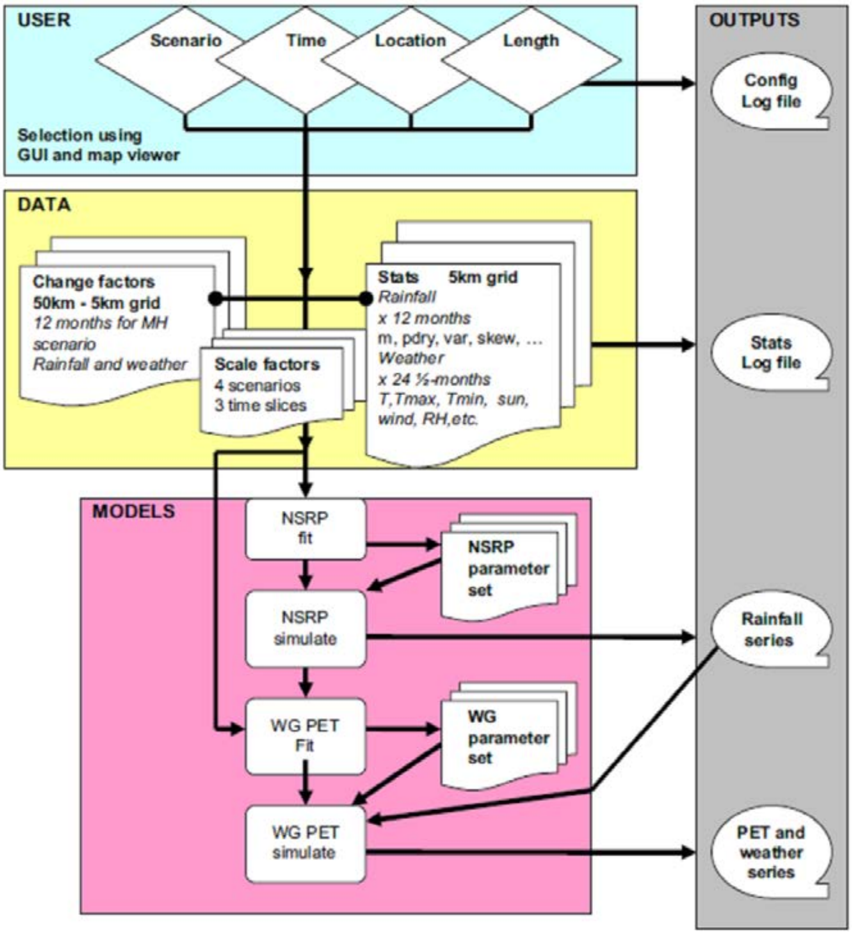


Figure 2.26. Schematic of EARWIG. Note that the rainfall series is produced before the other weather variables, as the PET calculation if dependent upon it. Reproduced from Kilsby et al., 2007.

Probabilistic weather generator information

A movement towards extending probabilistic data output from GCMs to WGs has been seen in recent years, having been highlighted as an area of great potential for progressing and improving statistical downscaling (Fowler *et al.*, 2007). A major milestone for probabilistic modelling was achieved with the development of the UKCP09WG (Jones *et al.*, 2009), which has phased out the use of previous-generation models with no such probabilistic outputs such as EARWIG (Kilsby *et al*., 2007) in the UK. Using WG sequences that relate to probabilistic ranges of climate model information allows them to be used in the more effective decision-making approaches discussed in Section 2.5, but does bring up some of the practical barriers described in Section 2.3.3.

Transient weather generators

Original applications of WGs assumed stationarity as a result of being representative of the past, and therefore the ability to progressively alter climatic conditions throughout a sequence provided little added value. Since WGs have been re-adopted for use in climate change studies over the last 10-15 years (Greene *et al*., 2012), most have produced simulations that exist within a stationary 'time-slice' representative of the future, where there is no progression (i.e. year x has the same climate as year $x_{...n}$). However, many water resource decision-making approaches have advocated the use of transient futures; where the time series reacts to a linear change in climate over time (Haasnoot *et al*., 2012; Hall *et al*., 2012(a)). As a result, providing transient information directly from WGs has become a key research challenge.

A working example of a transient WG has recently been produced by Blenkinsop *et al*. (2013), which built on a transient rainfall simulator described by Burton *et al*. (2010). The authors show that the technique is able to describe how climate conditions may change over the future in the case study catchment in Belgium, and further hypothesise that producing a large ensemble of such transient climate information could provide the best available information on judging system responses to climate change. Such information is ideally-suited to work such as Haasnoot *et al.* (2012) and Gersonius *et al.* (2013), where the life-expectancy of various adaptation options in the water industry can be measured against a shifting climate to develop 'pathways' of sustainable water management and flood management, respectively. Transient WGs would also enable the use of normalised drought metrics such as the standardised Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano *et al.*, 2013) in climate change studies. Presently, the use of stationary time-slices means there is no value in comparing SPEI across different time-horizons (see Appendix C).

Despite the advances in WG technology seen in recent years, there are still a number of key areas for improvement that would increase confidence in the technology (Wilby *et al.*, 2009; Maraun *et al.*, 2010). Some of the most important of these are:

Correcting underestimation

The underestimation of extreme events, particularly extended dry periods is gradually being addressed by incremental improvements to WGs, but the newest commercially available WG, UKCP09, still has limitations. The problem is due to an inability of the underlying RCM (HadCM3) to accurately reproduce meteorological blocking events that can produce long-standing episodes of heat, cold or drought (Jones *et al.*, 2009), a problem that is particularly prevalent in Europe (Maraun *et al.*, 2010). Examples of blocking events causing extreme events include the summer of 1976 drought, the cold winter of 1962-63 and the cold December of 2010. These episodes would be within the lower or upper 1-2% of a distribution, and it is unlikely that UKCP09WG would create a simulated equivalent. Although a ‘messy’ solution, producing an extremely long time series (e.g. 10 000 years) would enable the production of extreme return periods. However this approach would greatly increase data intensity and the wisdom of basing such a technique on an imperfect model is questionable.

Furrer and Katz (2008) discuss the most plausible approaches to improving the reproduction of extreme events within a WG framework, and recommend a “hybrid technique with a gamma distribution for low to moderate intensities and a generalised Pareto distribution for high intensities” as the best way forward. WACS-Gen, developed by Flecher *et al*. (2010), uses a weather state approach that is able to accurately reproduce the statistical properties of five multivariate daily time series. The main progression in this approach is discarding the ‘wet’ or ‘dry’ states that have formed the backbone of most parametric WGs, and in its place produces a model-based clustering algorithm to create a far greater selection of possible weather states upon which the derived parameters can be calculated. Chen *et al*. (2010) described the development of a WG that aims to retain the low-flow frequency of climate variability, with reasonable success. The authors utilised the observed power spectra of monthly and annual time series to estimate low-frequency variability, thus enabling a significant improvement over WGs that do not employ this technique.

Moving from single-site to multi-site weather generation

Single-site WGs, such as EARWIG, Climatic Research Unit WG (CRU WG) (Jones and Salmon, 1995) and UKCP09WG, are the most commonly used and least complex form of WG and therefore have the advantage of being computationally inexpensive (Semenov, 2008; Wilby *et al.*, 2009). The single-station nature of most commercially available WGs creates a problem in that a weather sequence produced at one site will not correspond in time with another station nearby, so an extreme event at station A will not occur on the same day as it does at station B, even if in reality those stations would be subject to the same large-scale weather system (Jones *et al.*, 2009). The size of the site can be increased (in the case of UKCP09WG, from 5km^2 to 10000km^2), but this involves spatially-averaging the area, thus reducing accuracy. For most catchment-scale assessments that involve a hydrological model, the preservation of spatial and temporal correlations is vital (Baigorra and Jones, 2010).

Multi-site WGs are more complicated and not part of the suite of tools provided by UKCP09. As a result of this commercial unavailability multi-site unaltered WGs are not currently useful for projecting future DO in the England and Wales water sector. For a review of multi-site and full-field WGs see Maraun *et al*. (2010). Recently, models of daily rainfall cross-correlation for the UK have been produced by Burton *et al*. (2013). These models are currently only relevant to observed datasets, as climate model projections of the future do not provide the necessary resolution required, but mean that once such information is available (through ongoing projects such as CONVEX) it will be possible to extend single-site WG approaches such as UKCP09WG to include multi-site information, thus significantly increasing their suitability to hydroclimatological impact assessments.

Mehrotra and Sharma (2009) compared three types of spatial rainfall models designed for inclusion in spatial WGs, namely the MS Markov Model (MMM), a reordering method and a nonparametric k-nearest neighbour (K-NN) model, finding that although all the techniques adequately reproduced the observed spatio-temporal pattern of the daily rainfall, there were differences when producing longer time scale temporal and spatial dependencies. MMM has the advantage of modelling varying orders of serial dependence at each point location while maintaining the observed spatial dependence accurately. Reordering is simple and easy to formulate but not as accurate as MMM. For a majority of statistics, MMM and reordering perform better than the nonparametric K-NN, which also uses more computer power. However, K-NN is the most successful at reproducing extended dry spells. Therefore, it is clear that different approaches to producing spatial WG information have their unique strengths and weaknesses (Table 2.2), and selecting the appropriate downscaling tool depends on the particular application intended.

Table 2.2. Advantages and limitations of three spatial WG approaches. It can be seen that the most accurate method for reproducing observed information depends on the parameter measured (reproduced from Mehrotra and Sharma, 2009).

Rainfall attribute	Observed	MMM	Reordering	KNN
No. of days in a year with area averaged wetness state >0.85	42.77	42.11	37.76	42.43
No. of days in a year with area averaged rainfall >25 mm	6.51	6.71	7.10	6.30
No. of times in a year with area average wetness state >0.60 (consecutively for 3–4 days)	7.42	7.61	6.84	7.25
No. of times in a year with area average wetness state >0.60 (consecutively for 5–6 days)	3.40	3.21	2.84	3.37
No. of times in a year with area average wetness state >0.60 (consecutively for 7 days or more)	1.12	0.98	0.82	1.15
Average rainfall amount with area average wetness state >0.60 (consecutively for 3–4 days)	36.06	35.45	39.77	34.63
Average rainfall amount with area average wetness state >0.60 (consecutively for 5–6 days)	73.61	64.45	76.05	62.95
Average rainfall amount with area averaged wetness state >0.60 (consecutively for 7 days or more)	132.55	106.74	123.59	109.76
No. of times in a year with area average wetness state <0.20 (consecutively for 5–7 days)	10.26	9.92	10.16	9.35
No. of times in a year with area average wetness state <0.20 (consecutively for 8–15 days)	3.21	3.17	3.12	3.64
No. of times in a year with area average wetness state <0.20 (consecutively for 15 days or more)	0.70	0.61	0.71	1.14

Need for observed data

Observed data is needed at a site at which a WG is used, upon which to base parameter estimates for weather generation. Deterministic approaches see deterioration of results when the model is not continually updated with instrumental data (as they are based on a state of the model directly influencing the next state (e.g. one day to the next) – an example of this is a weather forecast (Wilks and Wilby, 1999). Stochastic approaches do not have the future state totally determined by the initial state, so are better on longer timescales (i.e. decades – a deterministic approach would be useless after a few days, l*et al*one years). This does not mean that each state has totally random weather in a stochastic model, as each state (day) is related to the one that preceded it, but not totally governed by it (Fowler *et al*., 2007).

There is concern that the spatial density of locations where sufficient instrumental data is available may not be sufficient for the high-resolution purposes WGs are generally employed for (Soltani and Hoogenboom, 2003). Missing or erroneous data within the calibration dataset can skew results of the WG, as can an abnormal number of rain days (meaning the longer the historical dataset, the better) (Taulis and Milke, 2005).

2.6.4 **Examples of use in hydroclimatological assessments (non-UKCP09)**

Combining RCM ensembles with stochastic WGs to create daily weather parameters for future climates has become an increasingly used method for performing hydroclimatic impact assessments. A sample of recent WG-based assessments are introduced here, the details of which are provided in Table 2.3. A far more extensive number of studies stop short of applying a hydrological model to the WG data, focussing on future changes to rainfall and other weather parameters (e.g. Hashmi *et al*., 2011; Liu and Zuo, 2012; Zhang and Huang, 2013)

Evans and Schreider (2002) used WGEN (Richardson and Wright, 1984) to describe future flow conditions in the Swan River, Western Australia. The authors found that the magnitude of extreme dry events in the catchment is projected to increase in the area despite a reduction in mean average streamflow.

Minville *et al*. (2008) used the WeaGets WG (Chen *et al*., 2012) to account for climate variability in an assessment of climate change impacts on a hydropower-intensive catchment in Canada. The authors found that future hydrographs were shifted to earlier peaks across the GCM ensemble range, but there was disagreement on the change to amplitude (Figure 2.27). The shift in peak flow became more accentuated with more remote time horizons, as did the uncertainty ranges of every hydrological parameter studied (peak discharge, time of occurrence of peak and annual mean discharge).

Herrera-Pantoja and Hiscock (2008) used the CRU WG to assess the impact of climate change on groundwater recharge at three sites in the UK, finding significantly increased dry periods leading to a reduction in recharge at each site as the century progresses. Each site presents increased climatic variability in the future, with the dry season found to be particularly affected. They concluded that sites already under groundwater supply pressure will come under increased stress as the century progresses.

Using a case study in East Anglia, UK, Holman *et al*. (2009) recommended stochastic modelling rather than deterministic perturbation methods (i.e. CFM) when assessing vulnerable or sensitive groundwater systems. This enables improved understanding of future risks of drought severity and persistence as well as high recharge years causing groundwater flooding within a robustness analysis framework. The authors found that the range of uncertainty in terms of ‘very dry years’ and ‘very wet years’ was vast across the 100 simulations run for each future time-slice, but provided more useful information than a single CFM simulation of recharge for each time-slice.

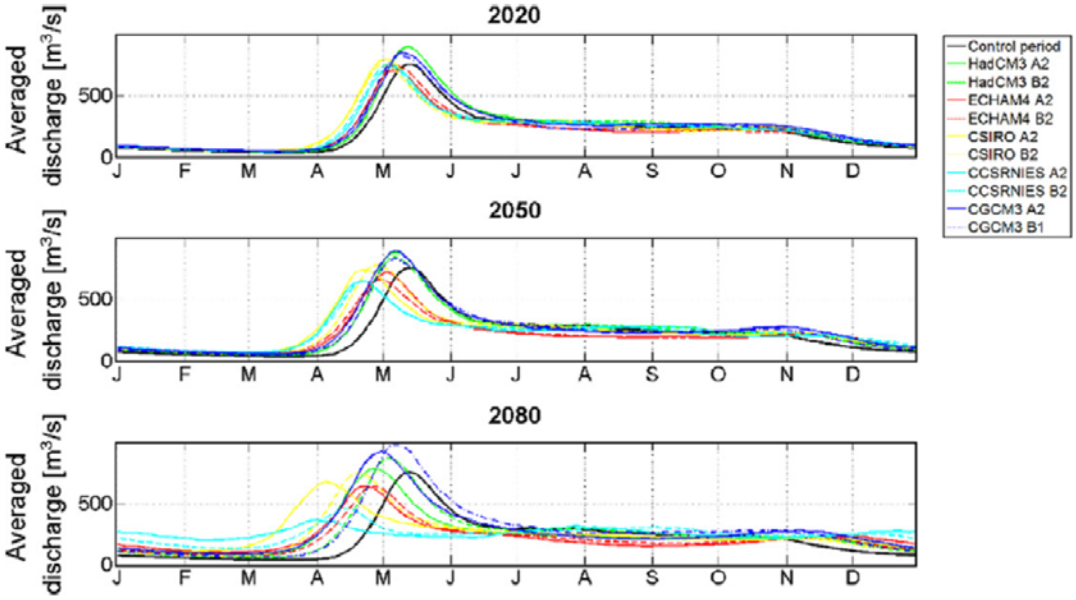


Figure 2.27. Shift in hydrographs for the Chaute-du-Diable catchment, Canada, in future simulations using the WeaGets WG. An ensemble of GCMs is used, all of which project earlier peak flows in the future. Reproduced from Minville et al., 2008.

Eum *et al*. (2010) used a K-nn approach WG (Yates *et al*., 2003) and the SSARR hydrological model (Speers and Singh, 1995) to develop streamflow impact assessments for a major basin in Korea. Information from only two GCMs was used by the authors (one representing a 'wet' scenario and the other a 'dry' scenario). Streamflows were found to increase in the 'wet' scenario and decrease in the 'dry' scenario for the 2010-2049 period. Despite providing a rudimentary application of climate models, Eum *et al*. (2010) provided a good example of how to apply spatial interpolation in order to produce sequences across a catchment.

Zarghami *et al*. (2011) provided an application of the LARS-WG (Semenov and Barrow, 1997) in a water-scarce area of North-western Iran with a very pronounced and short peak runoff season in May. The authors found that peak runoff is projected to be significantly reduced across the region, with little to no runoff outside of the peak season. This situation produces dramatic reductions to the De Martonne aridity index for the area, with the climate moving from semi-arid to arid by the 2080s. However, by only using one simulation for each time-slice, the results are overly precise and do not take into account GCM uncertainty (only HadCM3 is used).

Khazaei *et al*. (2012) developed a WG approach that used the same rainfall model as that described by Kilsby *et al*. (2007), and derived daily minimum and maximum temperatures using a first order auto-regressive process, in order to produce an assessment of extreme high flow events in future climates in Iran using the ARNO[4] rainfall-runoff model (Todini, 1996). Although the approach was found to underestimate observed flows, the authors were able to describe significant increases to flooding events of various return periods in future periods (Figure 2.28)

[4] The 'ARNO' model name is derived from it's first use on the Arno River, rather than an acronym.

Table 2.3 Examples of hydroclimatological studies using a WG as the downscaling approach

Author	Study area	Weather Generator	Type of assessment	Results
Evans and Schreider, (2002)	Swan River, Western Australia	WGEN (Richardson and Wright, 1984)	Streamflow impact	Significant increases to the magnitude of rare flood events despite decreases in mean streamflow levels.
Minville *et al*. (2008)	Chaute-du-Diable, Quebec, Canada	WeaGets (Chen *et al*., 2012)	Streamflow timing	Spring flood appearing 1-5 weeks earlier than in the historic record, with varying amplitude.
Herrera-Pantoja and Hiscock, (2008)	Three UK catchments	CRU WG (Jones and Salmon, 1995)	Groundwater	Increased prolonged dry periods leads to decreases in groundwater recharge at each site, but particularly in SE England.
Holman *et al*. (2008)	Coltishall, UK	CRU WG	Groundwater	Extensive range of 'very dry years' and 'very wet years' across 100 simulations.
Eum *et al*. (2010)	Nakdong River, South Korea	K-nn algorithm (Yates *et al*., 2003)	Streamflow impact	Disagreement on sign of change between two GCMs.
Zarghami *et al*. (2011)	NW Iran	LARS-WG (Semenov and Barrow, 1997)	Streamflow impact	Significantly reduced peak runoff, with large implications for aridity in the region.
Khazaei *et al*. (2012)	Pataveh, Iran	NSRP-based (Kilsby *et al*., 2007)	Flooding	Up to 48 - 153% increase in 50-year return period flood for 2067-2093 compared to 1974-2000, dependant on SRES.

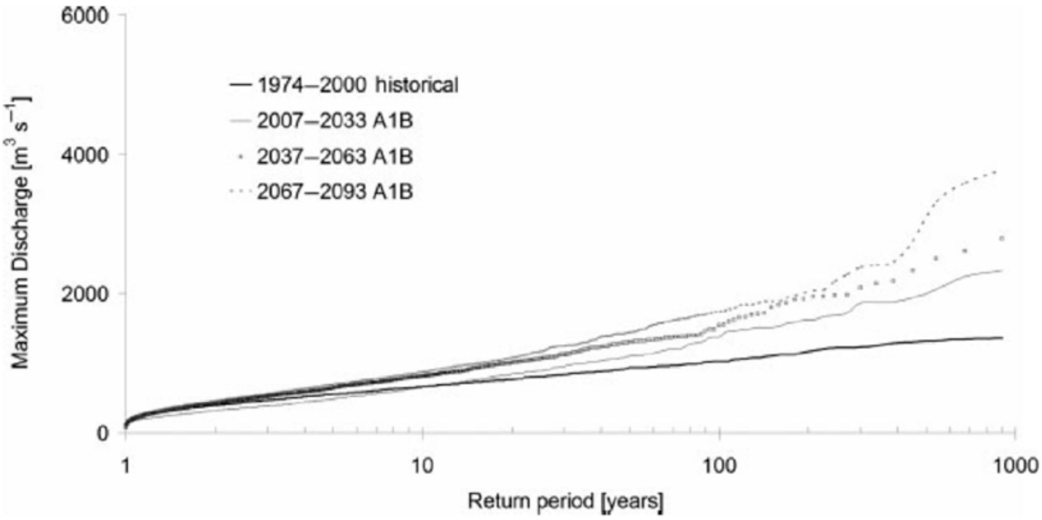


Figure 2.28. Return periods of flood events in the Pataveh basin, Iran, for three future time-slices. Rainfall and weather parameters were generated using a process based on the NSRP model, in a similar fashion to EARWIG and UKCP09WG (Kilsby et al., 2007; Jones et al., 2009). Extreme flood events are projected to become progressively more severe with time. Reproduced from Khazaei et al., 2012

2.6.5 **UKCP09 Weather Generator**

The UKCP09WG was developed in tandem with the movement towards probabilistic information in the overall UKCP09 work-stream, providing a uniform method for downscaling information from the lower-resolution UKCP09 probability distribution functions (PDFs) (Jones *et al.*, 2009). The provision of probabilities measuring how strongly different outcomes for climate change are supported by evidence (models, observation and understanding) is a significant step forward from the previous UKCIP02 projections. This has aided the use of UKCP09 in industries, as many users downscaled information from UKCIP02 tailored to their own needs, causing confusion and inconsistency across sectors (Jones *et al.*, 2009; Murphy *et al.*, 2009).

The architecture of UKCP09WG is similar to that presented by Kilsby *et al*. (2007) in the form of EARWIG (Figure 2.26), with the probabilistic element added. The WG involves applying CFs to baseline weather variables for each grid square needed which are derived from the UKCP09 projections. A NSRP stochastic rainfall model is then refitted using the perturbed rainfall statistics and the other variables are the calculated based on that rainfall sequence. This enables the UKCP09 to be used as a "tool to create synthetic time series of weather variables at 5km resolution, which are consistent with the underlying climate projections" (Jones *et al*., 2009). A web-based user-interface, again similar to that provided by Kilsby *et al*. (2007), makes UKCP09 easy-to-use and 'science-hidden'. For a detailed description of the UKCP09WG methodology, see Jones *et al*. (2009).

The aim of the UKCP09WG is to be "provide users with sufficient spatial and temporal detail for their needs" (Jones *et al*., 2009). However, despite improvements to the representation of rainfall and temperature extremes, sunshine hours and vapour pressure in an updated release in 2011, is not able to reproduce blocking events and thus multi-seasonal drought events (Jones *et al*., 2009; Maraun *et al*., 2010). Single-season droughts are generated that can be analysed, and it is possible to look at how periods of drought change under different climatic forcings. It can therefore be assumed that the WG would underestimate events with very high (top 1-2 percentiles) return periods (Jones *et al*., 2009). UKCP09WG remains a useful tool for the water industry and other sectors to exploit in their assessment of climate change impacts, although it is clearly imperfect. UKCP09WG has been used to varying degrees by water companies in the production of their CCRAs (e.g. Anglian Water, 2011; Severn Trent Water, 2011(a)).

2.7 Literature review conclusions

This literature review has shown that whilst there are major improvements being made in both the development of climate change (and particularly weather generator) data sources, and the methods with which data gathered from such sources can be applied into assessments of water resource risk and adaptation options, little progress has been made in terms of enabling these research streams to have a significant impact on the practices of industry. As a result, action on climate change in the England and Wales water industry lags the urgent calls for progress made in academia significantly. It is this middle ground between academic pursuit and industrial application that this research project aims to fill. The key research gaps covered by the following chapters are:

- Development of an applicable method for translating state-of-the-art weather generator technology into usable assessments of water shortage risk in a UK water company.
- Facilitation of increased acceptance of climate change risk as a key aspect of water resource management, and improved confidence in capital investment based on climate change information.
- Equipment of the water industry with the tools to approach uncertainty in climate change impacts as an advantage, rather than a limitation.
- Movement away from traditional water resource management metrics such as deployable output, towards more tangible and communicable notions such as

reservoir levels and the implications for customers, which are more suited to the analysis of uncertain climate change information.

- Extension of uncertainty analyses of future climate change impacts on flows to include water shortage probability, thus framing the issue in terms of the metric that can be used in the act of water resource management, rather than an intermediary metric (e.g. river flows).

3 MATERIALS, METHODS AND VALIDATION

3.1 Overview

The approaches used to ascertain the effect of climate change impacts on water shortage across the range of climatic uncertainty, and describe a framework for prioritising adaptation measures based on their ability to alleviate water shortage risk across that range, are based on the following principles:

- The techniques used must be based on readily-available UK Climate Projections 2009 (UKCP09) information (as a result of the requirements made by Ofwat in the 2009 Periodic Review) and should be usable and replicable by industry (following the review of current practices by Arnell (2011(b))).
- Taking into account a wide range of climate change uncertainty is vital.
- The use of a weather generator method (WGM) is required in order to produce entirely synthetic daily sequences of rainfall and potential evapotranspiration (PET) that are not constrained by the use of change factors (CFs) based on the instrumental dataset (Harris *et al*., 2012).

- The techniques used should allow for a robustness assessment (or robust decision-making (RDM)-type) to be applied, allowing a potentially limitless number of adaptation options to be tested against a broad range of feasible climate futures. However, the approach should exhibit a balance between scientific rigour and industrial practicality. With that in mind, the approach is described as RDM-type as not all the concepts of RDM are employed in this assessment (Lempert and Groves, 2010), such as Matrosov *et al* (2013).
- Whilst catchment-specific, the principles of the research presented here should act as a case study that could be replicated elsewhere. Indeed, the RDM-type assessment using UKCP09 and a multi-model setup should be extendable to other sectors and industries vulnerable to climatic change.

As a result, the use of UKCP09 weather generator (UKCP09WG), with some modifications (see Section 3.6), is deemed to satisfy all of the above criteria. However, as a result of the limitations of UKCP09WG in reproducing the most extreme dry events, as described in Section 2.6, this research makes the assumption that taking into account the fullest range of climate model uncertainty that is readily available is more important than accurate reproduction of the most extreme droughts. Future technologies, exhibiting a more complete understanding of extreme events, will be able to make full use of the decision-making framework described in this project. In the meantime, an approach for assessing future weather generator (WG) simulations against an approximated Level of Service (LoS) derived from the baseline validation period (1961-1990) is proposed (Section 3.11). This technique increases the scope for practical application of the research project in industry.

A schematic of the project is shown in Figure 3.1. The methodology is innovative in its overall approach to the use of uncertain information in the water sector, and ultimately provides novel results that facilitate better climate change adaptation in industry. The colour coding divides the approach into three distinct sections: assessment of climate change impacts on hydroclimatological variables (gold), assessment of climate change impacts on water shortage risk (blue), and an RDM-type approach to assessing adaptation options (green). Illustrative examples of the outputs from each section are shown in Figure 3.1, whilst the full results are found in Chapters 5, 6 and 7 (respectively). Chapter 4, an uncertainty analysis, concerns only the gold and blue sections (i.e. no adaptation options are employed).

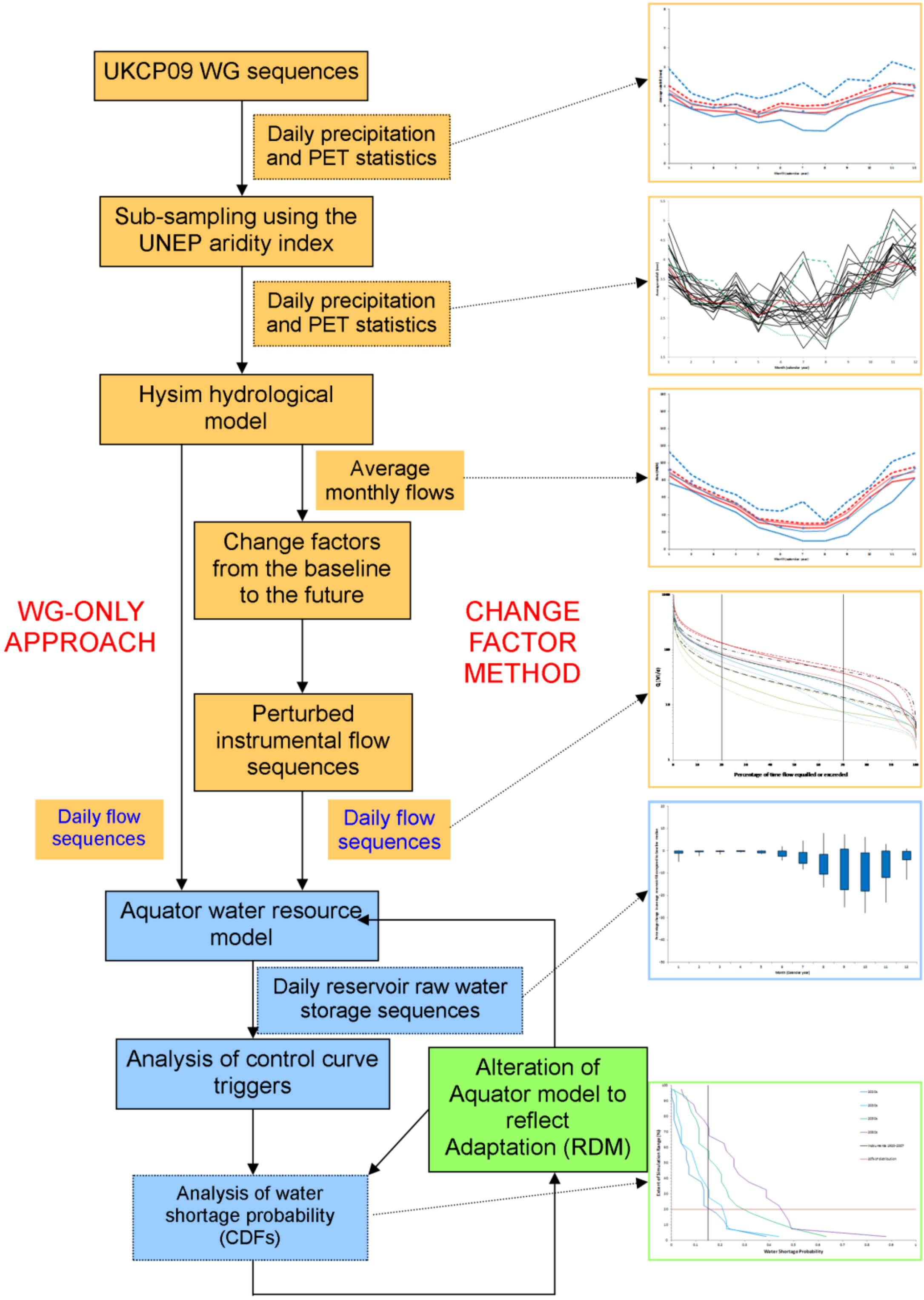


Figure 3.1. Schematic of the overall methodology. Gold-shaded boxes relate to the hydroclimatological impact assessment (results for which are found in Chapter 5), blue-shaded boxes are the water resource impact assessment (Chapter 6) and the green box is the RDM-type adaptation option assessment phase (Chapter 7).

3.2 The North Staffordshire Water Resource Zone

This research project is carried out at the North Staffordshire Water Resource Zone (WRZ) in central England, within which Tittesworth Reservoir serves as the main surface water resource (Figure 3.2). The region is managed by Severn Trent Water (STW) who act as a collaborator in this research project- and includes the Potteries Urban Area (Stoke-on-Trent and Newcastle-under-Lyme conurbation (population 469 000)), as well as multiple smaller towns including Market Drayton, Leek and Stone. Multiple groundwater resources are used in a conjunctive use system with the reservoir, meaning the resource state of the reservoir influences the extent of groundwater licences used.

The key drought management tools in the WRZ are based on the crossing of various control curves (i.e. live storage levels) at Tittesworth Reservoir. These include the Storage Alert Line (SAL), falling below which represents the first indication of dry conditions, the Drought Warning Trigger (DWT) which catalyses a variety of potential responses to the threat of water shortage, and the more severe Temporary Use Ban (TUB) which imposes restrictions on water use by customers. Output from the Tittesworth water treatment works (WTW) to the surrounding demand centres can be shut off completely during periods of drought provided sufficient groundwater is available, significantly reducing water stress at the reservoir.

Three small sub-catchments influence the reservoir; Upper Churnet (UC) (30km^2) provides all of the inflow whilst Deep Hayes (DHY) (10km^2) and Solomon's Hollow

(SOL) (6km^2) flow into the River Churnet downstream (Marked as * on Figure 1), reducing the compensation flow needed from the reservoir. UC produces the greatest flow of the sub-catchments (56.5 megalitres per day (Ml/d)), and is an upland area with greater average precipitation than elsewhere in the region. Groundwater resources are considered stable and largely robust to drought events by STW (internal communication); although more rigorous assessment of the climate change impact on groundwater models would be useful for further studies in the area.

The North Staffs region is considered suitable for this case study as: a) it represents an opportunity to test the practicality of a scaling approach to produce pseudo-spatial and temporally-consistent WG information due to the heterogeneity of the topography over the short distance between the relevant sub-catchments, b) it is an area subject to considerable water stress under present climatic conditions and takes up a significant amount of management time within STW, and c) adequately long and intact historical flow records exist against which to validate the WG and provide a basis for the change factor method (CFM) (see Section 3.9).

3.3 Instrumental data

A WG-based hydroclimatological study of future conditions (and therefore the water shortage assessment which follows-on) requires an understanding of the extent to which the model is generating synthetic weather sequences that are statistically consistent with real-world conditions. It is therefore necessary for an instrumental record of weather at a similar time-step to the WG outputs (in this case, daily) to be available during a pre-determined ‘baseline’ period. 1961-1990 is used as the baseline period for UKCP09, with simulations for this period supplied with every future projection. 100 baseline simulations, each of 100 years, are used to validate the instrumental data in this case.

A gridded Met Office rainfall record at 5x5 km resolution forms the dataset against which the WG baselines are validated. The data, which in raw form is freely available[5], is processed to represent Severn Trent Water sub-catchments as accurately as possible by Mott MacDonald, and has been updated for the STW 2013 Water Resource Management Plan (WRMP) (Severn Trent Water, 2013). The most reliable instrumental dataset runs from 1958-2010 (longer records for the North Staffordshire area merge datasets together), and thus encompasses the 1961-1990 baseline period used by UKCP09WG.

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[5] http://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/available/daily.html

Figure 3.3 shows that the precipitation profile is homogenous across the lowland area of the study region (the areas marked DHY and Wall Grange (WGR) in Figure 3.2). As a result, the precipitation sequences derived for DHY can be used as the direct rainfall recharge into the reservoir. The invariability across the lowland area was previously used in the construction of the North Staffs Aquator water resource model (Oxford Scientific Software, 2008 – see Section 3.10), with the WGR instrumental record taken as the precipitation series at Tittesworth Reservoir despite the considerable distance between the two sites (Figure 3.2). Figure 3.3 also shows that precipitation is significantly greater to the north-east of the WRZ, particularly at the UC sub-catchment which lies at higher ground than the other sub-catchments. Therefore, spatially-averaging a WG sequence over the entire area shaded pink in Figure 3.2 produces unmanageable errors (not shown).

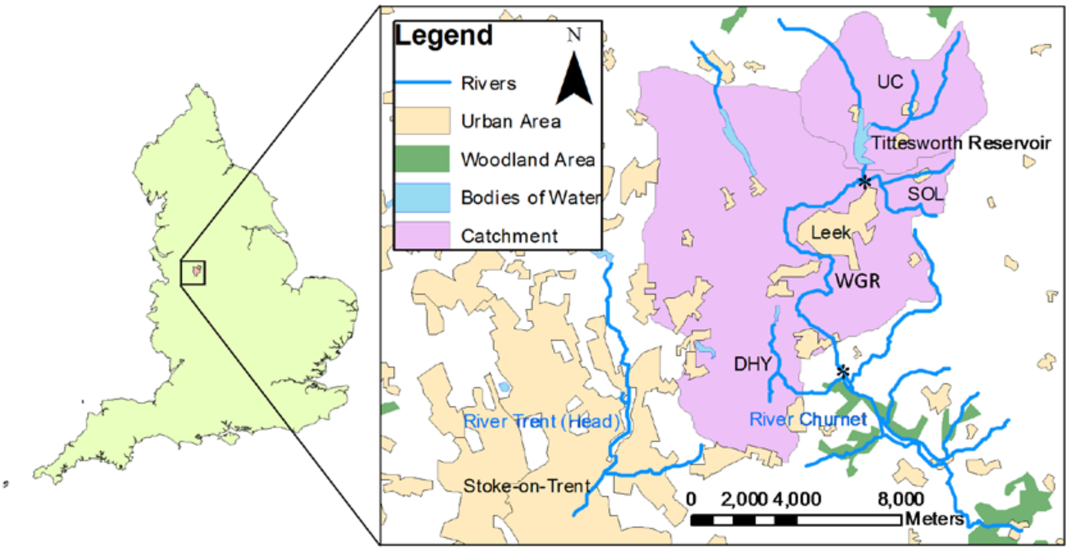

Figure 3.2. Map of the North Staffordshire WRZ in the context of the UK (Harris, 2013). The overall upper River Churnet catchment is shown in pink, whilst the UC, SOL and DHY sub-catchments can be approximated from the tributaries. As the River Churnet flows away to the SSE, water is piped from Tittesworth Reservoir to the major demand centre of Stoke-on-Trent. Confluences of the streams sourced at SOL and DHY with the River Churnet are marked with *. The position of the Wall Grange instrumental record is marked 'WGR'.

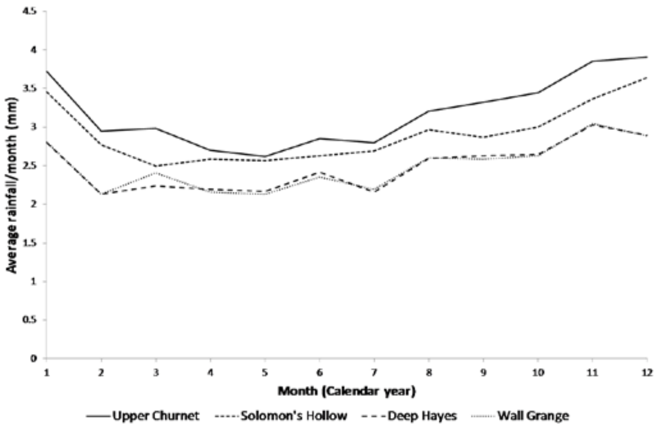

Figure 3.3. Average monthly precipitation in the period 1961-1990 at the four instrumental sites within the study region (i.e. the northerly section of the North Staffordshire WRZ containing the sub-catchments and reservoir). It can be seen how the Deep Hayes record can be substituted for the Wall Grange record to provide rainfall sequences for Tittesworth Reservoir. Differences in rainfall profile across the research are also evident.

Table 3.1. Average PET per day (mm) in 1961-1990 for MOSES grid-square 115 (which includes UC) and 106 (which includes Tittesworth Reservoir).

	J	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**
UC	0.2	0.4	0.9	1.6	2.5	2.9	2.8	2.3	1.5	0.7	0.3	0.2
Reservoir	0.2	0.5	0.9	1.6	2.5	3	2.9	2.4	1.4	0.7	0.3	0.1

Met Office Surface Exchange Scheme (MOSES)[6] (Cox *et al.*, 1999) grid-square values of PET show that there is negligible difference between the grids encompassing the UC catchment and Tittesworth Reservoir (Table 3.1). As a result, using UC PET information from UKCP09WG at Tittesworth Reservoir is a valid approach.

3.4 UKCP09 and UKCP09 Weather Generator

UKCP09WG produces both baseline (1961-1990) and future time-slice[7] (representative of a 30-year period) simulations. In order to produce daily weather statistics for the future, first the baseline simulations for the target area must be validated against instrumental data (see Jones *et al.*, 2009). Assuming this is satisfactory, the WG

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[6] MOSES was developed for a GCM to calculate surface to atmosphere fluxes of heat and water, and represents a significant advance over 'bucket' models and the intermediate complexity models previously used by the Met Office. (Cox *et al.*, 1999)

[7] Time-slices produced by UKCP09WG are temporally consistent, in that they do not show any evolution of climate change signal over their duration. This means that a simulation representative of a 30-year period could have many times that amount of years within it, and each would be representative of the climate within the stated 30 years (e.g. 2010-2039). For brevity, the time-slices are named after the central decade within them (i.e. 2010-2039 is referred to as the '2020s').

baseline simulations are perturbed using a number of change factors produced from the core set of UKCP09 future simulations (i.e. gridded data across the whole of the UK). Ten variables are perturbed, using a mixture of additive, multiplicative and formula-based approaches, and a further four variables are calculated. This produces a set of synthetic (i.e. not related to the instrumental record) daily weather statistics that are each representative of a future period based on data provided by the Hadley Centre Coupled Model, version 3 (HadCM3) perturbed physics ensemble (PPE). For a full explanation of this process, see Jones *et al.* (2011).

UKCP09WG information is downloaded from the user interface at http://ukclimateprojections-ui.defra.gov.uk/. The maximum of 1000 simulations from across the PPE range are obtained for a spatially-averaged area covering the three sub-catchments (Appendix B) and a single grid-square representing the UC sub-catchment (Section 3.5.1). In each case, the medium and high emissions scenarios (which represent the A2 and A1FI Special Report: Emissions Scenarios (SRES) scenarios (Nakicenovic, 2000), respectively, are used to produce the future simulations. The B2 (low) emissions scenario is discounted due to the lack of progress made globally on mitigating climate change since the release of UKCP09, making hopes of keeping emissions at this level unsubstantiated (Anderson and Bows, 2012). The selection of emissions scenarios remains an area of major uncertainty in any climate change impact assessment as the decision is generally made arbitrarily (for example the use of the A2 scenario only in the guidance for current water industry Climate Change Risk Assessments (CCRAs). 2020s, 2030s, 2050s and 2080s are selected as the future time-slices to be assessed

For each of the variations of UKCP09WG information considered in this research (see Appendix B and Sections 3.5 and 3.6), the method for acquiring the dataset is described followed by its validation against the instrumental record. In each stage, three key precipitation statistics for each calendar month are determined: average rainfall, daily variability of rainfall and number of dry days (<1mm). In circumstances where the WG performance is deemed satisfactory against these metrics, the baseline simulations are inputted to the hydrological model HYSIM (see Section 3.8) where they are further validated against instrumental flow records.

3.5 Validation of UKCP09 Weather Generator

3.5.1 Validation overview

It is necessary to validate data from a WG against a sufficiently long instrumental record in order to understand how well it reproduces past conditions at that grid-square (Jones et al., 2009). This is achieved by running a large number of simulations for 1961-1990 (often 100 or 1000) and analysing the fit of key statistics that are required for the proceeding study (e.g. monthly average rainfall, monthly maximum temperature) to those in the instrumental record. In this study, rainfall and PET statistics are of chief importance to the following flow and water resource risk data, and are thus validated below.

3.5.2 Single-site data validation

A single 5x5km grid-square, chosen by trial and error in order to find the best fit for monthly average rainfall, is used to simulate conditions at the UC catchment[8]. The position of the square is shown in Figure 3.4. Rainfall statistics at UC for the 1961-1990 baseline period are shown in Figure 3.5. Average rainfall in August is slightly underestimated, but observed values for all other months are within the sub-sampled range of baseline simulations. Standard deviation is similarly underestimated in August,

[8] The selection of grid-squares for describing sub-catchments remains an issue in climate change impact assessments using a WGM. In this case, a number of individual grid-squares and combinations of grid-squares in the UC sub-catchment were trialled before settling on the one/combination with the most accurate average monthly rainfall.

but within the sub-sampled range elsewhere. Baseline values of percentage days per month with rainfall <1mm (dry days) are overestimated to the extent that the observed values lay below the sub-sampled range on four occasions (January, March, May and August). These correspond with the months in which simulated rainfall is underestimated to some extent (as well as December, which is within the uncertainty bounds for dry days).

Figure 3.6 shows the United Nations Environment Programme Aridity Index (UNEP AI) value and maximum consecutive dry days for each of the 1000 baseline simulations at UC. UNEP AI is simply the ratio between precipitation and PET (P/PET), and has been used to gain an understanding of relative aridity and desertification across the world (UNEP, 1992). It can be seen that the instrumental record sits within the 95th percentile against both metrics, although the maximum consecutive dry days' value is underestimated by a majority of the baseline simulations. This suggests that the ability of the WG to produce extreme dry periods is limited. It is therefore not surprising that the median baseline UNEP AI value is greater than that for the observed record, suggesting simulated 1961-1990 conditions are too wet in a majority of the sequences.

Despite some limitation detailed in this section, the reproduction of 1961-1990 conditions at UC using the UKCP09WG is deemed adequate as a result of the successful reproduction of the annual rainfall cycle, as well as the mean, standard deviation and dry day probability of rainfall in most months. Crucially, performance is not improved by the selection of any other combinations of grid-squares in the sub-catchment. The median baseline average annual daily rainfall of 3.20mm is correct to two decimal places (with a sub-sample range of 3mm to 3.41mm), and the annual standard deviation of that rainfall is shown to be accurate for all but August (Figure 3.5). However, as a single-site WG, any further simulations for SOL, DHY or Tittesworth Reservoir would not be temporally consistent with those for UC, so an approach for producing sequences for the other areas from the UC dataset is required; this is the focus of Section 3.6.

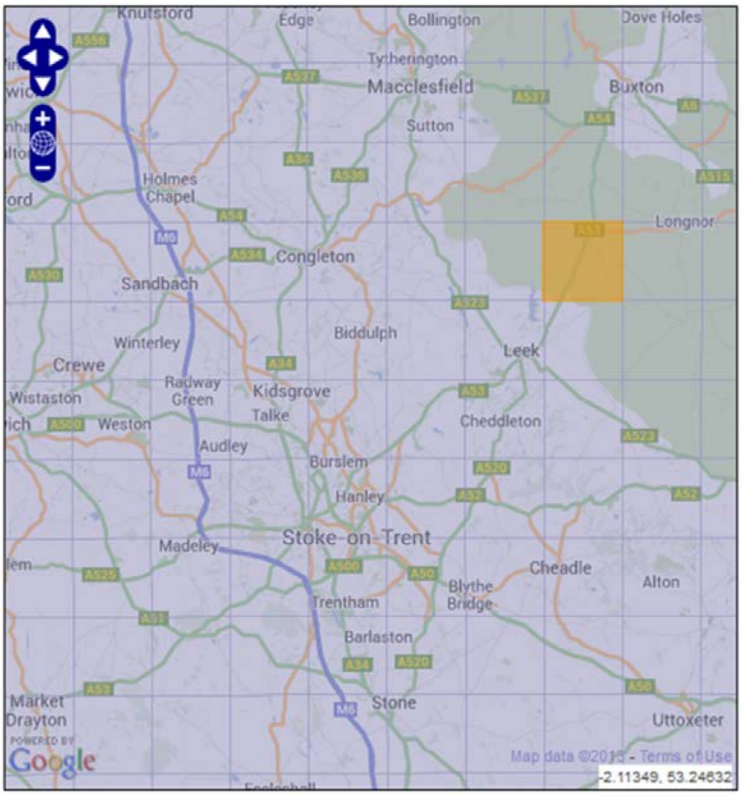

Figure 3.4. Screenshot from http://ukclimateprojections-ui.defra.gov.uk/ showing the grid-square selected for the Upper Churnet simulations.

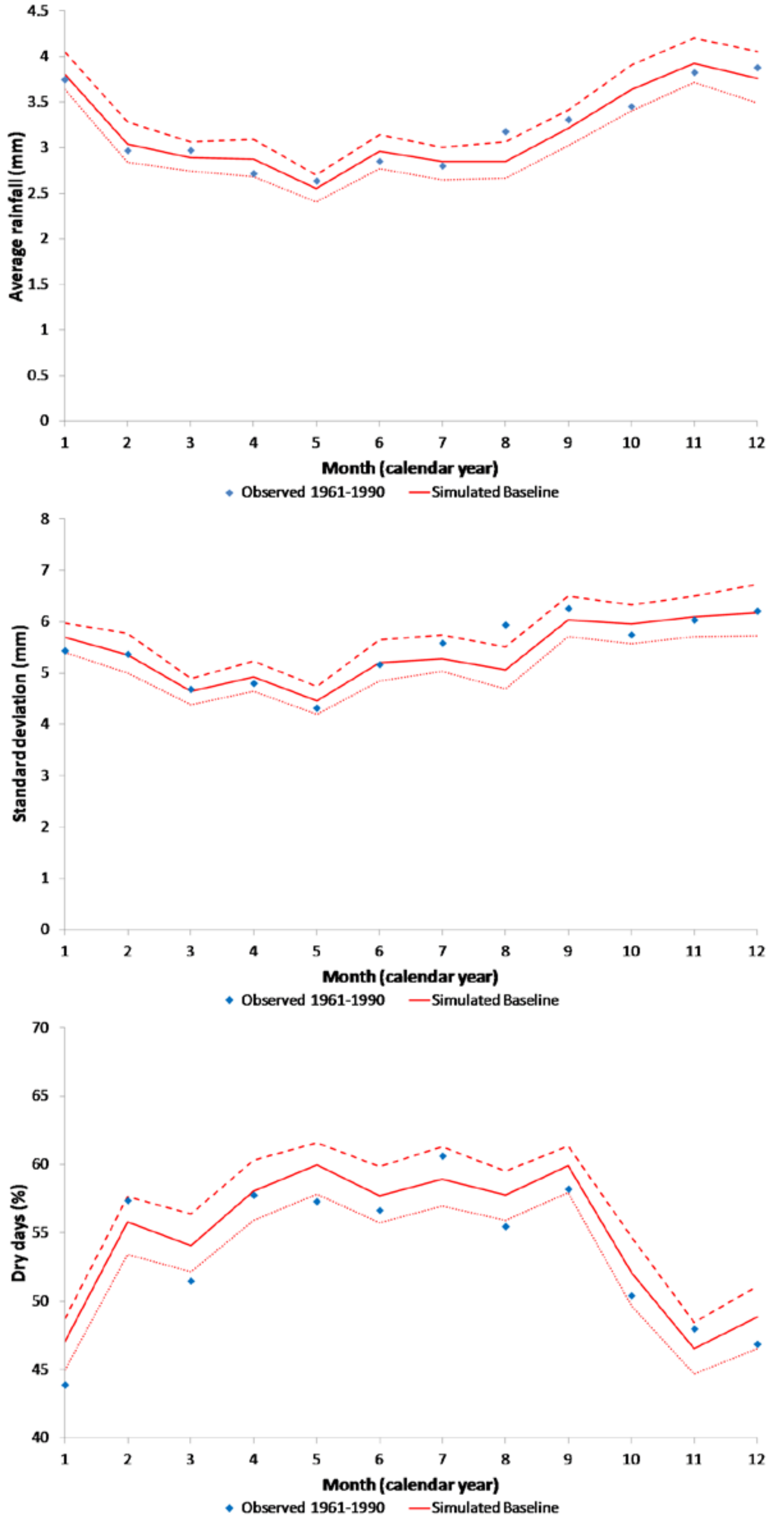

Figure 3.5. Precipitation statistics for Upper Churnet UKCP09WG baseline (1961-1990) simulations. In each plot, the central red line represents the median simulation, with outer bands showing the sub-sampled range. Blue rhombi represent the observed values for the same period.

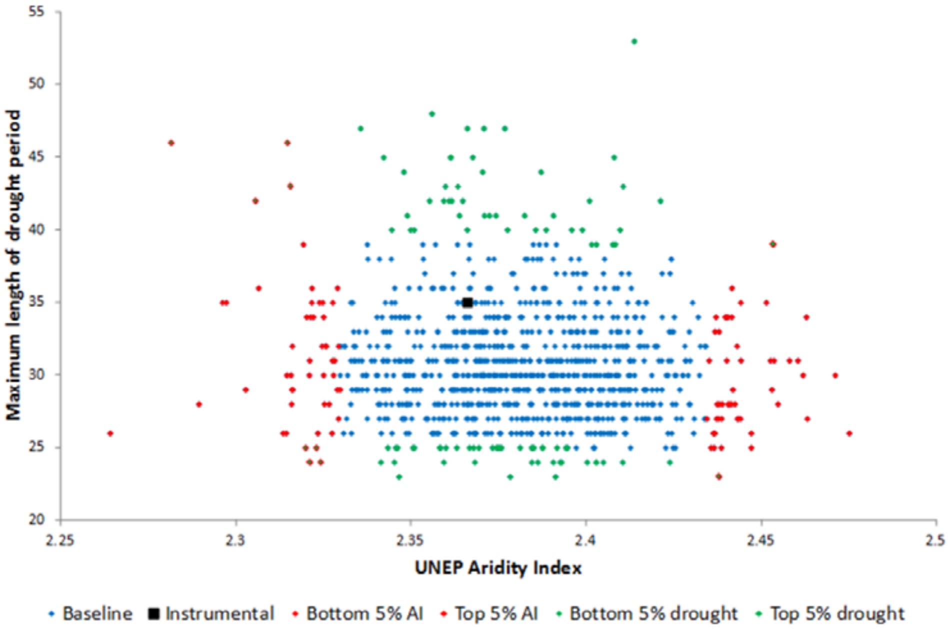

Figure 3.6. Scatterplot of UNEP AI and maximum drought length (consecutive days with <1mm rainfall) for each of the 1000 baseline simulations and the observed record. Points shown in red are outside 95% confidence boundaries for AI, points shown in green are outside 95% confidence boundaries for maximum drought length, and points shown in red and green are outside of 95% confidence boundaries for both AI and maximum drought length.

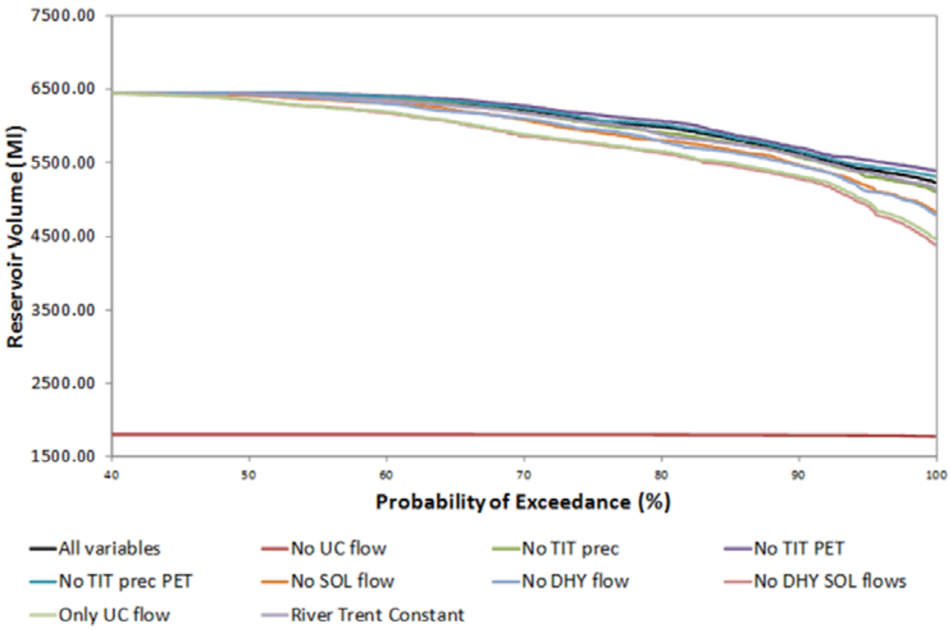

Figure 3.7. Sensitivity analysis of variables affecting Tittesworth Reservoir in the form of a probability of exceedance plot. A 3 year period of the observed record is used to assess reservoir capacities. Significant alterations to the volume of water in the reservoir occur when downstream flows (SOL and DHY) are taken away, and smaller reductions are evident when precipitation and/or open water evaporation are not taken into account. However, eliminating the inflow from UC to the model reduces the reservoir to the dead water line at all times.

3.5.3 **Potential Evapotranspiration validation**

Along with precipitation, PET rates are required for calculating flows at catchments and open water evaporation rates (PET * 1.25) are needed for calculating loss by evaporation from the reservoir. Precipitation is the dominant variable in both cases, but the effects of changes to PET should not be underestimated in hydroclimatological assessments (Harris *et al*., 2009). Table 3.2 shows that WG-simulated open water evaporation rates are lower at UC than at Tittesworth, which show good correlation with the STW dataset. This is in contrast to Table 3.1, which shows MOSES datasets for the areas encompassing the reservoir and UC with good agreement. Therefore, localised effects are occurring within the relatively large ($25km^2$) MOSES grid-squares.

The differences in WG-simulated baseline evaporation rates either side of the Roaches escarpment (which follows the line separating 'UC' from the rest of the shaded area in Figure 3.2) (Table 3.2) shows that the lower evaporation value at UC is likely to be more valid than it first seems, as the only evaporation values in the Aquator model (Supplied by STW) are for the reservoir specifically, and the MOSES square covers a large area. Therefore it can be said with reasonable confidence that the high spatial resolution of the WG accounts for the main differences between the simulated UC baseline and the MOSES 115 grid-square (Table 3.3). Open water evaporation errors between the Tittesworth WG simulation and the STW data are well within reason (internal communication, Mott McDonald) and show similar annual profiles and annual sums, so it can be assumed that the WG produces average PET values reasonably well at UC as well, especially considering the validity of precipitation and flow averages (Figures 3.5 and 3.12). However, no observed PET data exists for UC against which to validate this (i.e. at a higher resolution than the MOSES square).

Figure 3.7, an analysis of the sensitivity of Tittesworth Reservoir to various scenarios in which flow or PET sequences are removed from the Aquator model over the observed 1997-1999 period, shows that subtracting the open water evaporation sequence from the reservoir increases storage by 0.5% (as a sum of reservoir storage over the 3-year period) . This influence is larger than the other direct actor on the reservoir, rainfall, which accounts for a storage decrease of 0.4% when taken away. These values, however, are smaller than the effect of removing the catchment flows at UC, SOL and DHY from the model, which decreases total storage over the three years by 64.4%, 1.2% and 1.2% respectively. Figure 3.7 shows that the 64.4% reduction when the UC flow is removed equates to the reservoir being at the dead water level at all times above 40% probability of exceedance. These values suggest that small errors in the open water evaporation at the reservoir will be negligible in comparison to errors when producing accurate flows at UC, so the accuracy of PET at Tittesworth Reservoir is of less importance (Table 3.2). Given the relatively low sensitivity of Tittesworth Reservoir to direct evaporation, the original UC PET sequence used to produce flow sequences is used at the reservoir

Table 3.2. Total monthly open water evaporation in the instrumental record supplied by STW (1961-1990), the median WG simulation for Tittesworth Reservoir (WG TIT) and the median WG simulation for UC (WG UC).

	J	F	M	A	M	J	J	A	S	O	N	D
STW	12.1	18.8	43.5	65.1	100	103.1	113.2	93.4	56.1	32.4	13.2	9.6
WG TIT	17.1	19.5	40.1	63.9	94.5	103.7	106.3	92.4	58.4	33.1	18.5	14.8
WG UC	16.5	17.9	36.4	57.3	86.6	95.9	99.5	84.1	54.6	31.3	18.6	15.1

Table 3.3. Monthly PET/day (mm) in the WG-simulated UC baseline period (WG) and the instrumental MOSES grid-square 115 (which encompasses the UC sub-catchment) in the same period (1961-1990).

	J	F	M	A	M	J	J	A	S	O	N	D
WG	0.4	0.5	0.9	1.5	2.2	2.6	2.6	2.2	1.5	0.8	0.5	0.4
Inst	0.2	0.4	0.9	1.6	2.5	2.9	2.8	2.3	1.5	0.7	0.3	0.2

3.6 Scaling factor approach for creating spatial weather generator information

3.6.1 **Overview**

A technique is devised that creates artificial rainfall sequences for DHY and SOL based on the WG output at UC, using a z-transform approach that maintains temporal consistency. The situation of a relatively small upland area acting as a catchment for a surface reservoir surrounded by a larger lowland area containing demand centres is not uncommon, and the process detailed here would have significant scope for further use in the water industry, diversifying the usefulness of UKCP09WG. It should be made clear, however, that this approach is not conceived as a fully-fledged spatial rainfall model and would not be suitable where a very strong link between same-day precipitation across the entire research area is not evident. In this case, a spatial scaling approach is used instead of a spatial weather generator in order to maximise the application of this research in the UK water industry, where the user-friendliness and availability of tools is of great importance due to the simulation of future climates being but one of a great number of pressing concerns.

It is assumed that the same major weather systems are apparent at UC, DHY and SOL, and on the same day, given the short distances between them and the dominance of large-scale weather systems rather than convective effects in this area of the UK. This statement is justified by the high daily rainfall cross-correlation coefficients at zero lag between the sites (0.97 between UC and SOL, 0.92 between UC and DHY), and the correspondence of monthly dry day probability across the sites (not shown). The magnitude of small-scale weather effects on daily precipitation values is deemed insignificant compared to the homogeneity between the areas created by large-scale systems, and therefore a simple scaling procedure is undertaken to produce rainfall sequences across the sub-catchments.

3.6.2 Scaling approach methodology

To produce daily time-step simulations at SOL and DHY, the information from UC is scaled using a z-transform. The process for carrying out this procedure for SOL is shown as Equation 3.1.

$$\frac{P_{UC}-\mu_{UC}}{\delta_{UC}} \times \delta_{SOL} + \mu_{SOL} \qquad (3.1)$$

Where,

P_{UC} = Precipitation at UC on a given day (mm)

μ_{UC} = Monthly mean of UC rainfall in the simulation (mm)

δ_{UC} = Monthly standard deviation of UC rainfall in the simulation (mm)

δ_{SOL} = Monthly standard deviation of SOL, calculated by perturbation from UC

μ_{SOL} = Monthly mean of SOL rainfall, calculated by perturbation from UC

Using a z-transform approach means that under no circumstances can individual daily rainfall values be greater at SOL or DHY than the original amount at UC, which is not the case in the observed record. Table 3.4 shows the original UKCP09WG simulated rainfall sequence for the first fortnight of January in the first year of baseline simulation 1, with the scaled values for SOL and DHY. In this example, the January values are: $\mu_{UC} = 3.77$, $\delta_{UC} = 5.68$, $\delta_{SOL} = 0.93$, $\mu_{SOL} = 0.93$, $\delta_{DHY} = 0.75$ and $\mu_{DHY} = 0.78$. The values for δ_{SOL}, μ_{SOL}, δ_{DHY} and μ_{DHY} are based on the relationship between UC and the further catchments in the observed record and therefore do not change, whilst μ_{UC} and μ_{UC} are calculated for each simulation.

Table 3.4. Example sequence showing values for SOL and DHY derived from the sequence at UC using a z-transform approach.

Date	UC (WG sequence)	SOL	DHY
1/1/1900	0	0	0
2/1/1900	19.7	18.4	15.3
3/1/1900	15.6	14.5	12.1
4/1/1900	7.7	7.2	5.9
5/1/1900	0	0	0
6/1/1900	0.3	0.3	0.1
7/1/1900	5	4.6	3.8
8/1/1900	16.7	15.6	13
9/1/1900	3.5	3.2	2.6
10/1/1900	1.3	1.2	0.9
11/1/1900	0	0	0
12/1/1900	0	0	0
13/1/1900	0	0	0
14/1/1900	0.6	0.5	0.4

3.6.3 **Validation of scaling approach**

Figure 3.8 shows that the resultant average monthly mean precipitation statistics for the derived simulated sequences at SOL and DHY are in line with the original UC sequence in terms of reproducing the observed record, which has previously been deemed adequate. The error in reproducing mean conditions in August is carried over from UC to the derived catchments, but the average daily rainfall amount is accurate over a full year in each case. August precipitation variability is similarly outside of confidence bounds in both the original UKCP09WG simulation and those produced by the scaling procedure. Monthly dry days are well reproduced at SOL, but the larger variability discrepancy between UC and DHY leads to dry days being underestimated at DHY in February, July and November, unlike at UC or SOL. The range of variability across the simulations narrows as the scaling factors are reduced, although August remains the only month where observed values are outside the sub-sampled range at each sub-catchment.

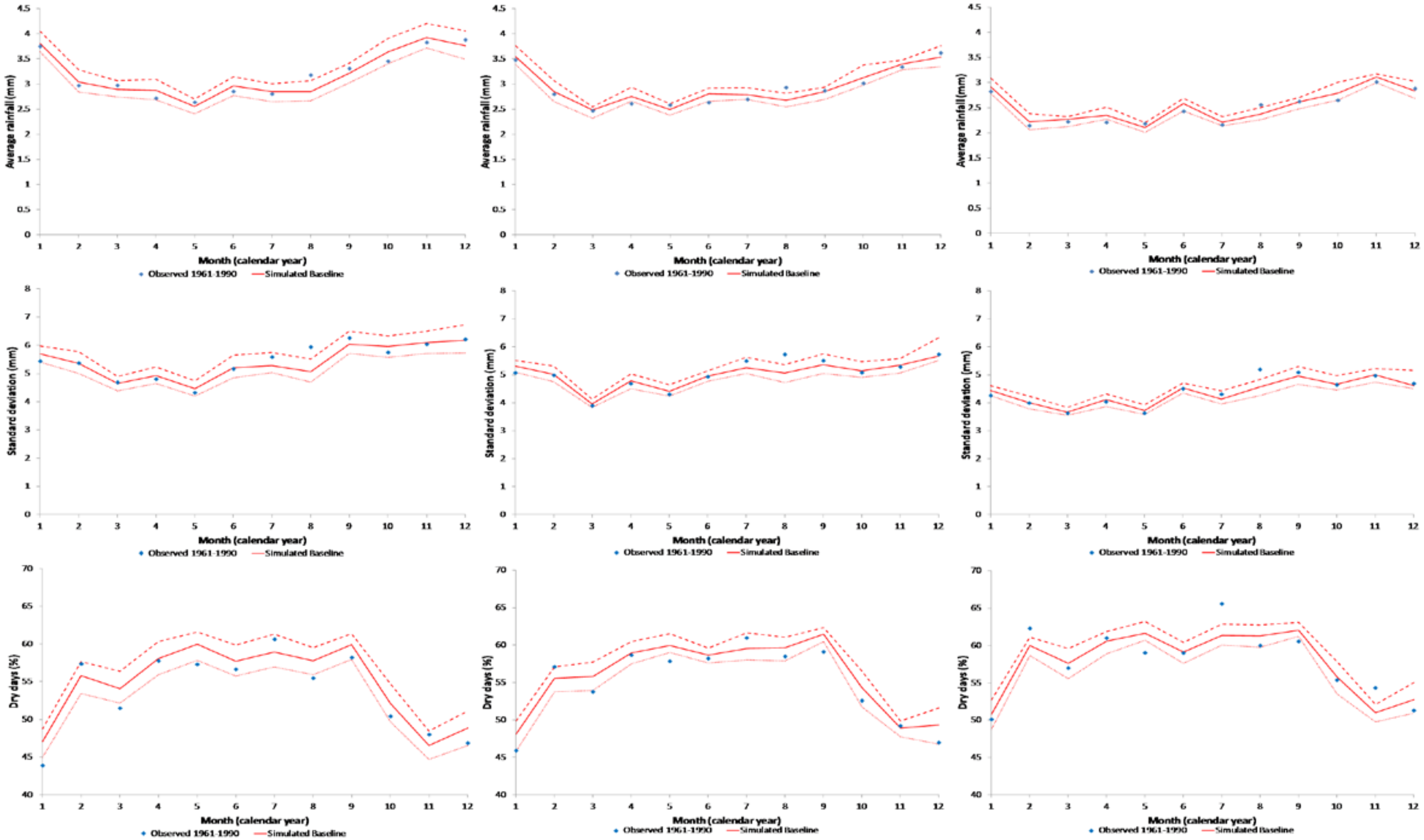

Figure 3.8. Precipitation statistics at each sub-catchment using the *z*-transform approach. Solid red lines show average daily precipitation per month (top), standard deviation of rainfall per month (middle) and percentage of days per month with <1mm of rainfall (bottom) in the median baseline (1961-1990) simulations at Upper Churnet (left), Solomon's Hollow (middle) and Deep Hayes (right). Outer boundaries represent the sub-sampled range of simulations. Blue rhombi describe the observed 1961-1990 statistics.

3.6.4 **Conclusions: scaling approach**

Three approaches to downscaling global climate model (GCM) information using the UKCP09WG to produce precipitation sequences are considered. Spatially-averaging over the research area introduces unmanageable errors in the reproduction of the observed period (Appendix B), but focussing on a single sub-catchment produces satisfactory results (Figure 3.5). In order to produce rainfall across the research area, a z-transform scaling approach is introduced which performs adequately at each sub-catchment (Figure 3.8). The scaling approach is viable in this situation but would not necessarily be transferrable to other catchments, where more complex procedures such as a k-nearest neighbour (k-nn) approach may be necessary. However, the scaling approach is deemed a simple, quick and practical approach to expanding the versatility of the UKCP09WG for hydroclimatological and water resource climate change impact assessments in the UK.

3.7 Sub-sampling of weather generator information

3.7.1 Overview

Due to the computational expense of the multi-model approach taken to produce water shortage risk estimates from the raw climate data, it is not feasible to use all 1000 simulations for each scenario, either in this project or in industry. A more manageable amount of simulations must be produced from the UKCP09 dataset before hydrological and water resource modelling is attempted. This practice is common in hydroclimatological research, and particularly so when the focus is on industrial application of the methodology.

3.7.2 Methodology

Following von Christierson *et al.* (2012), twenty simulations is taken as a reasonable compromise between scientific rigour and industrial practicality when using UKCP09. The aim of the sub-sampling process is to represent the distribution of water shortage in terms of frequency with which a control curve is triggered. It is postulated that the simpler UNEP aridity index (annual precipitation / annual PET) and stratified sampling approach creates a usable sub-sample. The UNEP aridity index benefits from using only the variables that are carried forward to the hydrological modelling phase, being computationally efficient and easy to reproduce in an industrial application.

Stratified sampling of the 2000 simulations for each time slice (1000 from the A1B scenario and 1000 from the A1FI scenario) is used to produce the sub-sample[9] of 20. In practice this consists of ranking the 2000 simulations in order of UNEP AI, placing them into bins of 50, and selecting one from each at random. This approach does not place any bias towards drier simulations, as is the case in the analysis by von Christierson *et al*. (2012), amongst others. As a result, a fair reflection of the entire UKCP09 range is produced, but extreme simulations are likely to be discounted.

3.7.3 **Sub-sampling validation**

The UNEP aridity index, the frequency of SAL-severity conditions and mean annual flow is calculated for each of the 1000 simulations in the 1961-1990 baseline period, in order to assess the relationship between the variables. Figure 3.9 shows that there is good correlation between UNEP AI and flow (R^2 = 0.9393), but more importantly that there is a clear relationship between the aridity of a simulation and the amount of days with SAL-triggering conditions at Tittesworth reservoir. Given the need for a fast and replicable sub-sampling technique for industrial applications, it is suggested that the UNEP AI is a practical approach to selecting twenty simulations from the UKCP09WG range. However, more detailed approaches to sub-sampling using Latin Hypercube Sampling (e.g. Burton et al., 2010) are more likely to give a better account of extreme

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[9] From this point onwards, the 'sub-sample' refers to the 20 simulations for each time-slice produced in this way.

simulations. This represents a limitation of the research undertaken here, but is justified given the necessities of an applicable and replicable approach in industry.

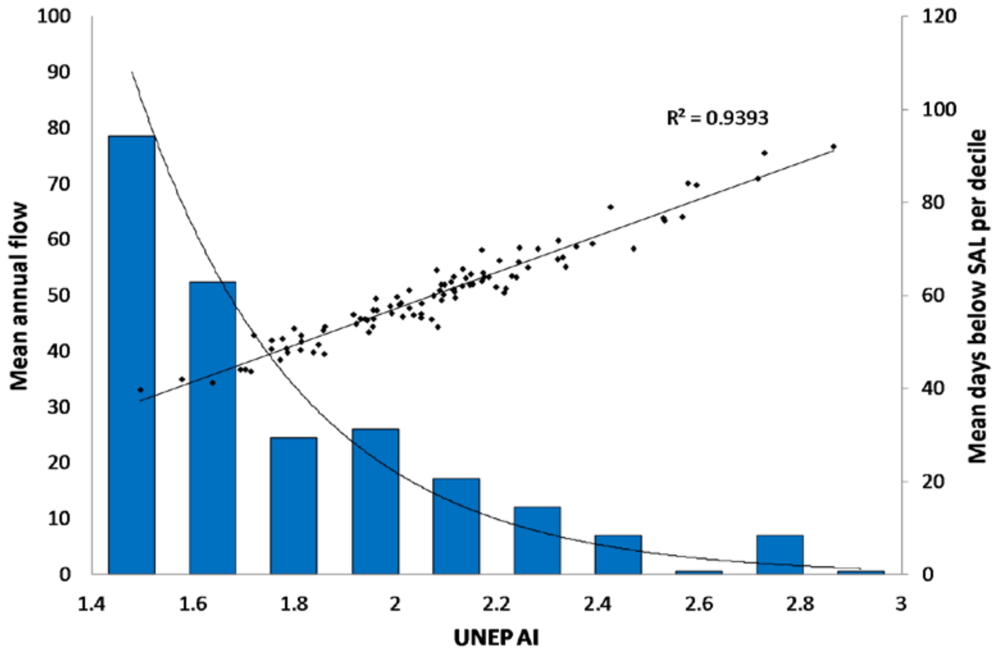

Figure 3.9. Validation of the sub-sampling approach using two approaches. The relationship of UNEP AI with mean annual flow (left axis, black rhombi- each representing one year of a 100 simulation) and mean days below SAL-triggering conditions (right axis, blue bars – each representing a decile of the UNEP AI range) both show good agreement.

3.8 Hydrological modelling

3.8.1 Application of HYSIM to the North Staffordshire Water Resource Zone

Flows sequences for the sub-catchments are simulated in HYSIM, a physically-based lumped conceptual rainfall runoff model (Manley, 1978) which has been used extensively in climate change impact assessments in the North Staffordshire WRZ and more generally across the UK (Murphy *et al.*, 2004; Severn Trent Water, 2010, 2011(a); 2012(b); Hall and Murphy, 2011).

HYSIM has been used regularly by STW to provide flows for the assessment of historical water resource management situations and derive LoS in Aquator models by way of maximum DO simulations. The hydrological parameters used in this project are based on an extensive survey carried out by Mott MacDonald and STW (Severn Trent Water, 2011(b)) to update the flow database for the entire STW area, in which a full validation and calibration of the hydrological model parameters used in this project can be found. It is assumed that relationships between hydrological variables in the catchment will remain constant in the future as the climate changes.

Three parameter sets that quantify the conditions of the UC, SOL and DHY sub-catchments are used. Confidence in the simulated flow series for UC are declared 'average' in the STW (2011) report due to the calibration being based on limited naturalised[10] data from a reservoir model. The modelled naturalised flows showed very good agreement with the observed naturalised flows but only a short period (2007-2010) of data exists, thus reducing confidence in the simulated outflow sequence stretching back to 1918. SOL parameters use the same catchment parameters as at UC,so only the rainfall and PET sequences are different. Therefore, a similar (albeit scaled-down due to the difference in catchment size) runoff regime to UC would be expected. DHY uses the Churnet at Basford catchment which shows good calibration, although the actual DHY sub-catchment itself is not calibrated, thus reducing confidence. The rationale for this is similar to the use of one rainfall sequence across the lowland area of the research area (Section 3.3).

UKCP09WG rainfall and PET sequences are substituted in for the simulated historical sequences described above in order to produce baseline (1961-1990) and future flow sequences. Therefore, the validation found below relates to the ability of UKCP09WG to reproduce the simulated observed 1961-1990 flow sequences at UC, SOL and DHY using the same parameter sets in HYSIM, which are in turn validated against naturalised

[10] Naturalisation of a flow record is the process of producing a flow that would occur at the outflow, or downstream, of a reservoir, were it not in place by utilising a reservoir model. This is a useful technique as inflow to a reservoir from a catchment is rarely measured (and has not been at Tittesworth), so enables the production of inflow series to the reservoir (i.e. at UC).

instrumental data in Severn Trent Water (2011)[11]. As described in Section 3.5.2, UC PET sequences from the WG are used for all three sub-catchments. 20 baseline simulations of 98 years (100 years minus a two-year wind-up period) are created to produce the validation.

3.8.2 **Hydrological modelling validation**

Average flows per day simulated across the UKCP09WG baseline ranges are shown in relation to the observed sequences at each sub-catchment (Figure 3.10). It can be seen that there is a slight overestimation of summer and autumn flow (with the exception of August, which is expected given Figure 3.8) and a slight underestimation in February. On four occasions (February, June, September and October) the observed flow averages are marginally outside the WG simulation range at UC, and on two occasions elsewhere (February and June at SOL, February and October at DHY). Agreement is good in other months, especially in the key reservoir recharge months of November, December and January. Average annual flow is reproduced well at all sub-catchments (Table 3.5).

Flow duration curves (FDCs) are used to show the extent of time a certain flow is equalled or exceeded within a dataset. Figure 3.10 is an FDC that describes the extent of

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[11] The simulated flow sequences representing the historical period are often referred to here as 'observed' for clarity (so as to be consistent with the observed rainfall sequence), although these sequences are not actually 'observed' but HYSIM-modelled hindcasts of flows based on rainfall and PET records. This is due to the actual observed flow records for the Tittesworth Reservoir area not extending back into the 1961-1990 period.

the overestimation of low flow events at UC, SOL and DHY in the simulated dataset compared to the observed sequence. Whilst high and medium flows are reproduced well, the simulated range deviates from the observed record at around the 65% point. This inaccuracy stems from the inability of the UKCP09WG to reproduce multi-seasonal drought events that account for the most extreme dry events, and thus the lowest flows (Jones *et al.*, 2009). The error is greatest at UC, and is less problematic at SOL, and particularly DHY, which have lower average runoffs.

Average monthly flows are deemed satisfactory for use as the basis of the CFM (Section 3.9) (Figure 3.10), although it would be expected that summer flows would continue to be underestimated and winter flows overestimated in the future. The overestimation of low-flows (Figure 3.10) presents a significant weakness of the weather generator method (WGM) to estimating future water shortage risk. Taken together, Figure 3.10 shows that the UKCP09WG is an imperfect tool for assessing future flows (and thus future drought risk), as would be expected given the precipitation validation in Sections 3.5 and 3.6. However, it remains the case that useful information can be derived from UKCP09WG using the derived LoS approach described in Section 3.11.

Table 3.5. Percentage average flow per day differences between the UKCP09WG range median and the observed values for each month and the annual sum (A). Occasions where the observed value is outside of the sub-sampled UKCP09WG range are shown in red.

	J	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**A**
UC	-2.4	-7.4	-5.6	-2.5	-2.4	18.1	13.9	-5.9	16.5	10	1.3	-5.4	0

SOL	-4.4	-6.9	-5.6	2.2	-0.5	19.5	16.2	-5.8	6.9	9.9	0	-7.1	-0.9
DHY	-4	-8.2	-6	-2.3	-1.6	17.6	10.2	-2.1	12.2	11.4	3.1	-9.3	-1.1

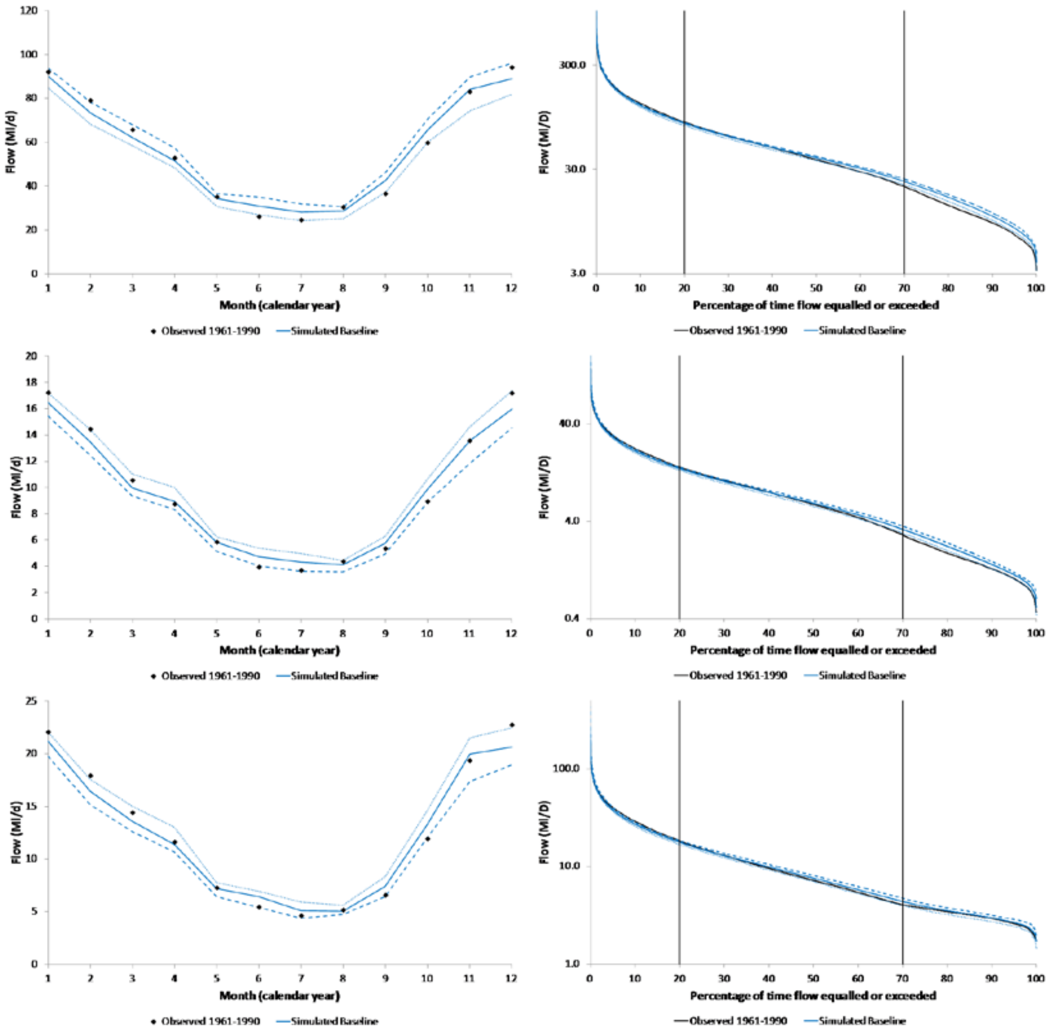


Figure 3.10. Flow statistics at each sub-catchment, modelling in HYSIM. Solid blue lines show average daily flow per month (left) and the FDC (right) in the median baseline (1961-1990) simulations at Upper Churnet (top), Solomon's Hollow (middle) and Deep Hayes (bottom). Outer boundaries represent the sub-sampled range of simulations. Black rhombi/lines describe the observed 1961-1990 statistics.

3.9 Change factor method

Due to the limitations of the WGM outlined in Sections 2.6 and 3.5, a secondary downscaling approach is undertaken to produce future flows as a comparison. Employing a CFM is the standard approach for using climate information in a risk assessment, and involves perturbing an instrumental record using mean monthly future projections for various statistics. Most commonly, daily precipitation and/or temperature from the instrumental record are scaled using the outputs from a GCM or regional climate model (RCM) simulation by multiplying it by a ratio of the future simulation to a baseline simulation (generally 1961-1990). This is usually done on a monthly, or twice-monthly basis so as to account for seasonal differences in change.

In this case, the same sub-sampled future WG simulations as used in the main methodology are used to produce CFs for mean flow, which are applied to the observed flows (1920-2010). The flows are perturbed, rather than the rainfall and PET statistics, as; a) the flow simulations had already been computed for the WGM; b) the difference between using the flow simulations and the rainfall/PET sequences was infinitesimal; and c) the instrumental flow record is longer and more reliable than the PET records.

Using the same instrumental flow record and WG flow simulations described previously, monthly CFs are created by comparing flows in each of the future time-slices to the median 1961-1990 baseline simulation (in terms of UNEP AI). These CFs are then applied to the 1920-2010 instrumental flow record (using more than the 1961-1990 period in order to gain a greater breadth of variability), thus producing 20 91-year daily flow sequences for each time horizon. Seeing as the instrumental record forms the basis of any future flow statistics (rather than a synthetic sequence as in the WGM), no further validation beyond that shown in Figure 3.10 is possible (or indeed necessary).

Applying a CFM to instrumental rainfall data in this way follows the same fundamental principles as the approach to perturbing the UKCP09WG to represent future climates, as described in Jones et al. (2009). However, in the case of the UKCP09WG, there is a significant array of ‘change factors’ taken into account (e.g. rainfall skew, vapour pressure, diurnal temperature range etc.), and the method of perturbation varies between applying a ratio (as is calculated for flow in this thesis), calculating a difference (e.g. temperature), or using a formula (probability of a dry day). The CFM used in this research takes these perturbed values of the future and relates them *back* to an instrumental record. It is acknowledged that the use of future WG data to perform this is ultimately an unnecessary step (only monthly data from the PPE would be needed to perform the perturbation of the instrumental record), but is justified in this case as the WG data already existed from the WGM described earlier, and a direct comparison of the two approach could be achieved by using the same sub-sample; running a new set of (non-WG) UKCP09 simulations would require producing a new sub-sample.

3.10 Water resource modelling

3.10.1 Application of Aquator to the North Staffordshire Water Resource Zone

Aquator ((Oxford Scientific Software, 2008), a commercially available conjunctive-use water resource system model, is used in this research project primarily due to the availability of a pre-constructed model built up over a number of years of collaboration between the developers, Oxford Scientific Software, and STW. The model allows for complex and conjunctive use water resource systems to be modelled in a way that takes into account hydrological conditions, thereby allowing for alterations to releases from reservoirs or the use of abstraction licences based on daily circumstances. Although the model includes built-in climate change functionality based on the application of CFs to historical sequences, in this research the new flow, rainfall and PET sequences described earlier are inputted to the model and executed in batch runs using Microsoft Visual Basic for Applications (VBA) code.

The North Staffordshire WRZ is reproduced in an Aquator model that contains the relevant infrastructure, demands, constraints and licences in the area, and is shown in schematic form in Figure 3.11. The model includes the demand centres Stoke, Moorlands, Market Drayton and Stone. These demand centres are fed by a combined use system that makes use of surface water resources from Tittesworth Reservoir, alongside groundwater sources across the region. STW would expect the flow from the southerly half of the model into Stoke at Hanchurch to be robust in any situation, with the northern section (north of Hanchurch Service Reservoir) more susceptible to drought due to the greater reliance on Tittesworth Reservoir. The current version of the model, produced for STW's WRMP 2013, contains the updated HYSIM flow database developed in 2011 (Severn Trent Water, 2011(b)), and the most up-to-date control curves for Tittesworth Reservoir and demand profiles shown in Figure 3.13. This version of the model was developed in 2012 by OSS as part of the construction of a wider STW strategic grid model.

There is a total compensation for the River Churnet at the termination of the model (i.e. where the River Churnet flows beyond the WRZ) at Basford Bridge of 19.2 Ml/d. A maximum of 4Ml/d of this can be provided by the DHY catchment and borehole, with the rest coming from Tittesworth and SOL. The main outflow from the reservoir is to the west to satisfy the demand centres and is controlled by the Tittesworth WTW. Stoke-on-Trent is further resourced by the Meir and Leek groundwater groups and the Hanchurch surface reservoir, which is fed by various groundwater reservoirs further to the south. Relatively minor groundwater resources at Eastwall, Peckforton, Elmhurst, Audley, Cheadle and Moddershall augment supply (see Figure 3.11 for the layout of the North Staffordshire WRZ in Aquator).

The model is used for two purposes; firstly, to assess the extent to which the future conditions created by the WG, manifested as flows from the UC, DHY and SOL catchments, effect the levels of Tittesworth, and therefore the water resource vulnerability of the Stoke and Moorlands demand centres. Secondly, the model is manipulated to represent potential water resource options and strategies that may be employed in the future in an attempt to increase the resilience of resource provision to the demand centres. Using the probabilistic datasets, it is possible to analyse the effectiveness of such strategies across the range of uncertainty.

3.10.2 Water resource modelling validation

Given the overestimation of summer flows in the baseline UKCP09WG simulations (Figure 3.10), the exaggerated 1961-1990 average reservoir fills compared to the observed data in Figure 3.12(a) is expected. Observed fills are outside of the sub-sampled UKCP09WG range in June and July, suggesting that early summer drawdown in future projections are overestimated, thus quantifications of summer drought risk will be conservative. Similarly, the departure of the simulated volume duration curve (VDC) (Figure 3.12b) from the observed data at Tittesworth Reservoir at around 85% probability of exceedance is expected, given Figure 3.10. The difference between the most extreme dry periods (85%+ probability of exceedance) in Figure 3.12(b) describes the lack of multi-seasonal drought events in the WG simulations, leading to more infrequent periods where the reservoir is severely drawn-down compared to the observed data. Again, this indicates future projections of water shortage probability will be conservative. The ‘observed’ Tittesworth Reservoir capacity data used here has been derived using the same Aquator model as long instrumental records of storage do not exist (see Severn Trent Water, 2011 for a description of this process), so it is not possible to comment on any discrepancies between the modelled data and instrumental records.

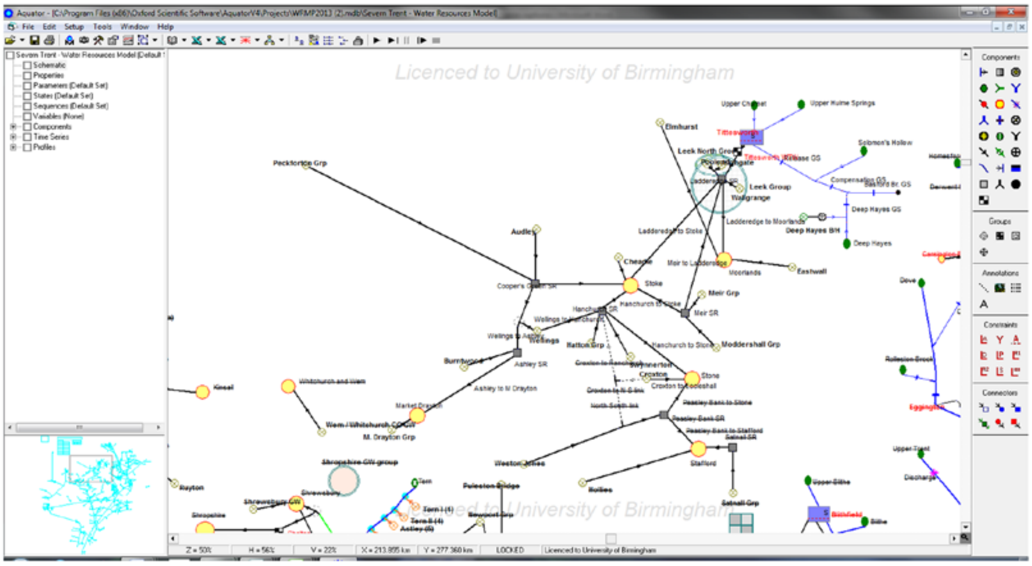


Figure 3.11. Schematic of the North Staffordshire WRZ in Aquator. Upper Churnet, Solomon's Hollow and Deep Hayes catchments, denoted in green, are found in the top-right (Upper Hulme Springs has nil flow, having been amalgamated with Upper Churnet into one reservoir inflow). Demand centres are shown as yellow circles, groundwater sources as crossed circles, WTWs as black-and-white checked boxes, service reservoirs as grey boxes, built linkages as black lines and natural watercourses as blue lines. The schematic shows the combined-use nature of the North Staffordshire WRZ, with resources from Tittesworth Reservoir being complemented by a number of smaller groundwater abstractions around the region.

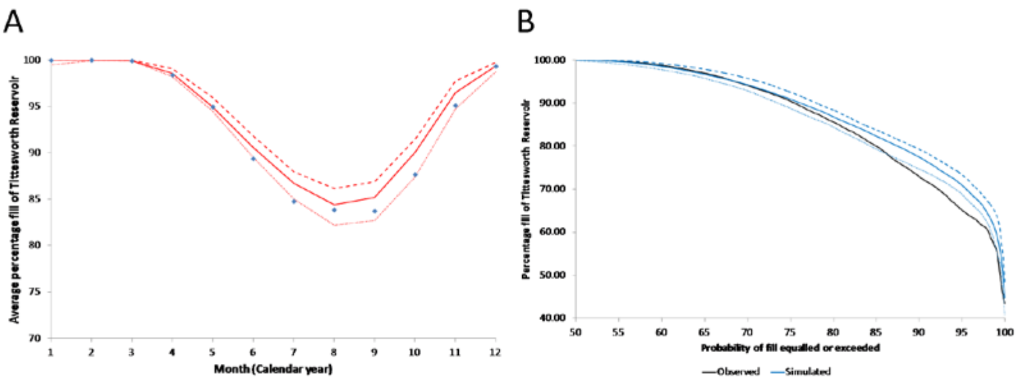


Figure 3.12.(A) Average percentage fill of Tittesworth Reservoir in each month in the median baseline (1961-1990) simulation (solid red line) and the sub-sampled range of simulations (outer bounds). Observed values for the 1961-1990 period are denoted as blue rhombi. (B) Volume Duration Curve (VDC) for Tittesworth Reservoir in the median baseline (1961-1990) simulation (solid blue line) and the sub-sampled range of simulations (outer bounds). Observed values for the 1961-1990 period are denoted as the black line.

3.11 Risk-based approach to assessing water shortage events

3.11.1 **Overview**

A risk-based approach to hydroclimatological assessment is used in this project to allow robust adaptation decisions to be identified. Passing a threshold that denotes a failure to reach a particular LoS is taken as a suitable metric of risk, in this case the probability of crossing a reservoir control curve in any given year (Brekke *et al*., 2009; Hall *et al*., 2012(a)). Calculating the probability of water shortage across the range of climate model uncertainty allows for decisions to be taken that serve to increase the robustness of the system, rather than optimise it. This allows decisions to be made on how to address the impact of climate change in the WRZ with a degree of confidence, despite the wide uncertainty regarding future conditions.

Three operational control curves at Tittesworth Reservoir are used in this assessment: TUB, DWT, and SAL, as described in Section 3.2. The curves can be seen in Figure 3.13. The number of years over a full 100-year simulation (or 91-year simulation when the CFM is used) in which a trigger of a certain severity is activated allows for an assessment of whether a LoS, which is a target probability of a trigger occurring in a year, has been met in each simulation.

3.11.2 Risk-based approach methodology

The process for incorporating uncertainty into water shortage risk assessment and the ensuing decision-making on adapting to that changing envelope of risk is laid out in Figure 3.14. Assuming a target frequency x (akin to a water company's LoS) of water shortage severity event $y_{...n}$ (i.e. TUB, DWT or SAL) occurring in a time horizon $t_{...n}$ (in this case the 2020s, 2030s, 2050s or 2080s), an 'acceptable risk' i a certain percentage of the modelled uncertainty range can be used to assess the robustness of the water supply system. By organizing the water shortage dataset into a cumulative distribution function (CDF) with x and i set by external drivers, the extent to which i is satisfied can be seen by comparing it to the actual percentage of the model range that lies beyond x, denoted as j.

Acceptable risk i is maintained as 20% of the simulation range; that is, it is assumed that a system that is robust to satisfying x in 80% of the simulation range would be an acceptable situation. 80% of the simulation range is taken so as to be in-line with STW practice regarding the confidence level they use when calculating target headroom: "We have chosen this level as we believe it delivers the best balance between the cost of closing the supply / demand deficit and the risk associated with planning uncertainties during the Asset Management Period 5 (AMP5) period, in particular, the potential impacts of climate change on our deployable output" (Severn Trent Water, 2010, p. 48). In a practical application, the approach put forward in this research would enable the effectiveness of approaches to be assessed gradually (i.e. looking primarily at ensuring robustness up to the 2030s and building-up an adaptation portfolio from then on), thus avoiding the expenditure on long term schemes that prove unnecessary that is stated as a concern in the company's WRMP. Therefore, *i* remains at a constant level beyond the WRMP time-horizons.

First, climate change-only projections of the future are built up (i.e. no non-climate change stressors on the system, and the system operation/infrastructure is kept the same as present day), therefore assessing the effect climate change has on *i* being satisfied. Then, should *i* not be satisfied, approaches to reduce the amount of the water stress distribution that lies beyond the target frequency *x* can be applied to the model until *i* is satisfied across each *y*. This approach is referred to as robustness assessment, and is expanded upon in Section 3.11.4.

In the illustrative example shown in Figure 3.14 (for an unspecified *y*), the water resource system could not be considered robust in *t1*, which can be taken to represent current operational conditions (i.e. no adaptations to the system) in a near-future time slice (such as the 2020s). In a farther afield time-slice (*t2*), $j < i$ and therefore the system is deemed robust. Cost, environmental impacts, land-use change and other factors are not taken into account in this approach, although the same framework for analysing ranges of information can be extended for use with other metrics (such as cost, water quality, groundwater licence usage etc.) and various non-climate change uncertainties can be brought in to the model (probabilities of unavailable groundwater resources, alteration to leakage rates etc.). However, this study is focussed on providing a case study that advocates how decisions can be made using probabilistic climate change information as a base, rather than providing a definitive assessment of adaptation options for the North Staffordshire WRZ given all of the complex interactions involved.

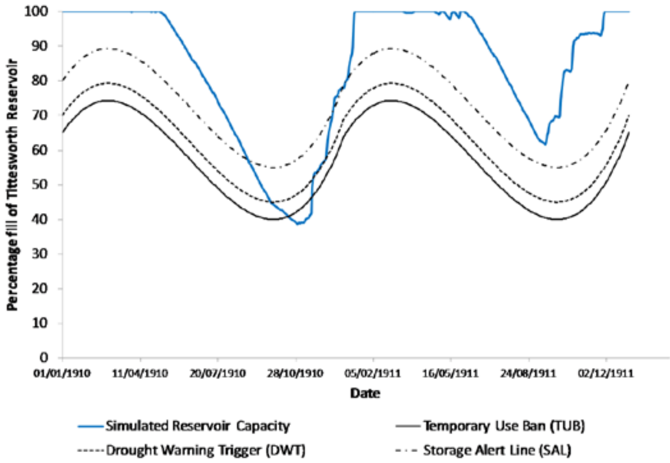


Figure 3.13. Example of control curves being triggered by low storage at Tittesworth Reservoir in a simulation. In the first year (1910), all three control curves are crossed, whilst in the second (1911) none are crossed.

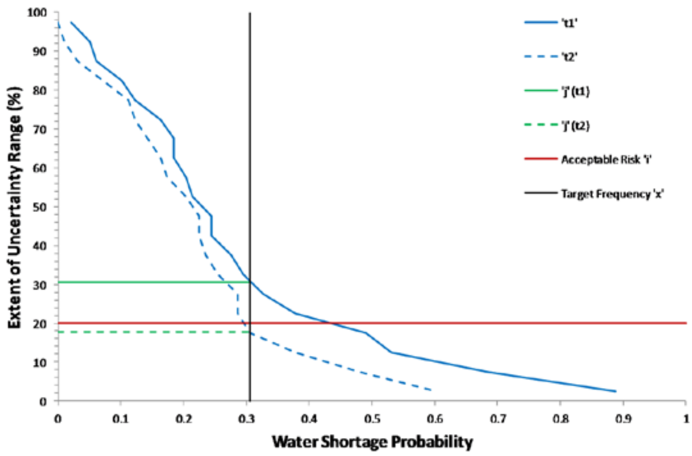


Figure 3.14. Hypothetical CDF describing the transformation of a range of Aquator simulations into an assessment of robustness.

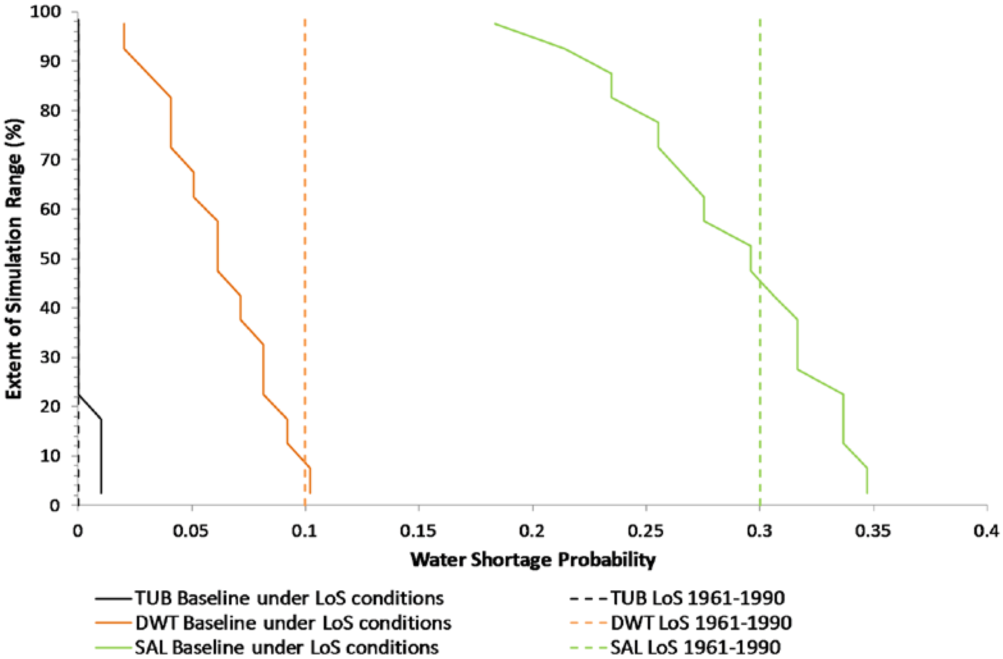


Figure 3.15. Assessment of water shortage probability in the range of baseline simulations (solid lines) with DF =1.25 (as for the maximum DO simulation) against the observed water shortages (dashed lines) in the 1961-1990 period. There are zero TUBs in the observed 1961-1990 period.

3.11.3 **Water shortage event validation**

It is necessary to validate the skill of the weather generator in reproducing instrumental water shortage events. Vertical lines on Figure 3.15 refer to the probability of a control curve being triggered in the observed record as described in Section 3.11.2, whilst the CDFs relate to the simulated UKCP09WG range. Seeing as the UKCP09WG can only be representative of the period 1961-1990, only this period is analysed. Probabilities of triggering control curves in the 1961-1990 period are lower than over the whole historical record as there are fewer dry episodes. In practice, this means that the LoS defined here are less severe than those found in the STW WRMP, which are based on the entire sequence (i.e. the target probability of triggering a control curve over a simulation period is lower). Similarly, the CFM simulations, which use the entire 1918-2010 period, have higher LoS targets than the WG simulations due to 1918-1960 and 1991-2010 having higher water shortage probabilities than 1961-1990.

The amount of control curve triggers in the maximum deployable output (DO) run over the entire historical period determines the LoS for the WRZ and thus defines company targets, so the 'inferred' 1961-1990 LoS are set as the targets against which future simulations and adaptation options are assessed. Therefore, LoS (*x*) for DWT and SAL are set at probabilities of 0.1 and 0.3 respectively. However, with demand factor (DF) = 1.25 (the DF of the maximum DO run for the full 1920-2010 period) there are still no TUB events in the 1961-1990 period, so the company-wide TUB LoS (*x*) of 3 events in 100 years is used, modified slightly to 3 events in the historical record (91 years), giving a probability per year of 0.033. This limits confidence in the TUB dataset, which is discussed in more detail in Chapters 6, 7 and 8.

Figure 3.15 shows the performance of the baseline data run through the Aquator model with DF=1.25 (akin to the maximum DO simulation). It can be seen that the median SAL simulation very close to the SAL inferred LoS (i.e. the centre of the simulation range is in agreement with the observed record). Performance in terms of DWT is not as strong, with only the dry tail of the simulation range exceeds the inferred LoS. This suggests that the UKCP09WG is effective at reproducing less-intense drought events that lead to a triggering of the SAL, but is not as adept at reproducing the frequency of more intense drought that lead to the triggering of DWT events (and, intuitively, TUB events, although no data is available to validate that statement). This is expected given the poor reproduction of the lowest observed levels at Tittesworth (Figure 3.12).

3.11.4 **Adaptation options assessment**

The selection of long-term water management approaches and climate change adaptation measures can be based on testing the response of various different options against the range of future scenarios. Those adaptation measures that perform statistically well in alleviating water shortage risk over the range of uncertainty (by reducing the amount of times a LoS is not met until an acceptable risk is satisfied), whilst remaining cost effective, environmentally sound and within the interests and values of customers and stakeholders, would then be deemed suitable for selection (Hall *et al.*, 2012(a)). In the case study provided in this research, only the impacts of climate change are assessed.

If the acceptable level of the chosen metric of risk is stationary throughout time (that is, the customer's expectations regarding the supply of water remains unchanged throughout time), then water management strategies must keep pace with the changing nature of the climate projections as the century progresses in order to maintain standards. To illustrate the concept, the CDFs *t1* and *t2* in the hypothetical Figure 3.14, previously described as two different time-slices, could equally represent two different adaptation scenarios (with *t2* satisfying acceptable risk and *t1* not).

The lack of transient climate change information (and thus the necessity to use separate time horizons *t*) means that the robustness of a climate change adaptation plan can only be assessed for one time-slice at a time. Therefore, it is assumed that once water shortage risk is deemed acceptable in an earlier time horizon (say, the 2020s), those strategies employed to make it so are carried over onto a later time horizon (2030s) and robustness is assessed again.

As the core objective of this research project is to provide a case study for how a RDM-type assessment based on water shortage probabilities using UKCP09 information can be carried out, the adaptations scenarios used are not necessarily viable and are largely for illustrative purposes only. The Aquator model parameters altered to create the scenarios are described in Section 7.2.2 (Table 7.1).

3.12 Conclusions

A methodology for assessing the impact of climate change on water resource shortage risk is produced that is applicable to, and replicable by, the water industry. The approach taken uses the UKCP09WG as it's basis, and applies the data gathered from it to both a hydrological and a water resource model by way of spatial-scaling and sub-sampling. A technique is described that takes the outputs from this process and utilises them in a way that enables decisions to be made by water resource managers despite uncertainty. The methodology is catchment-specific, but the structure used can be used in other similarly small catchments. Furthermore, the approach is in an excellent position to benefit from advances in technologies; particularly an increase in the availability and usability of spatial weather generators and better representation of extreme dry events.

4 UNCERTAINTY ANALYSIS

4.1 Introduction

This chapter aims to ascertain the relative scales of climate model uncertainty within the UK Climate Projections 2009 Weather Generator (UKCP09WG) simulations (i.e. perturbed physics ensemble (PPE) uncertainty) and Special Report: Emission Scenarios (SRES) scenarios (i.e. emissions scenario uncertainty) in terms of water shortage risk, which is a unique objective. The emissions scenario uncertainty concerns our inability to know how societies and economies will develop and therefore how much greenhouse gas will be emitted into the atmosphere and increase energy budgets within the Earth system. PPE uncertainty is analogous to climate model uncertainty, as probabilistic climate change projections essentially use multiple iterations of one climate model with parameters that describe the Earth system changed. This is a more thorough approach to that used by an ensemble of climate models, which each have their own 'best guess' as to the parameterisation of the Earth system model. The general need for a better understanding of PPE uncertainty comes as legislative pressure on water companies from the England and Wales water sector regulator, Ofwat, to use probabilistic UK Climate Projections 2009 (UKCP09) in their adaptation plans comes into force. The production of practical and replicable frameworks for the effective use of UKCP09 in the water industry, which explicitly requires a better understanding of uncertainty, is now crucial to the long-term sustainability of water resource supply (Arnell, 2011(b)). Conveying the range of uncertainty involved with a climate change assessment of future water shortage can facilitate the establishment of policies and strategies that are statistically robust to the range of plausible futures, therefore increasing resilience and reducing the possibility of maladaptation (Groves *et al*., 2008; Hall *et al*., 2012(a)).

As well as analysing the two uncertainty sources in terms of water shortage risk, a quantification of the effect of each on flows is also carried out which adds a catchment-specific case study to the extensive canon of work on the relative size of various uncertainty sources in hydroclimatological assessments (Prudhomme and Davies, 2009; Kay *et al*., 2009; Kingston *et al*., 2009; Arnell, 2011(a); Bormann, 2011; Dobler *et al*., 2012; Schoetter, 2012; Steinschneider *et al*., 2012; Bosshard, 2013; Paton *et al*., 2013; Velazquez *et al*., 2013) (see Section 2.4.3). However, by focussing on a specific metric of risk that is further along the modelling chain than flows, this research can be considered more similar to the work carried out by Gosling *et al*. (2012), which took future projections of temperature and transformed them into heat mortality risk metrics across a probabilistic range before carrying out an uncertainty analysis.

This chapter begins by describing the methodology used for quantifying uncertainties, which is broadly based on that found in Chapter 3 but contains some nuances (Section 4.2). A section detailing the differences between this work and other research undertaken in recent years in this area (Section 4.3) is followed by the uncertainty analysis results for precipitation (Section 4.4), flow (Section 4.5) and water resource shortage (Section 4.6), before conclusions are drawn (Section 4.7). A discussion of all the results in the thesis is provided in Chapter 8. The work presented here forms the basis of the published *Climatic Change* (Impact Factor: 3.634) journal article "Quantification of uncertainty sources in a probabilistic climate change assessment of future water shortages" (DOI: 10.1007/s10584-013-0871-8), the abstract of which is included in Appendix A2 (Harris *et al*., 2013(a)).

4.2 Data sources and models used

The methodology used in this section largely follows that found in Chapter 3 (which is primarily describing the approach used for Chapters 5, 6 and 7), including the production of precipitation sequences for the Solomon's Hollow (SOL) and Deep Hayes (DHY) catchments from the main Upper Churnet (UC) sequence. The approach follows the gold and blue shaded sections of the overall methodology schematic (Figure 3.1). However, in order to produce an uncertainty analysis, a different combination of simulations is required in order to produce a representation of the PPE uncertainty and the emissions scenario uncertainty. 1000 simulations, each of 100 years at a daily time-step are created for the low (B2), medium (A1B) and high (A1FI) International Panel on Climate Change (IPCC) SRES in the 2071-2100 time-slice. The A1B emissions scenario dataset is sub-sampled to produce 20 simulations that represent the larger set of 1000 (as per Section 3.7), the spread of which represents the PPE uncertainty. The median simulations according to the United Nations Environmental Programme aridity index (UNEP AI) are selected for each of the B2, A1B and A1FI datasets, the spread of which represents the emissions scenario uncertainty. By assessing the extent of these ranges for a given variable (in this case the water shortage probability metrics detailed in Section 3.11.2), the scale of uncertainty created by each can be determined.

As the aim here is to gain an understanding of climate-related uncertainties, all other variables that would affect water shortage risk in the future are assumed to remain unchanged, allowing for the explicit investigation of climate risks (following Donaldson *et al.*, 2001; Gosling *et al.*, 2012). Validations of the approaches and models used to produce sequences of flow across the sub-catchments, raw water resource at Tittesworth Reservoir and estimates of water shortage probability are found in Chapter 3 (Sections 3.9 and 3.10).

4.3 Differences to cited literature

Many studies have been carried out to assess sources of uncertainty in climate change impacts on flows (Prudhomme and Davies, 2009; Kay *et al*., 2009; Kingston *et al*., 2009; Arnell, 2011(a); Bormann, 2011; Dobler *et al*., 2012; Schoetter, 2012; Steinschneider *et al*., 2012; Bosshard, 2013; Paton *et al*., 2013; Velazquez *et al*., 2013). From this body of research, the disagreement between climate models and the methods used to downscale that climate model information are often found to represent the largest source of future flow uncertainty, although differences between emissions scenarios and other sources such as hydrological model error and statistical post-processing are often also found to account for significant uncertainty also and should not be ignored in practical applications (Bosshard *et al*., 2013).

This chapter extends such work to compare climate uncertainty within the UKCP09 PPE to emissions scenario selection uncertainty in terms of future water shortage probability, which, to the authors' best knowledge, has not been carried out using Levels of Service (LoS) as metrics of risk before. This is useful to water resource planners who are interested in communicating water resource vulnerability in terms of the future probability of unwanted outcomes such as water restrictions for customers, rather than more abstract terms such as deployable output (DO) (Hall *et al*., 2012(a)). In a robustness analysis of a water resource zone (WRZ), the probability of triggering a control line of a given severity can act as the metric against which the effectiveness of interventions to the system are judged (Groves and Lempert, 2007; Hall *et al*., 2012(a)), so the uncertainty in terms of future flows is less important and therefore demands less attention. By using these metrics of water shortage probability in order to quantify risk rather than values further up the process (e.g. precipitation or flow), this represents a novel and intuitive approach to quantifying uncertainties involved with managing water resources under changed future climates.

4.4 Perturbed Physics Ensemble and emissions scenario uncertainty: precipitation

Changes to average rainfall, standard deviation of rainfall and percentage of dry days (<1mm) from baseline conditions to the 2080s at each sub-catchment are shown in Figure 4.1. In each case the PPE range (sub-sampled A1B simulations) and the emissions scenario range (median simulations of the B1, A1B and A1FI datasets) are compared.

It can be seen that the range of A1B simulations are not consistent on the direction of change for any parameter in any month except the August dry days percentage. However, the median of the sub-sampled range (solid purple line) suggests that rainfall seasonality will become more dichotomous, with reduced rates in JJAS, increased rates in NDJFMA and minimal change in October and May. Median standard deviation of rainfall is increased in winter and unchanged in summer, suggesting more intense periods of rainfall and more dry days are expected in the summer. All of these factors point towards increased single-season drought. This is assessed in greater detail in Chapter 5.

In nearly all cases, the monthly values for each of the simulations describing emissions scenario uncertainty lay within the broader A1B sub-sampled range representing the PPE uncertainty. The exceptions to this are one of the SRES median simulations for average rainfall in February and November, standard deviation in June, and dry days in November. This means that the SRES median simulation average rainfall, standard deviation of rainfall and dry days statistics are within the PPE medium emission range

96.2% of the time. The discrepancies are consistent across the sub-catchments. The presence of the A1B overall median as an outlier in February and November for average precipitation shows that it is likely that values for the emissions scenario simulations arise primarily due to the imperfect sub-sampling procedure.[12] Although it isn't possible to quantify the extent to which the PPE uncertainty is greater than the emissions scenario uncertainty in terms of rainfall parameters from Figure 4.1, it can be seen by eye that it is clearly large. As the main objective of this uncertainty assessment is to assess uncertainties in terms of water shortage metrics, a quantitative assessment of uncertainty using rainfall parameters is not sought.

[12] The UNEP AI used to sub-sample the UKCP09 range gives equal weighting to PET and rainfall, so when only one parameter is assessed outliers such as this are possible. The overall median A1B simulation (i.e. from the full dataset of 1000 simulation), denoted as black dashed line with cross in Figure 4.1, lying outside the range of the sub-sampled 20 simulations from the same dataset is possible as the overall median simulation is not (necessarily) also in the sub-sampled range of simulations.

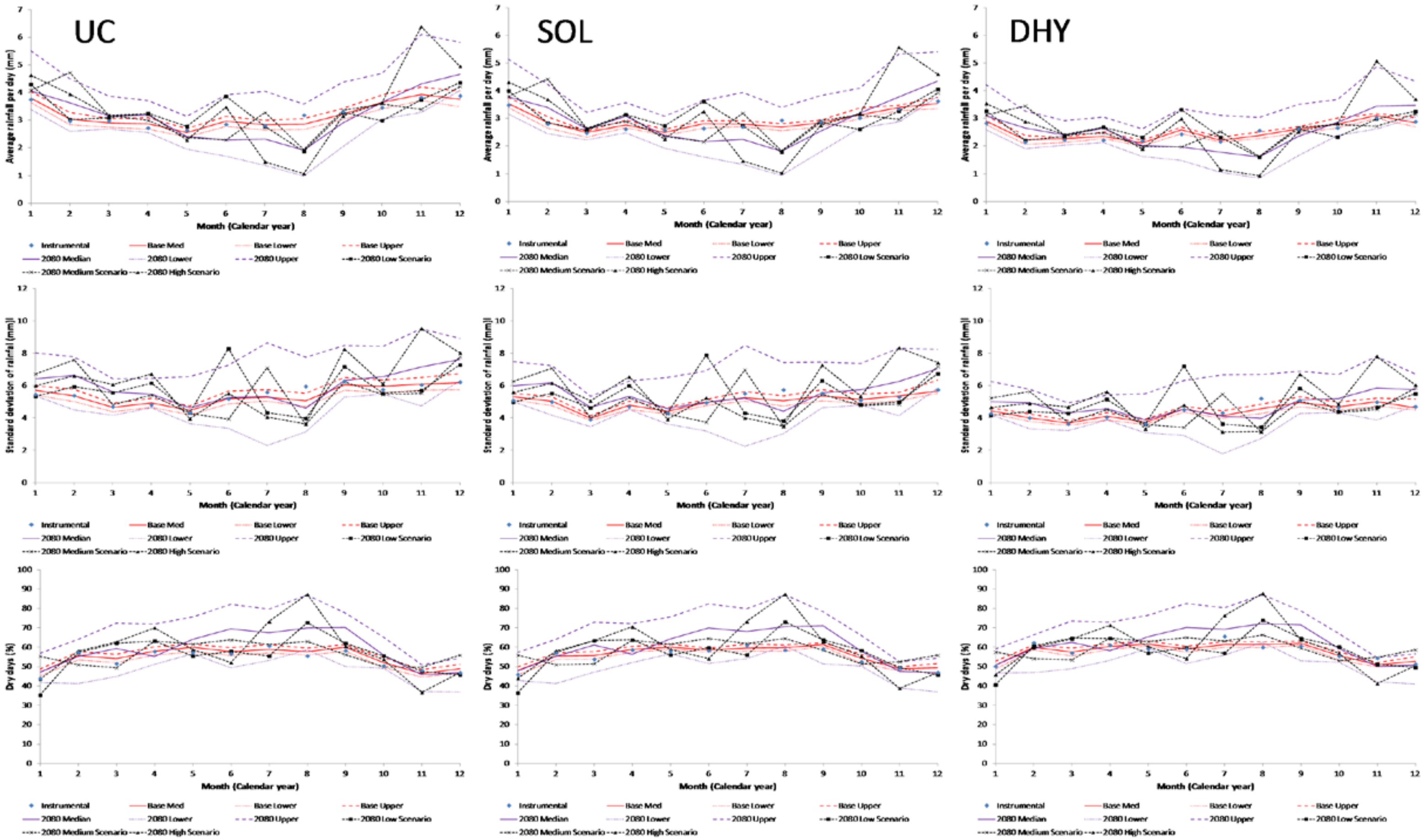


Figure 4.1. Precipitation statistics for the sub-sampled PPE uncertainty range and emissions scenario range in the 2080s compared to the baseline simulations (1961-1990) and the observed record (1961-1990) at UC (left), SOL (middle) and DHY (right).

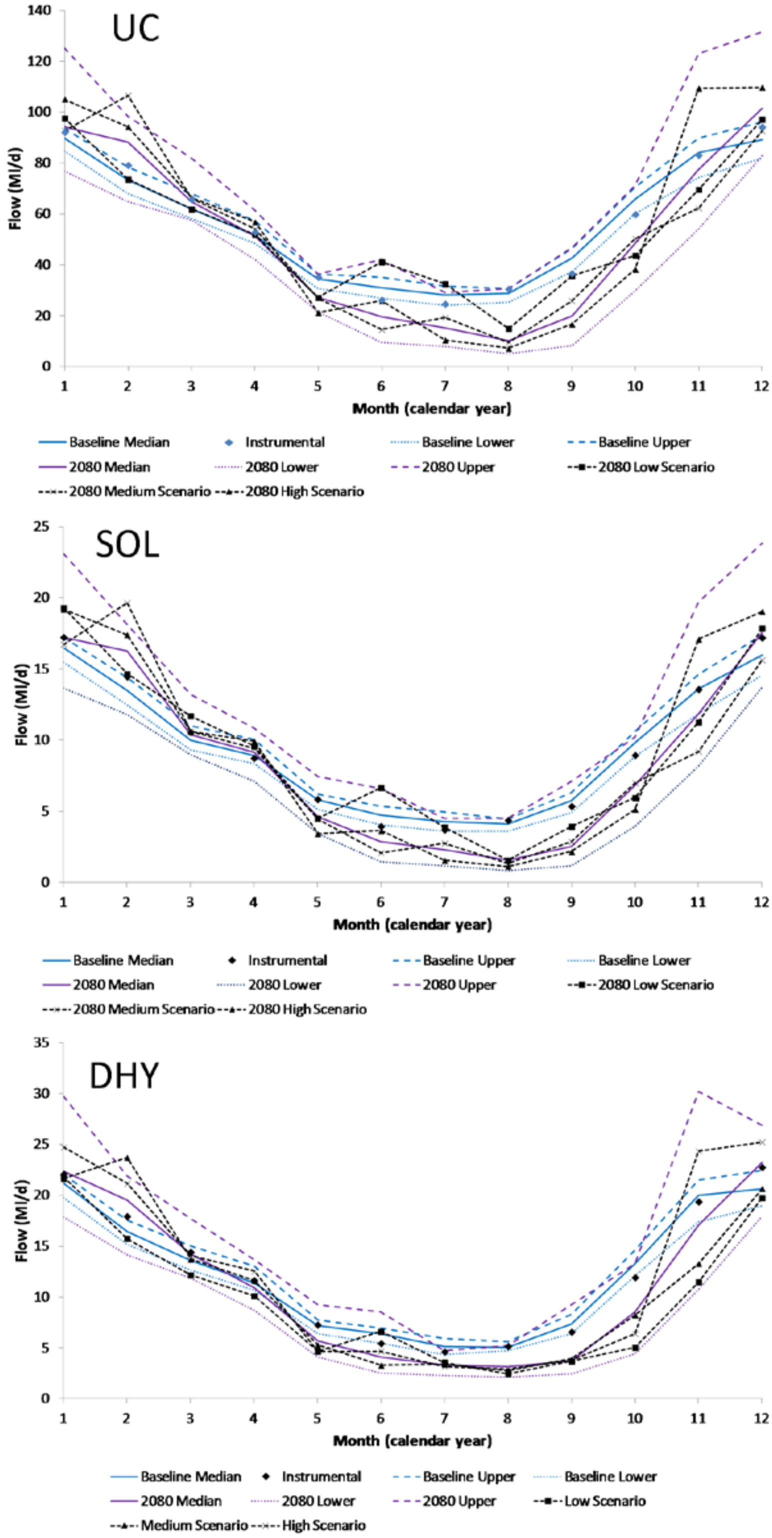


Figure 4.2. Flow statistics for the sub-sampled PPE uncertainty range and emissions scenario range in the 2080s compared to the baseline simulations (1961-1990) and the observed record (1961-1990) at UC, SOL and DHY

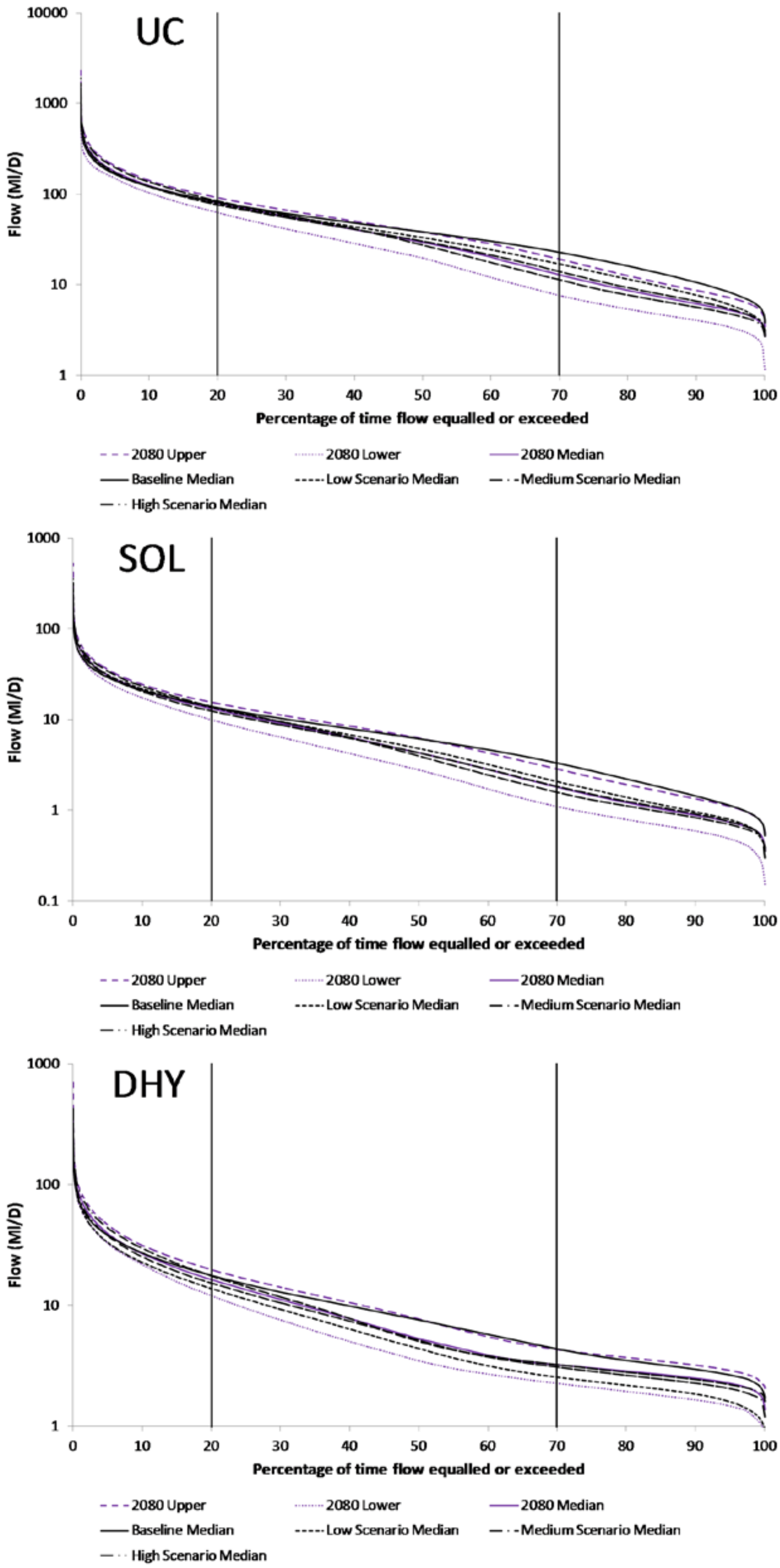


Figure 4.3. FDCs of annual flow in the 2080s for the sub-sampled PPE uncertainty range and emissions scenario range compared to the baseline simulations (1961-1990) at UC, SOL and DHY.

4.5 Perturbed Physics Ensemble and emissions scenario uncertainty: flow

Changes to flow in the 2080s from baseline conditions at the three sub-catchments are shown in Figures 4.2 and 4.3. Average monthly flow (Figure 4.2), and flow duration curves (FDCs) of annual, summer half-year (AMJJAS) and winter half-year (ONDJFM) flow per day (Figure 4.3) at UC, DHY and SOL for the A1B scenario in the 2080s are used to show the PPE uncertainty, with the emissions scenario uncertainty described by the median simulation for each scenario. Logarithmic y-axes accentuate the low flow section of the FDCs.

Annual profiles of flow at the three sub-catchments show that in all cases the spread of the PPE uncertainty is greater than that for emissions scenario (Figure 4.2). In February and July at UC, the difference between the two uncertainty ranges is small as the 2080 A1B median simulation exhibits a particularly high average February flow (the 2080 A1B scenario median simulation is not used in the sub-sampled range of 2080 A1B simulations, and can therefore exceed that range) and the 2080 B1 median simulation has high July flows. The February outlier is repeated at the other sub-catchments, but the July one is not. The 2080 A1B median simulation having average flow for a month outside of the sub-sampled PPE range highlights that the UNEP AI is an imperfect technique for sub-sampling, and thus also for selecting the median simulation from a range. However, it is clear that across the sub-catchments the simulations representing emissions scenario range normally sit within the wider PPE uncertainty range, particularly in the low flow months throughout summer and autumn. Alteration to the seasonal dichotomy of flows is significantly less under the low scenario than the medium or high scenarios (I.e. winters are less wet and summers are closer to the baseline conditions).

All the simulations at UC and SOL exhibit a move towards reduced annual (Figure 4.3) and summer (not shown) low flows in the 2080s compared to the baseline median simulation, and 85% of the simulation range show reduced winter flows (not shown). Annual medium flows are also reduced in most of the simulations. The similarities between UC and SOL are expected given the same hydrological parameters are used in the HYSIM model. Although the spread of simulations is high, the sign of low flow change is consistent. DHY is notably less affected by changes to future conditions, although a vast majority of the climate model uncertainty range produces lower flows than the baseline period, especially in terms of the most extreme values. This highlights the importance of producing impact assessments with high spatial resolution and taking into account hydrological characteristics of each sub-catchment.

The low flow sections of the FDCs show that the three median simulations, representing emissions scenario uncertainty, sit within the broader sub-sampled range of simulations from the A1B scenario, which represents PPE uncertainty, in every sub-catchment/season combination. This shows that PPE uncertainty influences the magnitude of low flows more than emissions uncertainty at each sub-catchment, and is therefore in agreement with Figure 4.2.

As figures 4.2 and 4.3 have indicated qualitatively, the PPE uncertainty creates a wider range of flow in the 2080s than the emissions scenario uncertainty source, which is in-line with the results for precipitation (Figure 4.1). By calculating the maximum percentage difference in impact on flows from the baseline to the 2080s between two A1B simulations and comparing that to the maximum percentage difference between two emissions scenario median simulations, it is possible to quantify to what extent that qualitative assessment holds true. The maximum difference between two simulations of summer half-year flow at UC from across the A1B range is 97.3%, whilst the maximum difference between the SRES medians is 31.8%. The dominance of PPE uncertainty over emissions scenario uncertainty is in line with hydroclimatological research using GCM ensembles (Wilby and Harris, 2006; Prudhomme and Davies, 2009; Paton *et al.*, 2013). It can therefore be concluded that the uncertainty involved with PPE-based probabilistic flow projections in future climates is greater than the selection of emissions scenarios.

4.6 Perturbed Physics Ensemble and emissions scenario uncertainty: water resource shortage

R_{ex} plots describe the extent of water shortage uncertainty within the PPE range and the emissions scenario selection (Figure 4.4). The R_{ex} value in the corner of each plot relates to the amount of the PPE range that lies beyond the emissions scenario range. R_{ex} values at three different levels of severity are 50%, 55% and 45% for temporary use ban (TUB), drought warning trigger (DWT) and storage alert line (SAL), respectively, showing that around half of the PPE range from the A1B scenario is beyond the boundaries of the emissions scenario range. This indicates that a large proportion of the feasible future water shortage probability range in the North Staffs WRZ is as a result of climate model uncertainty rather than the emissions scenario that is chosen. This is in-line with the results for flows in the catchments shown in Figures 4.2 and 4.3.

Figure 4.5 shows how the PPE uncertainty relates to the emissions scenario uncertainty in terms of water shortage frequency across different severities. The simulation ranges are organised into CDFs (see Figure 3.16 for explanation) that communicate the probabilistic range of water shortage probability at the three severity levels. The probability of water shortage per year in the median simulations is also shown for comparison.

It can be seen that the median UNEP AI simulation for the A1B scenario projects that the probability of water shortage satisfies current LoS for the TUB and DWT severity level, but not the SAL level, in the 2080s. However, much of the wider A1B scenario range does not conform to LoS in each case (38%, 68% and 80% for TUB, DWT and SAL, respectively), all of which would constitute being outside of acceptable risk if the robustness criteria is for the system to remain within current LoS across 80% of the range of feasible futures. This highlights how using a precise projection of the future can lead to over-confidence, and that the possibility for maladaptation is vast, as the range of probabilities of water shortage in the 2080s deviate greatly from the central estimate.

All of the emissions scenario median simulations sit within the A1B range for each severity level, again showing that PPE uncertainty substantially outweighs emissions scenario selection uncertainty in all cases at the North Staffordshire WRZ. Current UK water industry practice is to use a sub-sampled range from the A1B scenario only, and this research shows that doing so gives a reasonably large uncertainty range and would overlap the median low and high emissions scenario projections. However, the process for selecting emissions scenarios for climate change assessments in the water industry is rather ad-hoc and requires further justification.

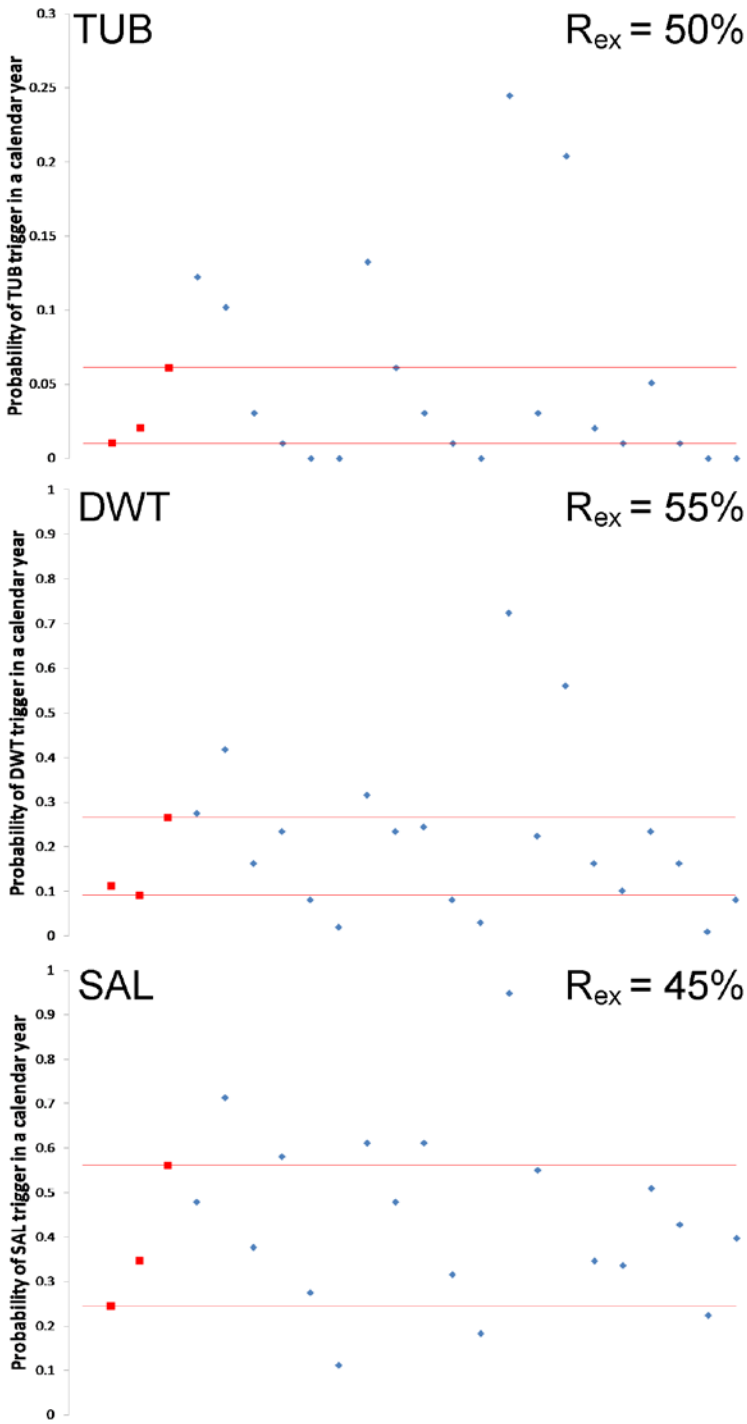


Figure 4.4. R_{ex} plots showing water shortage trigger probabilities for TUB, DWT and SAL. The R_{ex} value quantifies the amount of the simulated PPE uncertainty range (blue dots) that lays outside the range of the emissions scenario uncertainty range (red lines/dots).

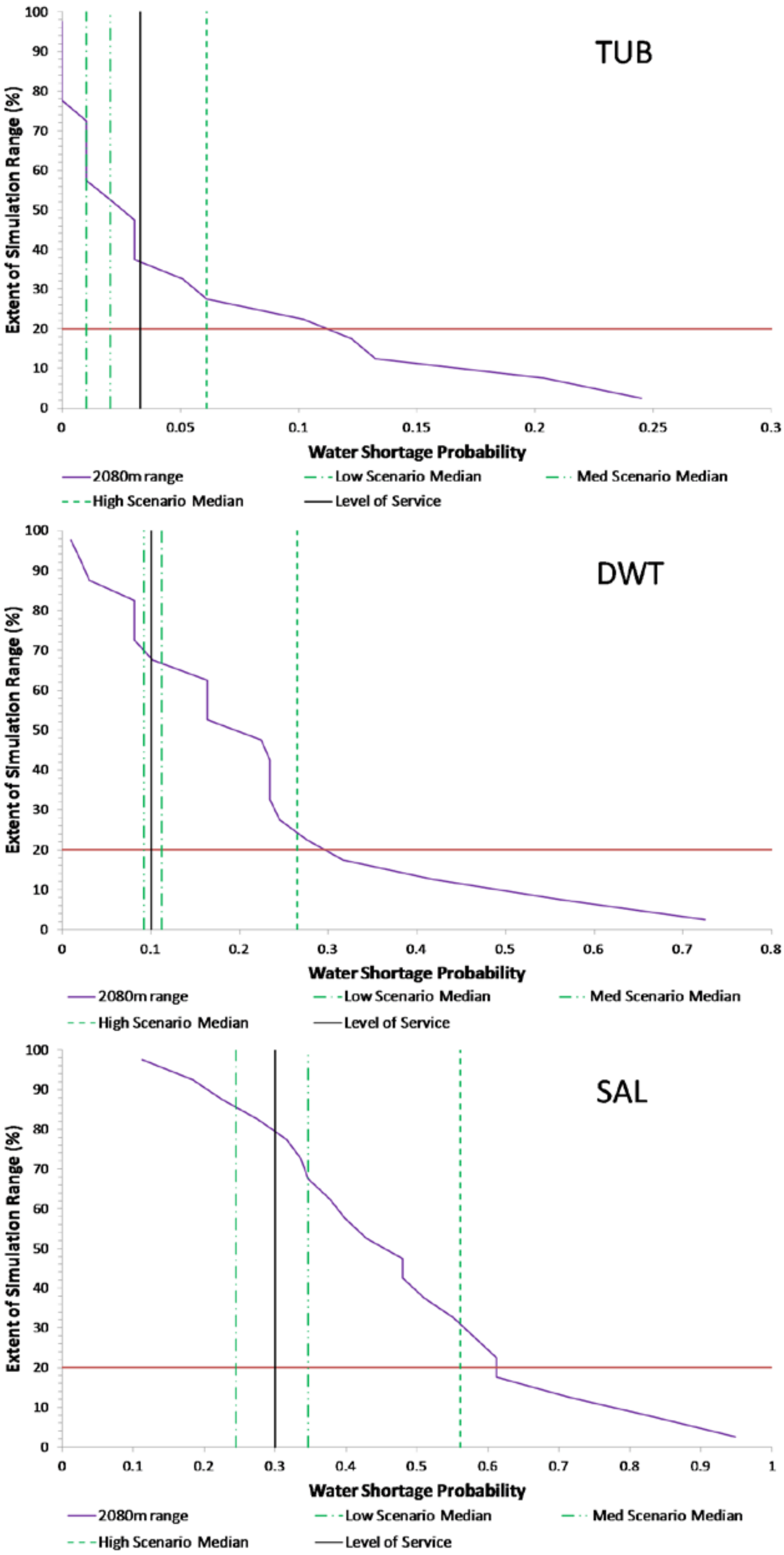


Figure 4.5. CDFs of water shortage probability for three severities across the PPE uncertainty range, compared to the emissions scenario uncertainty range in the 2080s.

As Figures 4.4 and 4.5 have indicated, the PPE uncertainty creates a wider range of water shortage probability for each level of severity than the emissions scenario uncertainty source. The probability ranges for PPE uncertainty and emissions scenario uncertainty in the 2080s are:

- Severity 1 (TUB): 0 to 0.24 (PPE) and 0.01 to 0.06 (SRES)
- Severity 2 (DWT): 0.01 to 0.72 (PPE) and 0.09 to 0.27 (SRES)
- Severity 3 (SAL): 0.11 to 0.95 (PPE) and 0.24 to 0.56 (SRES)

It is therefore clearly shown that climate model physics uncertainty accounts for a vast majority of future projections of water shortage uncertainty in UKCP09, regardless of which event severity is scrutinised. This understanding of the scales of the two key uncertainty sources is important as the movement towards water shortage risk approaches to climate change assessment continues to increase in prominence in the UK water sector. Although this information does not explicitly answer the question of how many and which emissions scenarios should be used by water resource decision-makers, it does highlight the greater importance of including the range of PPE uncertainty within the UKCP09 projections when assessing future water shortage.

4.7 Conclusions

The relative uncertainties from the PPE (used to construct the probabilistic range of UKCP09 climate projections) and emissions scenario selection on water shortage probability in the future (2080s) are determined using a unique multi-model approach. PPE uncertainty from the UKCP09WG is found to be much larger than uncertainty sourced from emissions scenario selection, with 45-55% of the water shortage described by the climate model range outside the water shortage range described by the median projections for each emissions scenario, dependent on which water severity metric is considered (Figures 4.4 and 4.5). This confirms that climate model uncertainty represented by UKCP09 significantly outweighs emissions scenario uncertainty in terms of water shortage. However, it is acknowledged that PPEs such as UKCP09 do not fully represent structural climate model uncertainty. Further uncertainties sourced from hydrological models are not searched for, but are expected to not outweigh those for climate model selections and emissions scenario selection based on previous research (Bosshard et al., 2013).

It is found that using median projections from the range of water shortage probabilities cannot be assumed to relate to the most ‘likely’ outcome in terms of water shortage (Figure 4.5). The importance of introducing probabilistic climate change projections into assessments of water security in the water industry in order to avoid costly maladaptation is highlighted by the substantial range of future water shortage event projections.

A further qualitative analysis is undertaken of the uncertainty sourced from the PPE and emissions scenarios in terms of precipitation and flow. These are the parameters on which much of the literature is based (including assessments of other uncertainty sources) and so less importance is given to them. Unsurprisingly, given the results for water shortage probability, the PPE uncertainty is found to be significantly greater than the emissions scenario uncertainty for both parameters (Figures 4.1, 4.2 and 4.3).

5 HYDROCLIMATOLOGICAL IMPACT ASSESSMENT

5.1 Introduction

This chapter details the range of projections of meteorological and hydrological futures in the North Staffordshire water resource zone (WRZ) from the weather generator method (WGM) and change factor method (CFM) as outlined in Chapter 3. These projections are interesting in their own right, and provide an illustration of the possible conditions in which water resource supply operations will need to operate in the future, but are primarily the basis for the water resource shortage metrics given in Chapter 6. However, a thorough hydroclimatological impact assessment of the North Staffordshire WRZ using probabilistic information has not been carried out before, so this stage of the research represents unique information that adds to the canon of work on catchment-specific impacts in the UK.

The chapter begins by explaining the nature of the dataset used and the unique features of this study in comparison to previous literature. Sections 5.4 to 5.8 present the projections of various hydroclimatological parameters and postulate the implications for water resource supply as a result of them, before conclusions are drawn (Section 5.9).

5.2 Data sources and models used

The research in this stage of the research concerns the gold-coloured sections of the methodology flow diagram (Figure 3.1). A1B (medium) and A1FI (high) emissions scenarios are used for the future UK Climate Projections 2009 weather generator (UKCP09WG) simulations and are treated with equal likelihood, with the simulations selected for hydrological modelling sub-sampled from within that dataset indiscriminately (there are not necessarily equal numbers of A1B and A1FI simulations in the analysis of each time-slice). Combining emissions scenarios in this way can be problematical as each scenario has probabilities associated with them (but are not equally probable), and the selection of scenarios is based on expert judgement rather than any strict criteria.

For each of the A1B and A1FI scenarios, 1000 weather generator (WG) simulations are produced for the 2020s, 2030s, 2050s and 2080s, from which the United Nations Environment Programme aridity index (UNEP AI) (total annual precipitation/total annual potential evapotranspiration (PET)) of each is calculated in order to determine those sequences that are sub-sampled. 20 simulations selected for hydrological modelling purposes, theoretically covering the vast majority of the perturbed physics ensemble (PPE) and emissions scenario uncertainty range. Although it is not possible to model the entire range of climate futures, the methodology used here provides a basis for decisions to be made based on a wide spectrum of feasible futures quickly and without restrictive computational expense.

In all plots, the future hydrometeorological variable series are presented in relation to the baseline (1961-1990) simulations. A validation of those baseline simulations against the instrumental records is provided in Chapter 3. The CFM uses perturbations of flow rather than precipitation records, so there are no results for that approach until that point in the methodology (i.e. Section 5.8).

5.3 Differences to cited literature

Assessments of flow response to climate change forcings are by no means uncommon (e.g. Fowler *et al*., 2007(a); Buytaert *et al*., 2010; Kim and Chung, 2012) and recent studies have utilised UK Climate Prjections 2009 (UKCP09) datasets in combination with hydrological models at various resolutions for both industrial and research purposes (e.g. Severn Trent Water, 2011(a); von Christierson *et al*., 2012). The key differences between such studies lay in the treatment of the climate data (including the extent to which the uncertainty involved is incorporated), the spatial resolution of that climate data and the location.

The results provided in this chapter are not unique in their formulation from UKCP09WG information to produce entirely synthetic flows for future time horizons, but the inclusion of applying scaling scaling factors between the sub-catchments provides a novel future flow dataset that increases the adaptability of the UKCP09WG but is uncomplicated enough for regular use in industry. Furthermore, the work provides important information for Severn Trent Water (STW) on a vulnerable water resource area at a spatial resolution not considered previously. The thoroughness of the modelling, effectively taking into account the vast majority UKCP09WG uncertainty range (bar the low emissions scenario, the rationale for which is outlined in Section 2.1), provides a depth of understanding on future flows in the North Staffordshire area previously not attempted.

As a result of these nuances this chapter stands up as a piece of unique research in its own right, but the key aim remains to lay the foundation for the water shortage risk and robust adaptation approaches that follow in Chapters 6 and 7.

5.4 Projections of changes to precipitation

5.4.1 Average monthly rainfall

Changes to monthly average rainfall per day at the sub-catchments throughout the 20th century are shown in Figure 5.1 and Table 5.1(a). Throughout the 21st century it can be seen how the climate change signal progressively increases in comparison to the natural variability signal across the North Staffordshire WRZ, with the median simulation exhibiting a pronounced seasonality of rainfall in the latter 21st century in each sub-catchment. However, the sign of change is not consistent across the simulations, with a proportion suggesting increased daily average rainfall in summer, and some showing decreased average rainfall in winter. This is to be expected given previous work using UKCP09 such as von Christierson *et al*. (2012).

In each of the summer months (JJA) in each time period, the median simulation suggests drier conditions in the North Staffordshire WRZ. Table 5.1(b) shows that the agreement between the simulations increases over time until a vast majority of the uncertainty range projects drier summers in the 2080s (85%, 85% and 90% for June, July and August, respectively).

The sign of change from the baseline to the 2080s is not consistent across the simulations for any winter month except December in the 2080s, but there is greater confidence in wetter conditions as time horizons become more distant (Table 5.1(b)). By the 2080s, 100%, 90% and 95% of the uncertainty range projects wetter conditions in December, January and February, respectively. There is little agreement between the simulations regarding average rainfall projections in spring and autumn, where the extremity of change is less than in summer and winter.

Figure 5.2 shows the different summer/winter rainfall projections for the 20 sub-sampled projections in each time-slice. It can be seen that drier summers with wetter winters is the most frequent projection for the Staffordshire WRZ in all time horizons, and the scale of that enhanced seasonality gradually expands over time. However, two simulations show drying in each season in the 2020s and several suggest wetter summers with neutral or wetter winters. No simulations in any of the time horizons indicate that the seasonality will shift completely (drier winters with wetter summers).

Figure 5.3 depicts the seasonal profile of the 20 simulations in the 2020s taken forward to the hydrological modelling phase, as well as the most extreme high and low UNEP AI simulations from the full set of 2000. This shows how the sub-sampling process produces a substantial proportion of the potential rainfall profiles within the UKCP09 dataset, justifying the use of the UNEP AI as a metric. Furthermore, Figure 5.3 re-affirms how using one climate future results in a precise projection of the annual rainfall profile that is poor practice, as the influence of climate change on seasonal rainfall profiles in the catchment is highly uncertain.

In particular, Figure 5.3 depicts substantial disagreement between models regarding summer rainfall profiles in the 2020s, with average July daily rainfall ranging from -

39.2% to +48% compared to baseline conditions. Increases in average rainfall throughout winter are projected with more confidence, with less evidence for drier conditions, particularly from the 2030s and beyond (Table 5.1(b)). The extreme high and low UNEP AI simulations for the 2020s show little difference from each other in rainfall in the spring and autumn, whilst the extreme low UNEP AI simulation suggests greater rainfall than the extreme high AI simulation in some winter months, but the summer averages are highly divergent (Figure 5.3). Therefore summer rainfall, alongside differences in temperature (which will be relatively small in the 2020s compared to later time horizons), accounts for the majority of disagreement between simulations in terms of UNEP AI.

5.4.2 **Standard deviation of rainfall**

The variability of the monthly rainfall simulations are expressed as standard deviations in Figure 5.4. Given the architecture of the daily rainfall data scaling process, it is not surprising that the sub-catchments express a similar profile, with the greatest standard deviation at Upper Churnet (UC) and the least at Deep Hayes (DHY). The most prominent feature of Figure 5.4 is the substantial widening of uncertainty in the summer months even by the 2020s, with some simulations suggesting a far more planar summer rainfall profile, and others vice-versa. Winter standard deviation is less pronounced in the 2020s and 2030s, but is heightened significantly thereafter.

Figure 5.4 illustrates that there is substantial uncertainty in the UKCP09 data with regards to the extremity, or otherwise, with which the altered rainfall projections shown in Figure 5.1 will fall. Indeed, in the 2020s and 2030s the median of the standard deviation dataset stays within the baseline range in the majority of months up until the 2050s at each sub-catchment, suggesting that future trends in the variability of rainfall cannot be speculated with any confidence. There is good evidence that heavier rainfall will become more apparent in the winter months, with a vast majority of the projection range moving towards increased variability over time.

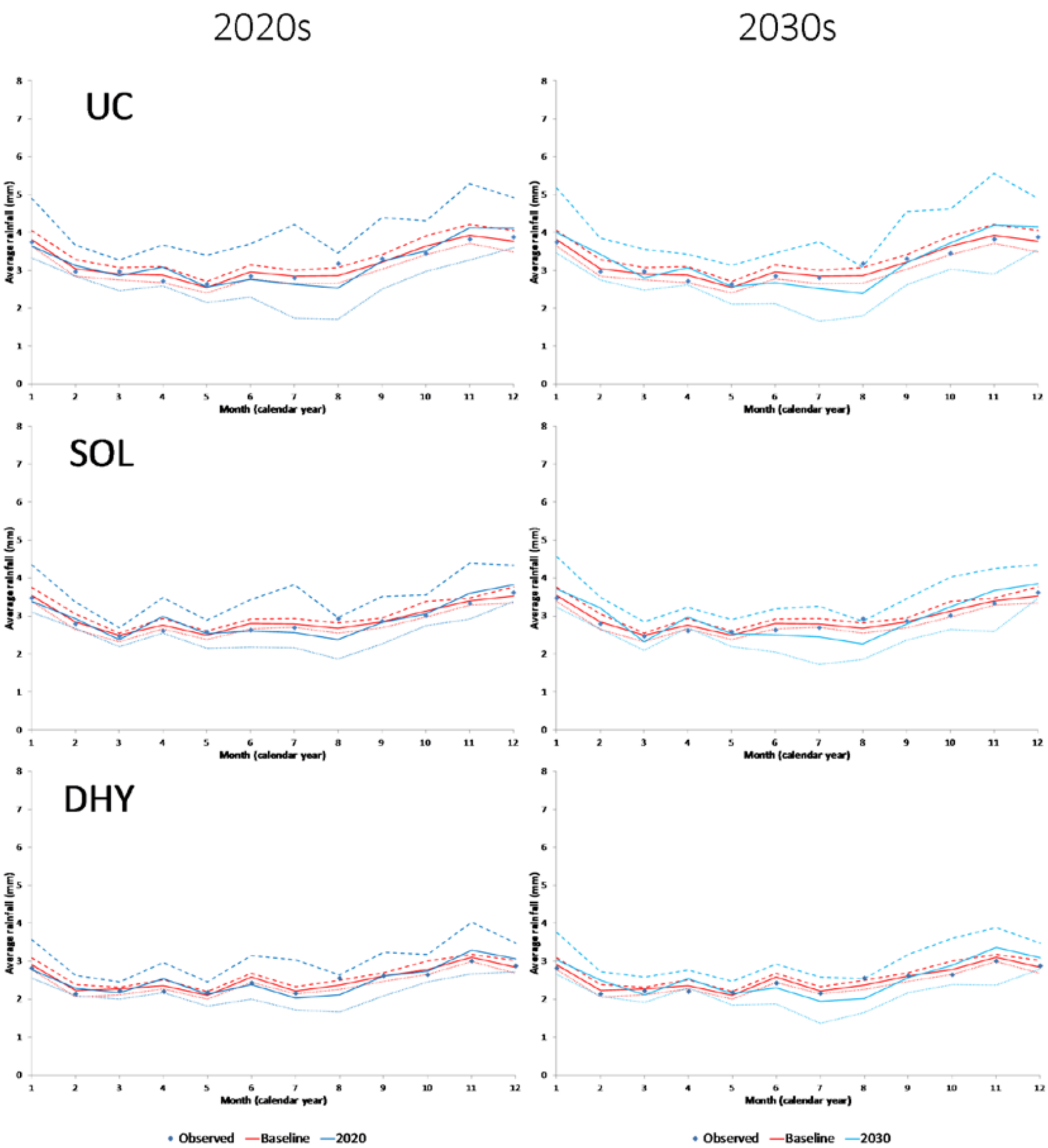


Figure 5.1. Baseline average rainfall per month (red lines) validated against instrumental data (blue rhombi), with changes to those statistics in the 2020s, 2030s (this page), 2050s and 2080s (overleaf) overlain. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively. Top: Upper Churnet, middle: Solomon's Hollow, bottom: Deep Hayes

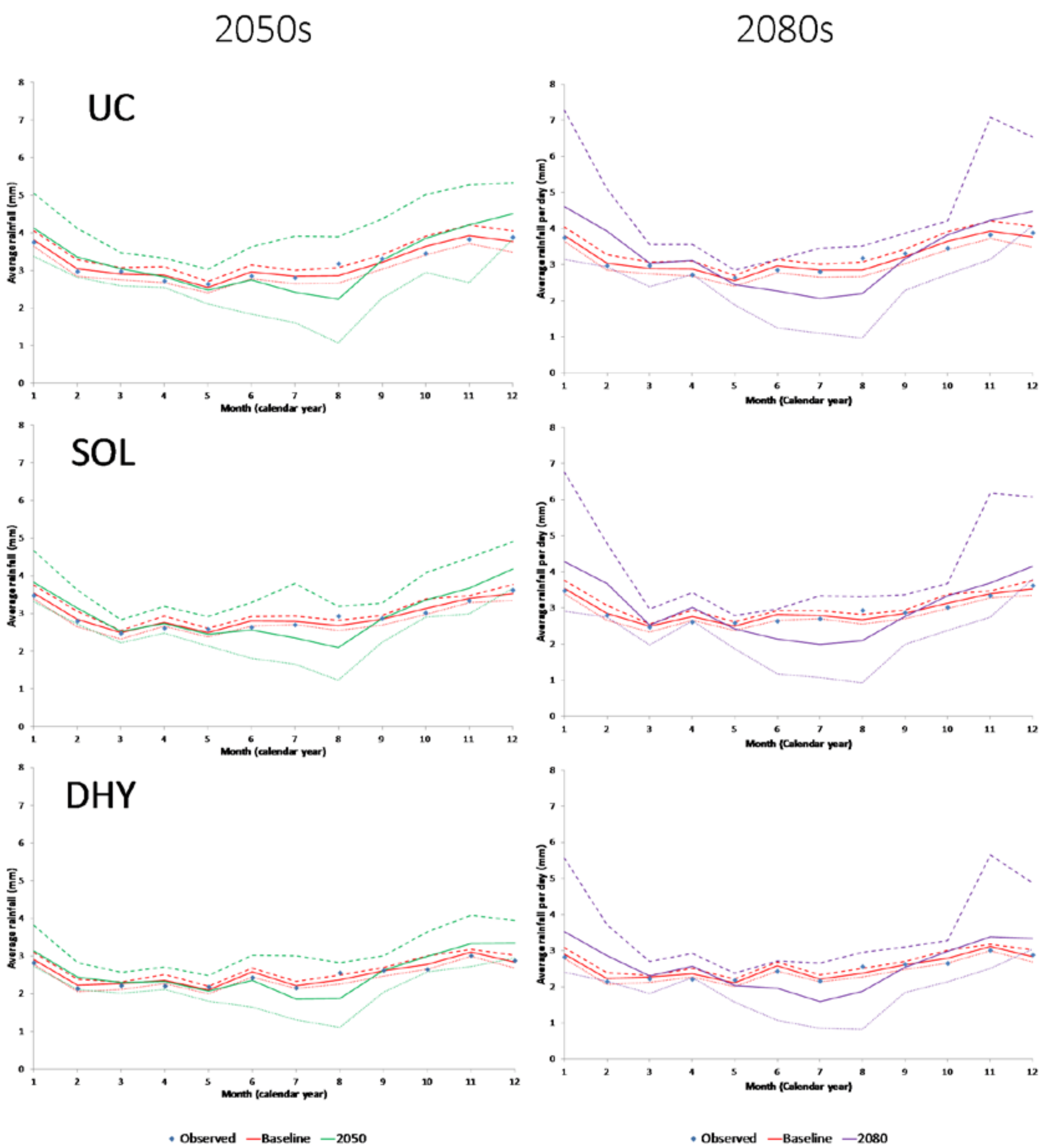


Figure 5.1. Continued from previous page.

5.4.3 **Dry days per month**

Further evidence for a more extreme winter rainfall profile at the North Staffs WRZ in the future is found in the limited change to winter dry days found in Figure 5.5 and

Table 5.2. Given the widely projected increases to precipitation over winter months (Figure 5.1), a largely unchanged number of dry days per month would indicate that the rainfall is occurring in heavier events. The large increase in summer dry days over most of the simulation range suggests an increase in single-season meteorological drought events (Table 5.2). Indeed, there is 100% agreement across the simulation range that August in the 2080s will have more dry days than the baseline median. Together, the median projections for summer and winter suggest that the rainfall profile will become less dependable from a water resource perspective, with more reliance on intense winter rainfall to re-fill Tittesworth Reservoir. The signage of changes to spring and autumn dry days per month is not projected with confidence, although there is evidence that higher amounts of dry days are likely extend further into the autumn later in the century (Table 5.2).

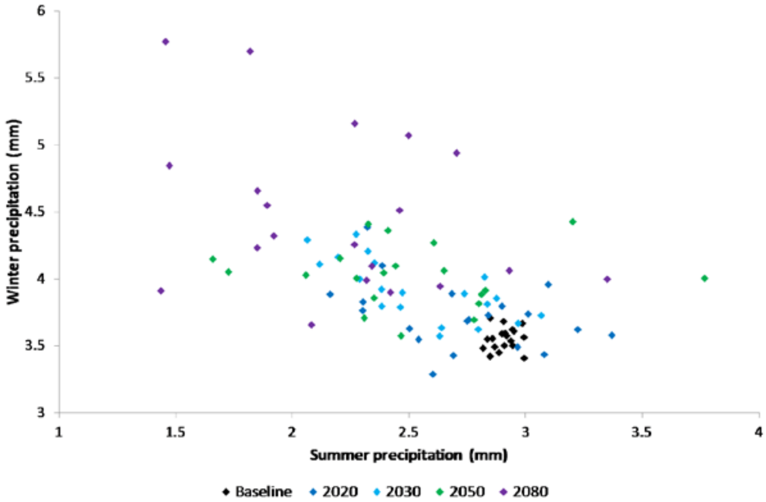


Figure 5.2. Average summer half-year (AMJJAS) rainfall plotted against average winter half-year (ONDJFM) rainfall for each sub-sampled simulation. Black: baseline; dark blue: 2020s; light blue: 2030s; green: 2050s; purple: 2080s.

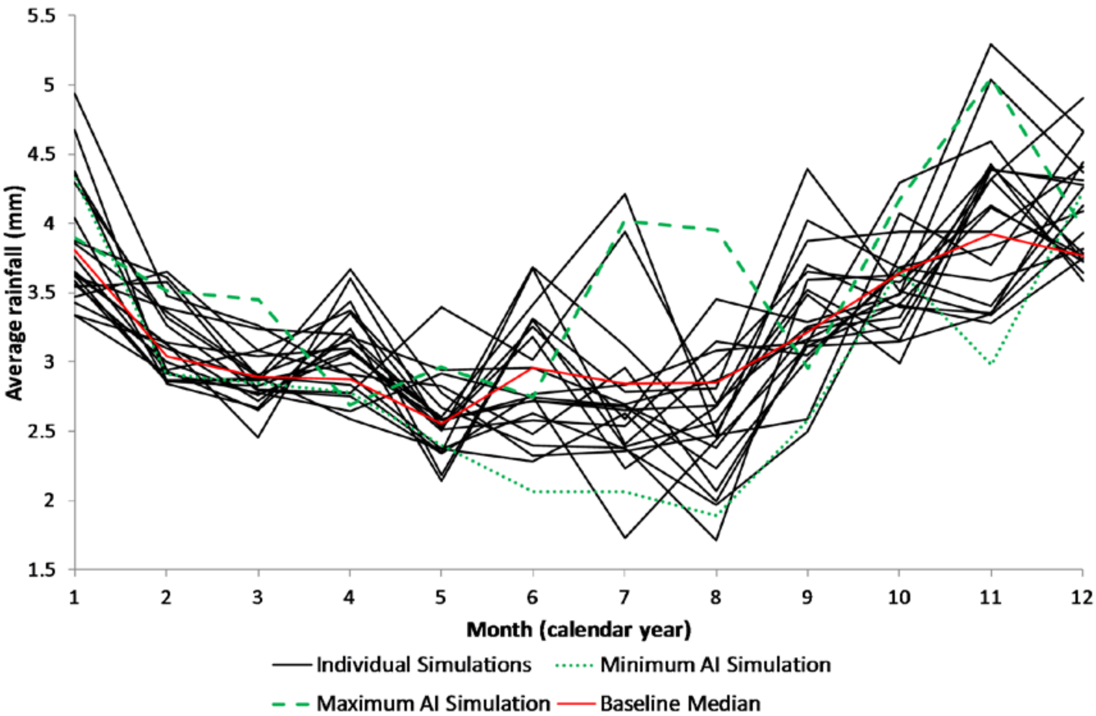


Figure 5.3. Average rainfall per month profiles for each of the sub-sampled 2020s simulations superimposed over the median baseline simulation and the minimum and maximum UNEP AI simulations for the 2020s. The pattern of monthly precipitation varies greatly between simulations, particularly in summer months.

Table 5.1 (a). Percentage changes of average precipitation/day at UC in each month in the future time-slices from the baseline median. The minimum, median and maximum of the simulation range is given in each case. Red/orange boxes denote less rainfall compared to the baseline and blue more, with the strength of colour denoting the scale of that change. The colouring is based on the median simulation in each future time-slice.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January	-12.6	-4.2	28.9	-0.4	5	35.9	-11.4	8.3	32.7	-17.4	21.2	91.4
February	-6.4	2.6	20.5	-9.7	12.8	26.4	-7.2	10.2	35.5	-3.7	28.6	68.2
March	-15	-1.2	13	-14.4	-3.2	22.5	-10.8	5	19.6	-17.8	4.6	22.8
April	-10	7.4	27.8	-8.8	6.9	19	-11.4	-1.8	15.9	-4.9	8.2	23.5
May	-16	0.6	33.1	-17.4	1.1	22.8	-17.2	-2.7	18.8	-26	-4	11.3
June	-22.6	-7	24.7	-28.2	-9.8	16.5	-37.9	-7.4	22.6	-58.1	-23.5	6.2
July	-39.2	-7.5	48	-41.9	-11.4	31.8	-43.3	-14.9	37.4	-61.4	-27.5	20.8
August	-40.2	-11.4	21.3	-37.3	-16.3	8	-62.6	-21.9	36.7	-66.3	-22.8	22.7
September	-22.2	1	36.5	-18.5	-0.4	41.7	-29.7	1.6	35.7	-29	-1.7	20.4
October	-18.3	-3.7	18	-16.8	2.2	26.8	-19	5.9	37.7	-25.3	4.6	15.8
November	-16.7	4.9	34.6	-26.2	6.65	41.4	-31.8	7	34.4	-20	7.8	79.8
December	-4.5	9.1	30.5	-5.5	10.2	29.9	2.1	19.7	41.6	7.5	18.5	73.7

Table 5.1 (b). Median percentage changes of average precipitation/day at UC in each month in the future time-slices from the baseline. Red/orange boxes denote less rainfall compared to the baseline and blue more, with the strength of colour denoting the scale of that change. The size of the font describes the percentage of the simulation range that agrees on the signage of change. Underlined font denotes 100% agreement on the signage of change (see annotations for examples).

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January		-4.2			5			8.3			21.2	
February		2.6			12.8			10.2			28.6	
March		-1.2			-3.2			5			4.6	
April		7.4			6.9			-1.8			8.2	
May		0.6			1.1			-2.7			-4	
June		-7			-9.8			-7.4			-23.5	
July		-7.5			-11.4			-14.9			-27.5	
August		-11.4			-16.3			-21.9			-22.8	
September		1			-0.4			1.6			-1.7	
October		-3.7			2.2			5.9			4.6	
November		4.9			6.65			7			7.8	
December		9.1			10.2			19.7			18.5	

50% agreement

75% agreement

100% agreement

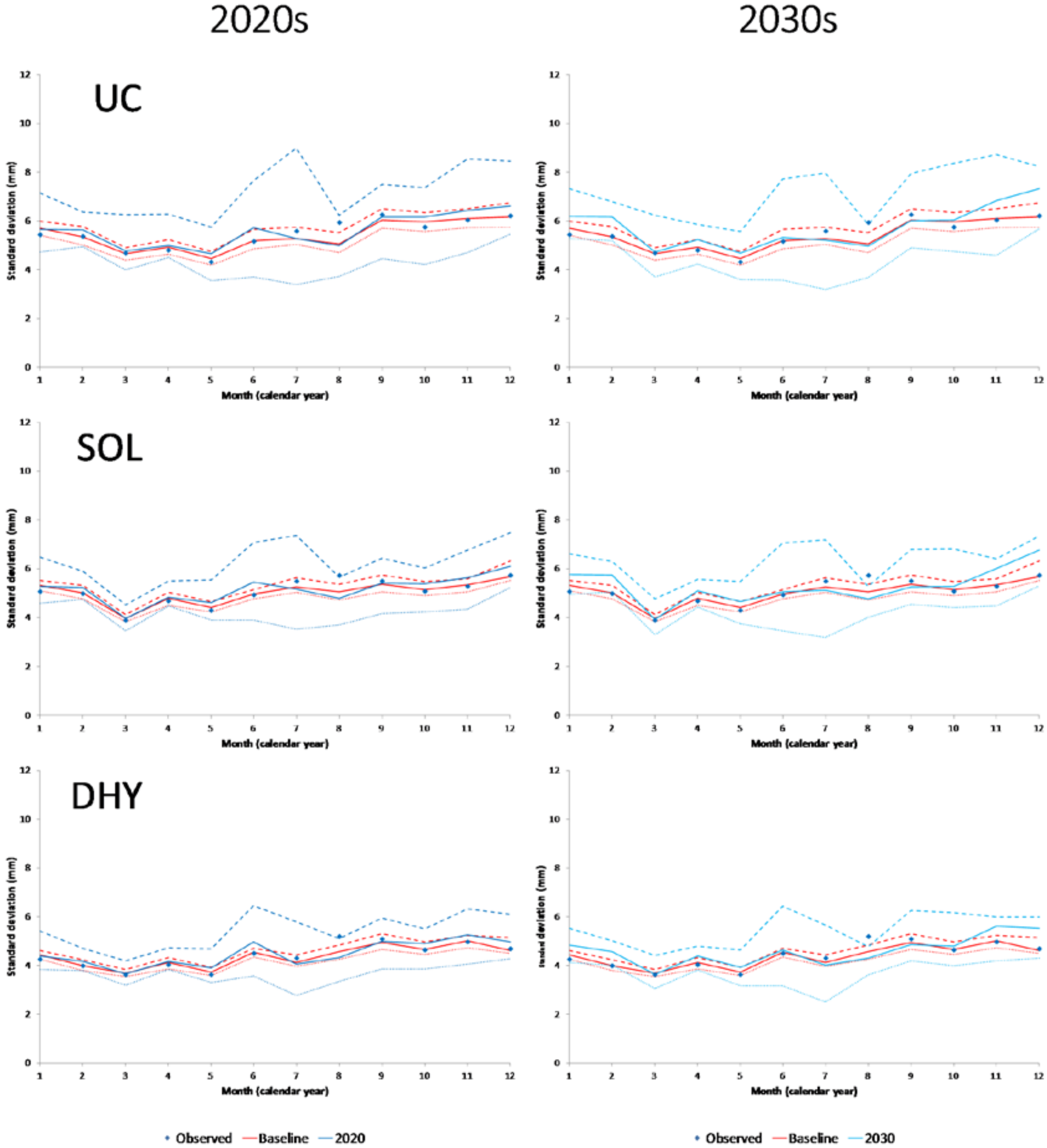


Figure 5.4. Baseline standard deviation of rainfall per month (red lines) validated against instrumental data (blue rhombi), with changes to those statistics in the 2020s, 2030s (this page), 2050s and 2080s (overleaf) overlain. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively. Top: Upper Churnet, middle: Solomon's Hollow, bottom: Deep Hayes

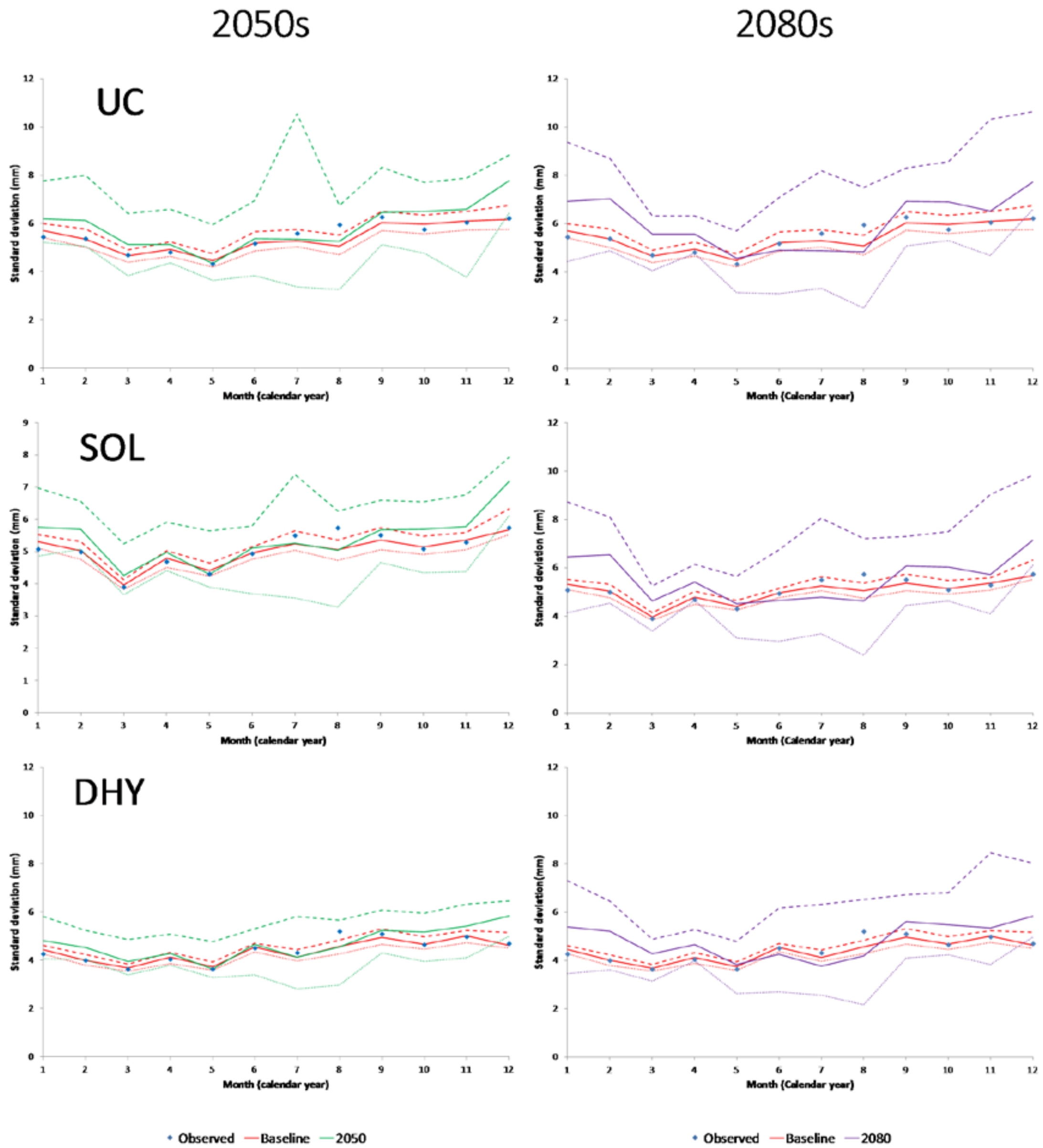


Figure 5.4. Continued from previous page.

5.5 Projections of changes to temperature and rainfall profiles

Average annual (Figure 5.6) and seasonal (summer and winter half-years) (Figure 5.7) temperature and rainfall projections at UC for each sub-sampled simulation in each time-slice are presented. It is shown that annual temperature increases are projected in all simulations to varying extents (bar one simulation for the 2020s), more so farther afield into the future. The signage of annual rainfall change is not consistent (as would be expected given Figure 5.3), although an increase is likely by the 2080s with more substantial winter rainfall (Figure 5.1, Table 5.1).

A discernible relationship between annual daily temperature and annual daily precipitation is not forthcoming, although Figure 5.6 does show that the most extreme temperature increases are associated with high annual rainfall increases in the 2080s (upper-right of the plot). Exploring this further, Figure 5.7 shows how the more extreme temperature increases tend towards having high winter half-year rainfall and low summer half-year rainfall, explaining the positive and negative correlations found in the winter half-year and summer half-year time horizon median simulations over time, respectively. Analysis of the simulations in each time-slice also suggests higher summer half-year temperatures equates to reduced average rainfall, with R^2=0.4377 in the 2020s, and R^2=0.5308 in the 2080s (where the temperature spread is broader). As a result it can be concluded that the higher the temperature increase in the future, the greater the likelihood of a more dichotomous seasonal rainfall profile in the North Staffordshire WRZ.

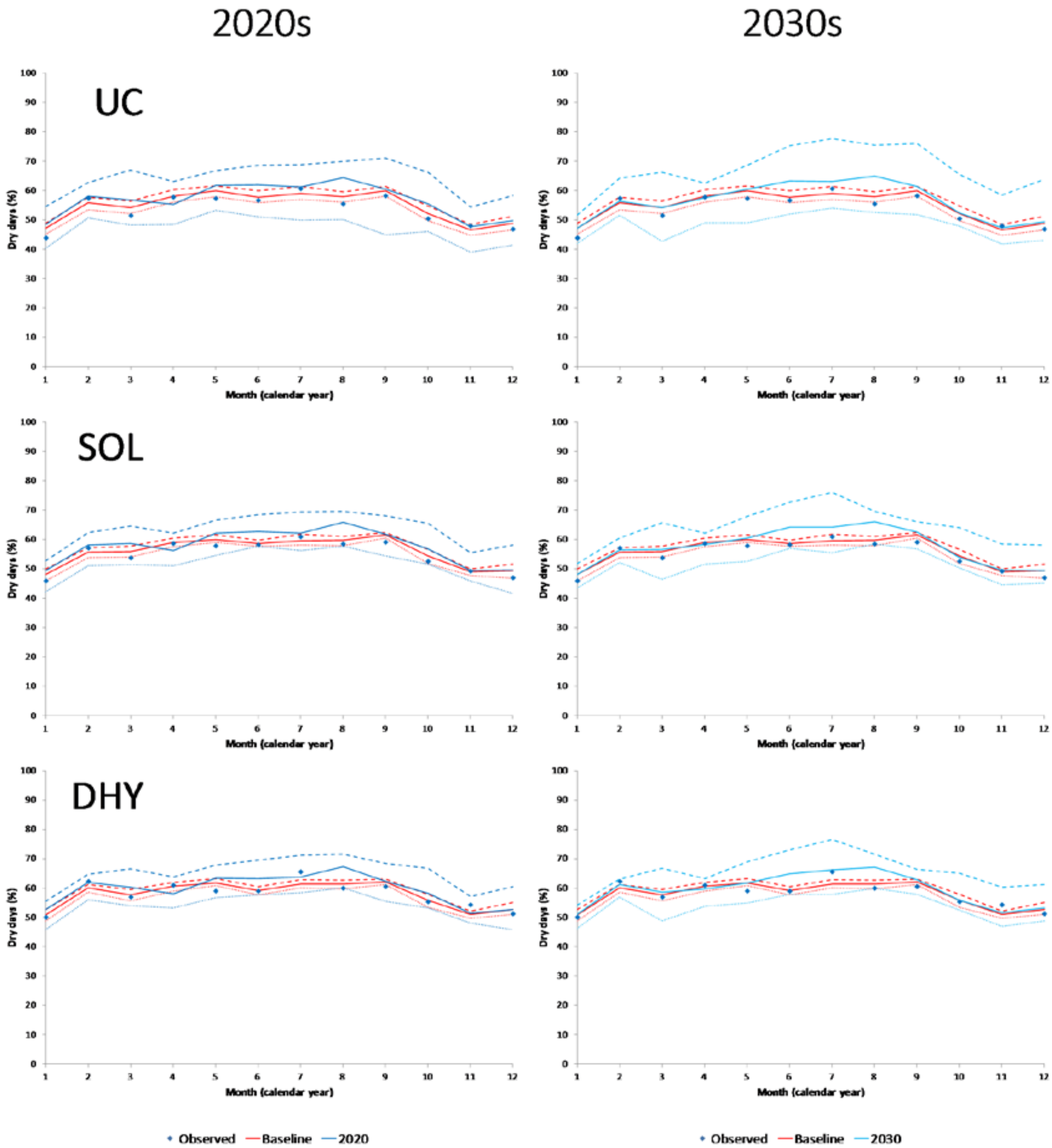
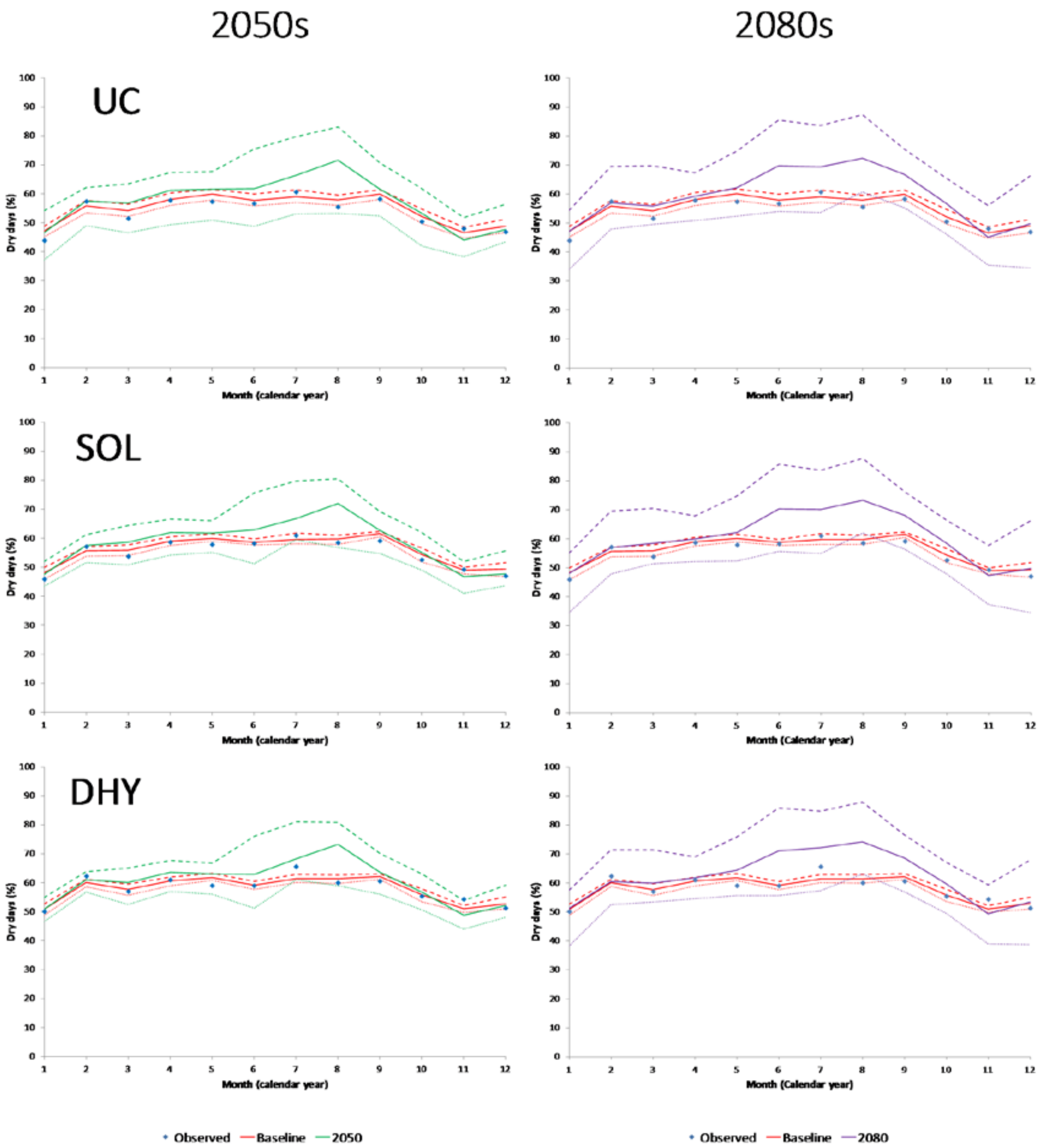


Figure 5.5. Baseline percentage dry days per month (<1mm rainfall) (red lines) validated against instrumental data (blue rhombi), with changes to those statistics in the 2020s, 2030s (this page), 2050s and 2080s (overleaf) overlain. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively. Top: Upper Churnet, middle: Solomon's Hollow, bottom: Deep Hayes



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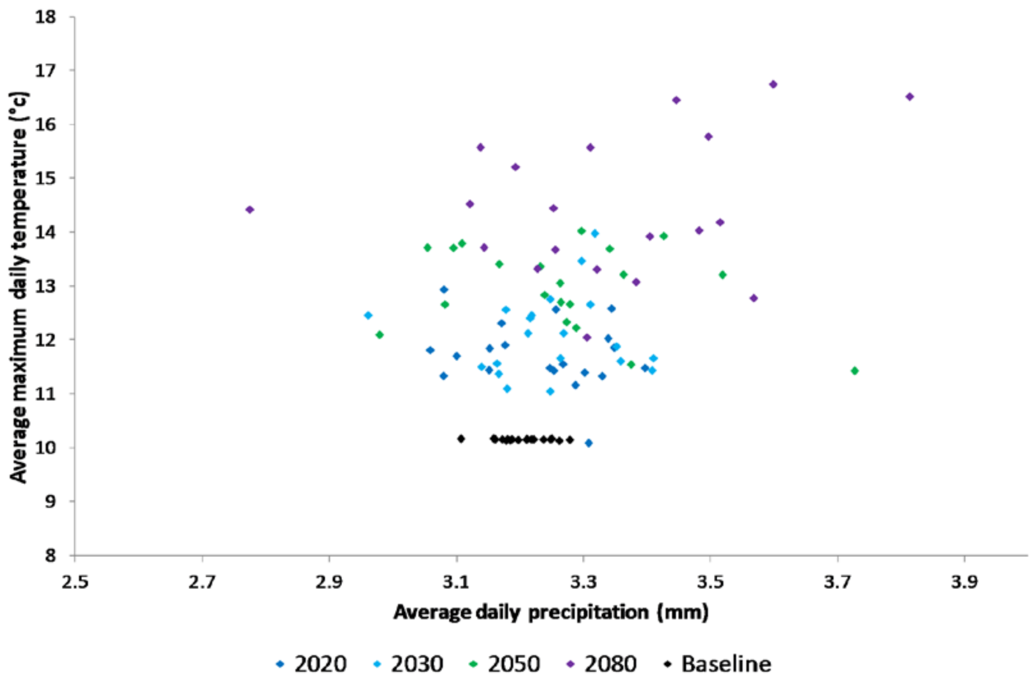


Figure 5.6. Average daily precipitation (over an entire simulation) plotted against average daily temperature for each sub-sampled simulation in each time-slice.

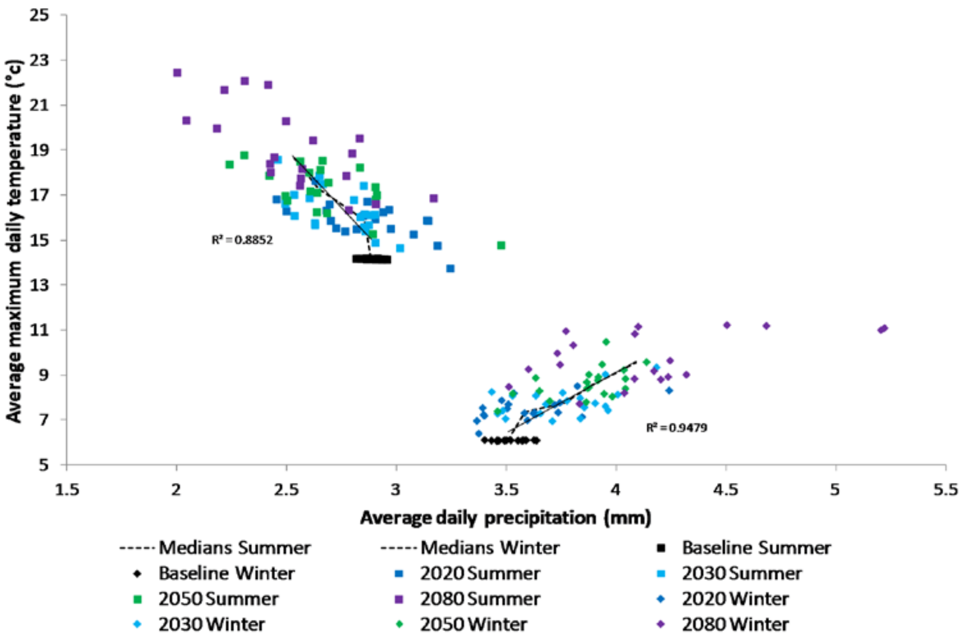


Figure 5.7. Average daily precipitation plotted against average daily temperature for each sub-sampled simulation in summer half-years (AMJJAS) and winter half-years (ONDJFM) for each time-slice. The dashed lines show the changes to the median values over time, along with a linear trend line and corresponding R^2 value.

5.6 Projections of changes to aridity

Using the UNEP AI, the projected alterations to annual aridity over the century are outlined in Figure 5.8 It can be seen that the normal distribution of the 2000 simulations moves steadily towards greater aridity as the century progresses, and the envelope of uncertainty expands with time. Although the trend is clear, even by the 2080s the 'wet' tail of the distribution contains higher UNEP AI values than the baseline, so those simulations would, on average, be expected to produce increased annual flows and associated reduced water stress. This represents a good example of the 'loaded dice' analogy (Hanson *et al*., 2012), where although it is difficult to classify any individual drought event as being a result of climate change per se, the possibility of an event of a significant magnitude 'x' occurring is clearly greater in a climate with an aridity distribution like that for the 2080s in Figure 5.8 than that for the 2020s.

Figure 5.9 shows average daily open water evaporation at Tittesworth Reservoir, where marked spring and autumn increases are projected in most of the simulation range up to the 2050s, and in all non-winter (DJF) projections (bar one outlier in July) by the 2080s. This means that there is a smaller proportion of the year in which reliable rainfall not affected by evaporation from the reservoir is available for water resource supply purposes, exacerbating water stress. Table 5.3(a) suggests that in the summer (JJA), open water evaporation median projections for the 2080s increase by 30.2 to 34% compared to baseline conditions, with the high-end projections showing a 116% rise in August.

Table 5.2 (a). Percentage changes of average dry days per month at UC in each future time-slice from the baseline median. The minimum, median and maximum of the simulation range is given in each case. Red/orange boxes denote more dry days compared to the baseline and blue less, with the strength of colour denoting the scale of that change. The colouring is based on the median simulation in each future time-slice.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January	-14.4	2.7	16	-11	0.1	9.5	-21	-0.9	15	-28	0.2	15.3
February	-9.4	3.8	12.3	-7.6	1.2	14.9	-12.1	3	11.4	-14.3	1.8	24.4
March	-10.9	5	23.9	-21	0.2	22.4	-14	4.9	17.4	-8.6	3.3	28.7
April	-16.7	-4.8	8.5	-15.8	-1.1	7.5	-15.1	5.5	15.9	-12.4	2.1	16
May	-11.2	3	11.3	-18.3	0.9	14.4	-15.2	2.7	12.9	-13	3.3	24.5
June	-11.8	7.4	18.7	-10	9.4	30.3	-15.6	6.9	30.8	-6.8	20.6	48
July	-15.3	3.9	16.7	-8.5	6.9	31.7	-10	12.5	35.2	-9.1	17.5	41.8
August	-13.3	11.4	21	-9.3	12.3	30.5	-7.9	23.8	43.6	4.7	25.1	51.1
September	-25.1	0.9	18.3	-13.5	2.5	26.9	-12.8	2.6	17.9	-8	11.3	25.8
October	-11.6	6.4	26.9	-8.2	0.4	25.6	-19.6	2.2	18.4	-11.6	8.8	25.4
November	-16.1	2.3	16.9	-10.3	1.5	25.5	-17.8	-5.7	11.3	-24	-3.1	20.3
December	-15.2	1.6	19.3	-11.9	1	30.5	-11.3	-2.5	15.2	-29.7	1.7	35.4

Table 5.2 (b). Median percentage changes of average dry days per month at UC in each future time-slice from the baseline. Red/orange boxes denote more dry days compared to the baseline and blue less, with the strength of colour denoting the scale of that change. The size of the font describes the percentage of the simulation range that agrees on the signage of change. Underlined font denotes 100% agreement on the signage of change.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January		2.7			0.1			-0.9			0.2	
February		3.8			1.2			3			1.8	
March		5			0.2			4.9			3.3	
April		-4.8			-1.1			5.5			2.1	
May		3			0.9			2.7			3.3	
June		7.4			9.4			6.9			20.6	
July		3.9			6.9			12.5			17.5	
August		11.4			12.3			23.8			25.1	
September		0.9			2.5			2.6			11.3	
October		6.4			0.4			2.2			8.8	
November		2.3			1.5			-5.7			-3.1	
December		1.6			1			-2.5			1.7	

Agreement between the simulations is very strong throughout the year, particularly from March through to November. By the 2080s there is a 100% agreement that open water evaporation will increase in 8 months of the year (Table 5.3(b)). It is also shown that the signage of monthly open water evaporation change at Tittesworth Reservoir can be predicted with more confidence than either average rainfall or the amount of dry days (Tables 5.1(b) and 5.2(b)). Taken together, Figures 5.8 and 5.9 and Table 5.3 underline the importance of taking PET rates into account when conducting climate change impact assessments on water resources, rather than focussing purely on changes to rainfall regimes.

5.7 Projections of changes to meteorological drought and extreme wet events

The metrics of water shortage described in Section 3.11 essentially equate to various states of water shortage drought. Before getting to that stage, by assessing the entire set of raw WG data before it is applied to the HYSIM model, it is possible to assess future meteorological drought (i.e. drought determined by a lack of rainfall rather than the effects of said rainfall on water resources or agriculture). The maximum amount of consecutive days with <1mm of precipitation in a simulation is used as a metric to describe drought conditions in Figure 5.10.

Figure 5.10(a) shows that maximum drought events (which, given the length of each simulation, are 1 in 100-year events for that time horizon) progressively increase in duration from the baseline median as the century progresses for almost all of the uncertainty distribution. Some outliers show a reduction (particularly the extreme wet 2050s sequence), although no simulations for the 2080s exhibit a maximum drought length less than the least extreme baseline simulation. Figure 5.10(b) shows the full range of 2080 medium scenario simulations compared to the baseline simulations (based on Figure 3.8), from which it can be seen that a strong trend towards increased aridity and increased maximum drought length is projected.

In order to gain a clearer understanding of meteorological drought projections, annual maximum drought duration data per year is plotted for the median UNEP AI simulation in each time-slice (Figure 5.11). An increase in extreme drought duration is projected over time, with a 1 in '*x*'-year event showing greater severity with each progressively remote time horizon. From the evidence in figure 5.11 it is clear that meteorological drought is exacerbated as a result of climate forcings. A more detailed assessment of average rainfall over multiple seasons/months in the data would potentially be more useful in a decision-making context than is provided here, as the longest period of rainless days is an imperfect metric of meteorological drought, but seeing as these events would show up as a water resource drought event (which is the focus of Chapter 6), greater depth of analysis of meteorological drought is not required in this case.

Table 5.3 (a). Percentage changes of average PET/day at UC in each month in the future time-slices from the baseline median. The minimum, median and maximum of the simulation range is given in each case. Red/orange boxes denote higher PET compared to the baseline and blue lower, with the strength of colour denoting the scale of that change. The colouring is based on the median simulation in each future time-slice.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January	-11.7	-3.5	12.4	-9.4	2.1	17.4	-16.8	-0.9	11.6	-5.8	11.1	34.5
February	-7.6	2.7	9.3	1.4	6.9	19.2	-6.8	5	28	-4.7	15.7	42.2
March	4.1	9.6	20.2	2.2	11.3	20	4.3	12	27	9.6	25.8	45.4
April	-1.4	7.2	12.3	-2.2	9.4	20.2	-0.5	14.1	29.8	2.9	18.8	46.4
May	-7.4	9.6	22	-8.4	10.5	28.6	1.2	14.1	30.9	2.3	21.3	57.8
June	-8	12.3	32.5	-7.1	17	33.2	-6.9	13.7	30.7	11.1	30.2	67.3
July	-7.2	8.6	39.3	-6.3	13.3	55.8	-3.3	8.4	51.2	-18.9	30.5	84.6
August	0	11.9	29.7	-3.7	16.7	52.8	-1.8	17.9	54	10	34	116
September	-11	6.5	17.4	-2.3	12.5	23.2	-5.2	10	43.9	8.8	27.7	66.8
October	2	9.1	18.7	0	10	20.3	-3.3	10.4	23.2	10.2	22.4	56
November	-0.3	9.1	14.5	-3.8	8.2	24.2	1.7	12	24.8	10.2	18	45.7
December	0.8	4	18.7	-11.9	5.8	16.1	-6	8	22.9	-0.6	14.2	38.5

Table 5.3 (b). Median percentage changes of average PET/day at UC in each month in the future time-slices from the baseline. Red/orange boxes denote higher PET compared to the baseline and blue lower, with the strength of colour denoting the scale of that change. The size of the font describes the percentage of the simulation range that agrees on the signage of change. Underlined font denotes 100% agreement on the signage of change.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January		-3.5			2.1			-0.9			11.1	
February		2.7			6.9			5			15.7	
March		9.6			11.3			12			25.8	
April		7.2			9.4			14.1			18.8	
May		9.6			10.5			14.1			21.3	
June		12.3			17			13.7			30.2	
July		8.6			13.3			8.4			30.5	
August		11.9			16.7			17.9			34	
September		6.5			12.5			10			27.7	
October		9.1			10			10.4			22.4	
November		9.1			8.2			12			18	
December		4			5.8			8			14.2	

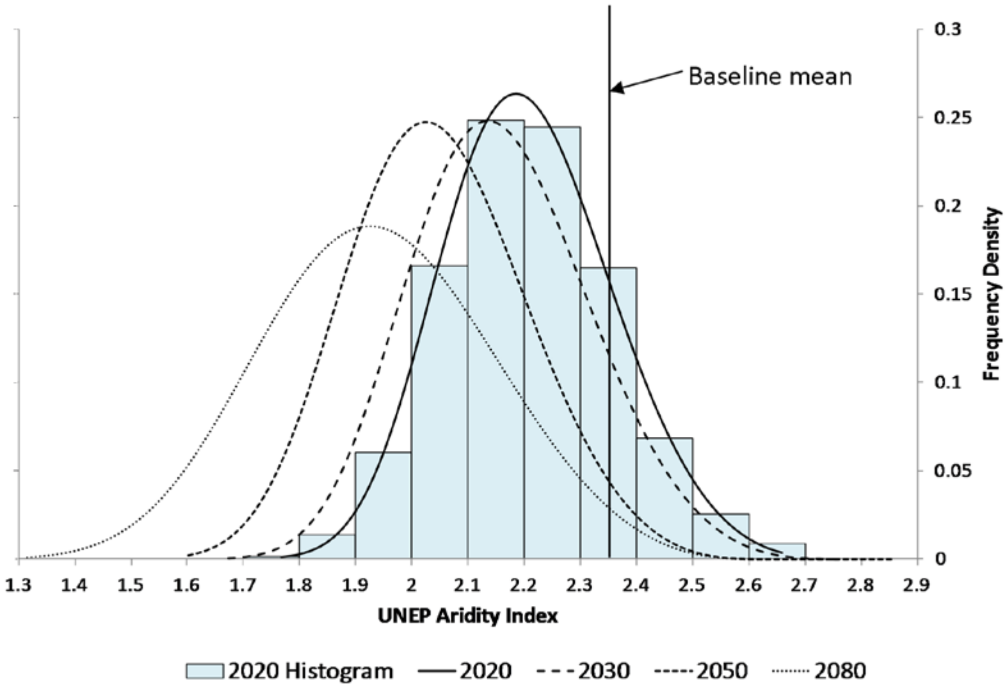


Figure 5.8. Alterations to the range of UNEP aridity index in the modelled simulations. The zenyth of the baseline (1961-1990) distribution is indicated rather than shown in full to maintain the clarity of the chart as the peak frequency density is far greater than the future simulations.

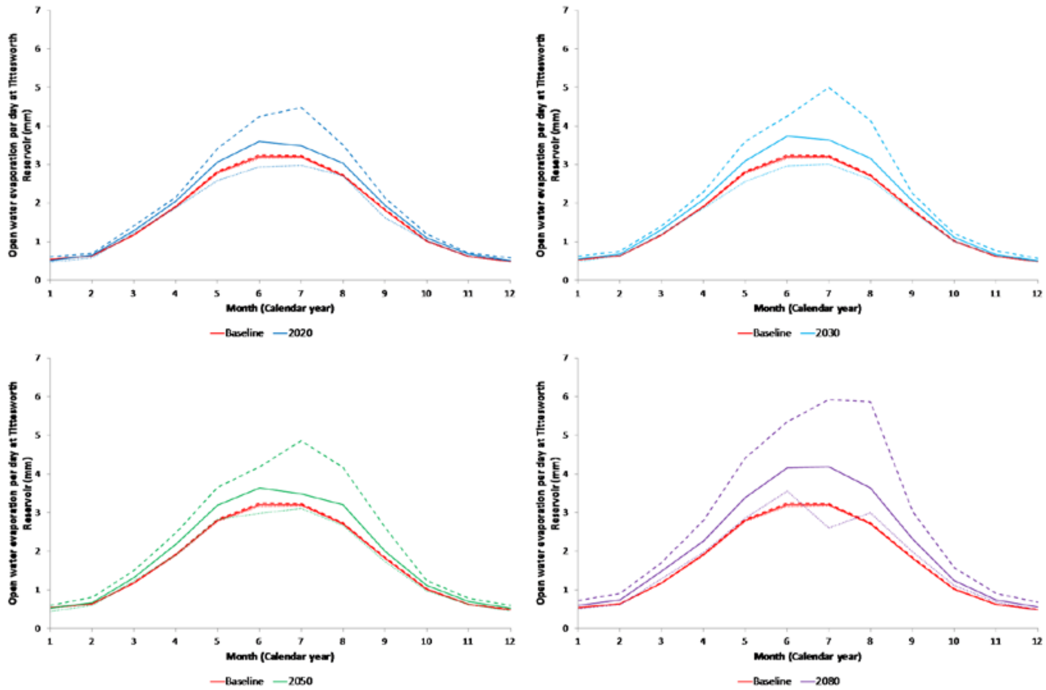


Figure 5.9. Monthly average open water evaporation at Tittesworth Reservoir in the baseline period and the 2020s, 2030s, 2050s and 2080s. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively.

5.8 Projections of changes to flow

5.8.1 Average monthly flow

An assessment of changes to flow statistics throughout the 21st century is carried out for each of the sub-catchments in the North Staffs WRZ. First, plots of average monthly flow for future time horizons are shown to describe changes to the annual profile of flows and assess the effect of climate forcing on flow seasonality compared to baseline conditions using the WGM (Figure 5.12), which is then compared to the CFM for the 2080s (Figure 5.13). Second, flow duration curves (FDCs) describe the simulated flow sequences in terms of low, medium and high flow events (designated following Yilmaz *et al.*, 2008) in order to show how the future flow profiles are altered from the baseline (Figure 5.14) using the WGM. Table 5.4(a) presents the key information depicted in Figure 5.12 and the degree to which the signage of change is consistent for each month is described in Table 5.4(b).

Annual flow profiles for the future (Figure 5.12) show similar characteristics to the precipitation profiles in Figure 5.1, with some uncertainty regarding the signage of change in nearly every month of every time horizon (Table 5.4(b)), but a vast majority of the uncertainty distribution showing reduced summer flow in the future. However, the median simulation projects reduced flows extending from the summer through the autumn to November, whereas as the median simulation precipitation averages are increased in October and November (Table 5.1). This indicates that evaporation rates are high enough to reduce the flow during these months despite the increased rainfall

(Table 5.3). This, along with the projected increase in autumnal dry days (Table 5.2), suggests that summer droughts are likely to be prolonged into the autumn and early winter in the future, and therefore confirms the conclusions drawn from the meteorological variables; that resources for water supply are likely to become dependent on a shorter amount of the year with an increased likelihood of summer drought events occurring.

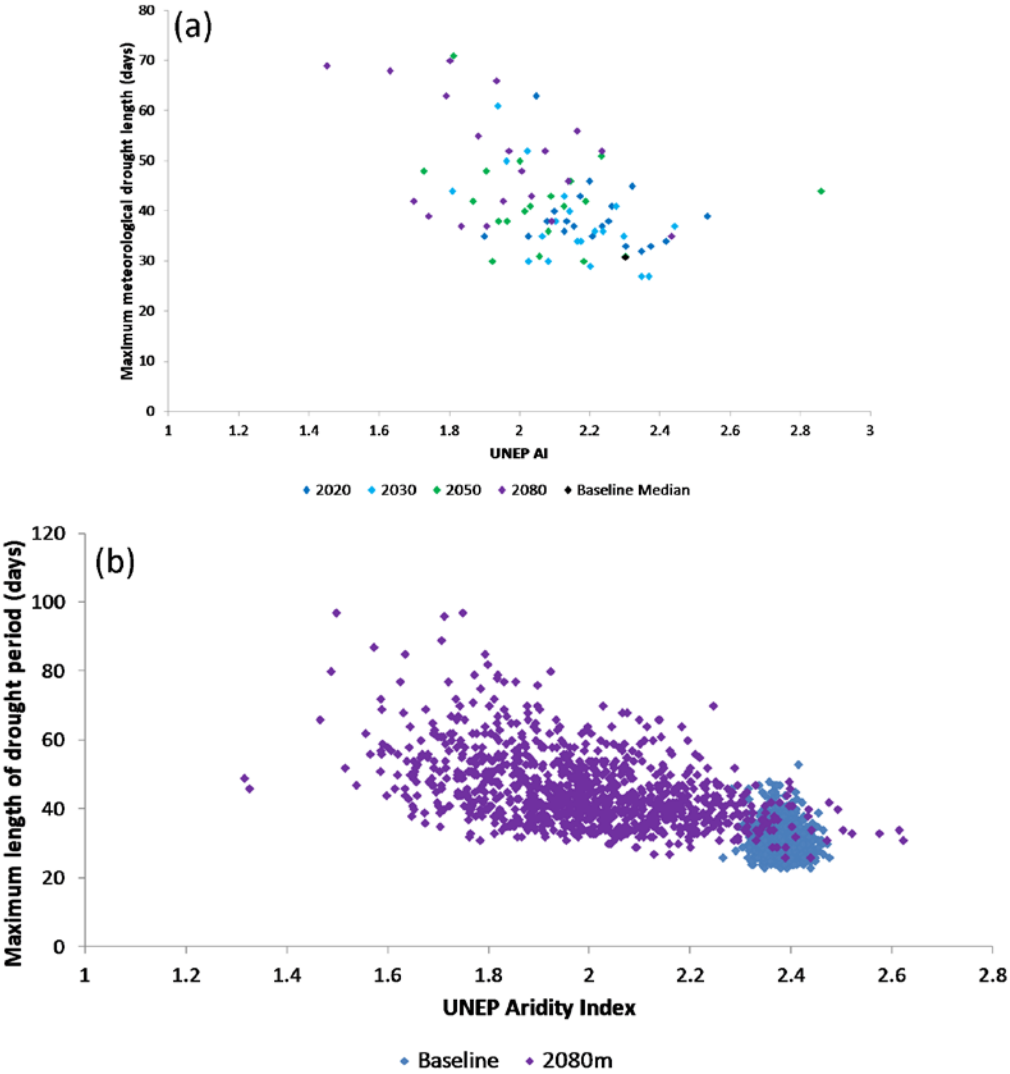


Figure 5.10. (a) Average UNEP AI plotted against the maximum drought event length (consecutive days with <1mm of precipitation) in each sub-sampled simulation. (b) Average UNEP AI plotted against the maximum drought event length in each simulation of the UKCP09WG 2080 range. Blue: Baseline (1961-1990). Purple: 2080s.

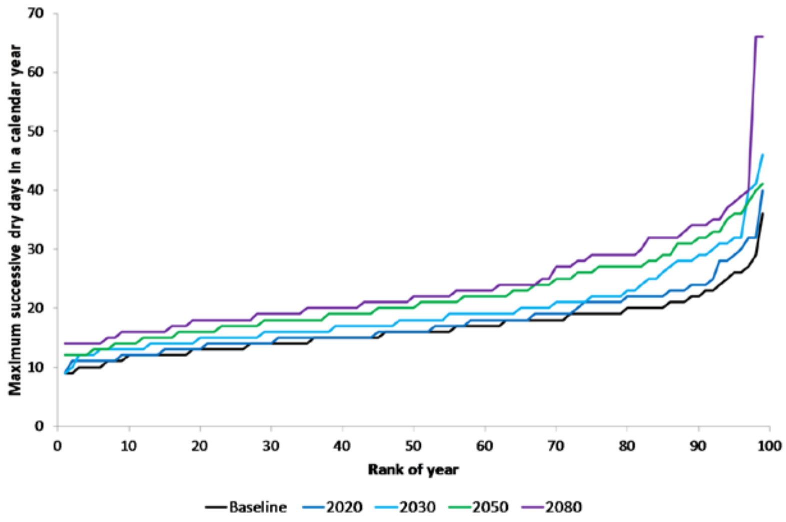


Figure 5.11. Rank of the maximum annual drought event duration (consecutive days with <1mm precipitation) in the median simulations for the baseline period, 2020s, 2030s, 2050s and 2080s.

The alterations to monthly flow profiles occur linearly with time, with gradually more extreme summer reductions with more distant time horizons as well as, to a lesser extent, elevated winter flow (Figure 5.12, Table 5.4(a)). The very extreme wet 2050 simulation is visible as in Figures 5.1c and 5.7 in the form of very high summer flows, although winter flows are not out of keeping with the median shift for that time-horizon. Future flow profile trends are very similar across the three sub-catchments, as would be expected given Figure 5.1.

The effect of applying the CFM based on the 2080s monthly flow averages to the instrumental data is shown in Figure 5.13. It can be seen that whilst the general trends of seasonal flow profile are consistent, there are some disparities between the two approaches.

- The median CFM simulation projects lower average flows in all months except February and August (due to the slight over-estimation of August rainfall in the WG baseline sequences).
- The greater average flow projected for February in the 2080s in the CFM compared to the WGM is influenced by the baseline simulation underestimating flow when compared to the instrumental record. The same phenomenon is seen to a lesser extent in August and vice-versa in June and September.
- Spring flows are reduced in the CFM projections compared to the WGM to such an extent that March and April maximum flows using the CFM are less than the median WG simulation flows. This is as a result of the inability of the WG to produce multi-seasonal droughts, with most years in the fully-synthetic sequence projecting a full recharge of Tittesworth Reservoir, whereas this is not the case in the instrumental record (and therefore the future projections based upon it). This would imply, as expected, that periods of water shortage with high severity (temporary use ban (TUB)) will be more frequent in the CFM simulations than when the WGM is used.
- From July through to January, agreement between the two approaches on 2080s median and extreme low-end flow at UC is strong.

5.8.2 **Flow Duration Curves**

FDCs are used to show the extent of time a certain flow is equalled or exceeded within a dataset. Due to the focus on water shortage events in this study, the y-axes of the FDCs shown in Figure 5.14 are logarithmic to accentuate the low-flow sections of the plots. Furthermore, the median, minimum and maximum flow rate simulations are selected based on total flow in the low-flow section of the dataset. This means that the ‘high’ and ‘medium’ sections of the FDCs do not necessarily show the median or extreme simulations for those parts of the plot. Separate FDCs for annual, winter half-year (ONDJFM) and summer half-year (AMJJAS) periods are provided in order to assess the effect of the changed flow seasonality shown in figure 5.12 on flow profiles. All FDCs relate to the WG dataset; CFM simulations are assumed to produce more extreme low-flows in line with Figure 5.13.

The median simulated annual low flows are reduced from the baseline in the annual and summer half-year series at UC, DHY and Solomon’s Hollow (SOL) in the 2020s, and become progressively more so with further afield time horizons (Figure 5.14). By the 2080s, the entire range of simulations show reduced low flows conditions at UC and SOL, with a small proportion of the range at DHY suggesting an increase in low flows. This reduction in the amount of river flow during dry conditions is expected given the increased drought severities shown in Figure 5.11. Seasonal FDCs at UC are shown in Figure 5.15, and suggest that over time gradually more of the simulation range projects reduced summer half-year low flows, and, to a lesser extent, winter half-year low flows. By the 2080s, signage of net change in low streamflow rates at UC is definitive for summer half-year and annual periods, and is broadly consistent across the simulation range in terms winter low flows (Figure 5.15). The biggest reductions to extreme low flows are seen in the winter half-year FDCs (Figure 5.15). This is caused by the summer droughts extending into October (Table 5.4(a)).

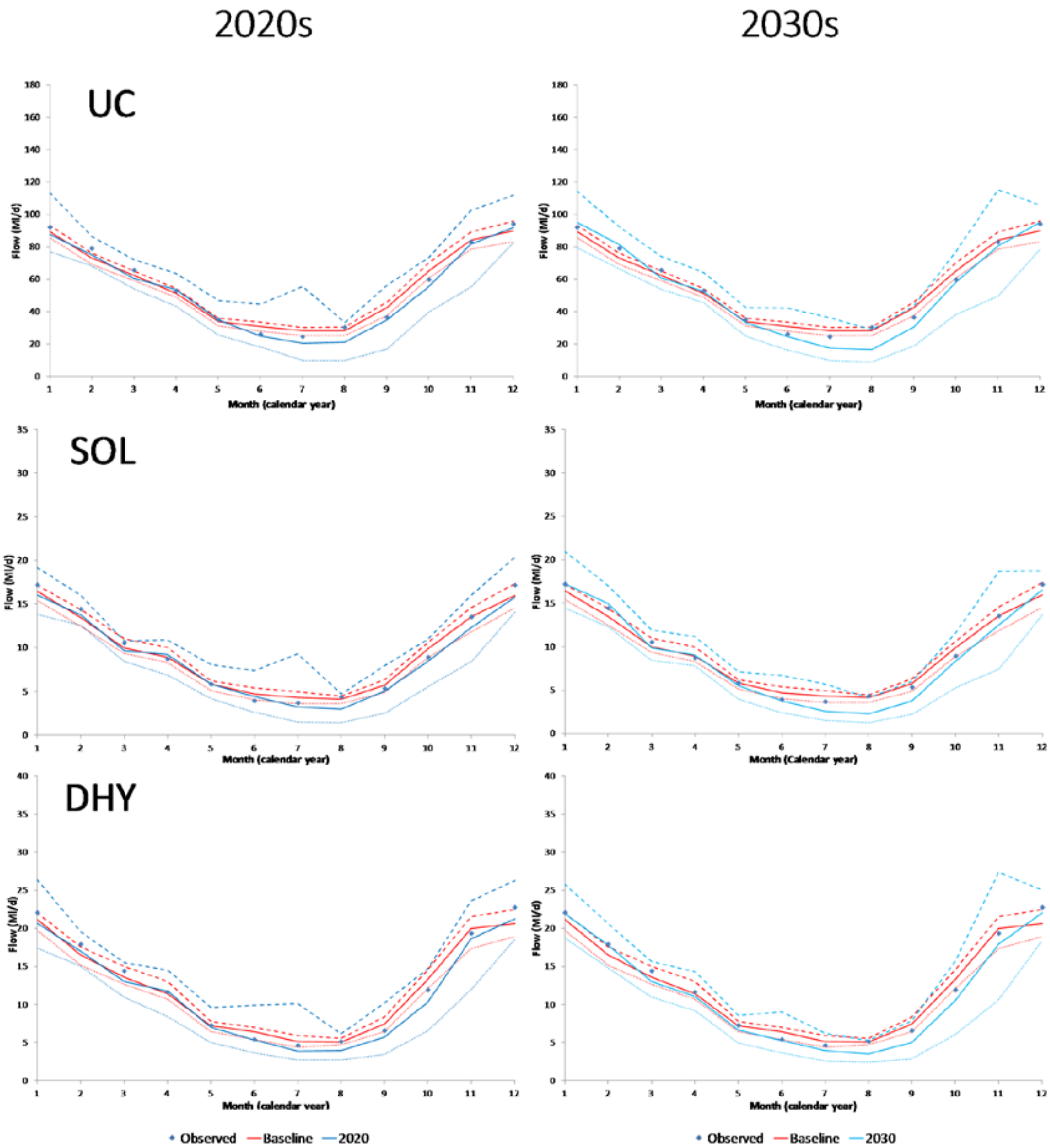


Figure 5.12. Baseline average flow per month validated against instrumental data, with changes to those statistics in the 2020s, 2030s (this page), 2050s and 2080s (overleaf) using the WGM approach overlain. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively. Top: Upper Churnet, middle: Solomon's Hollow, bottom: Deep Hayes.

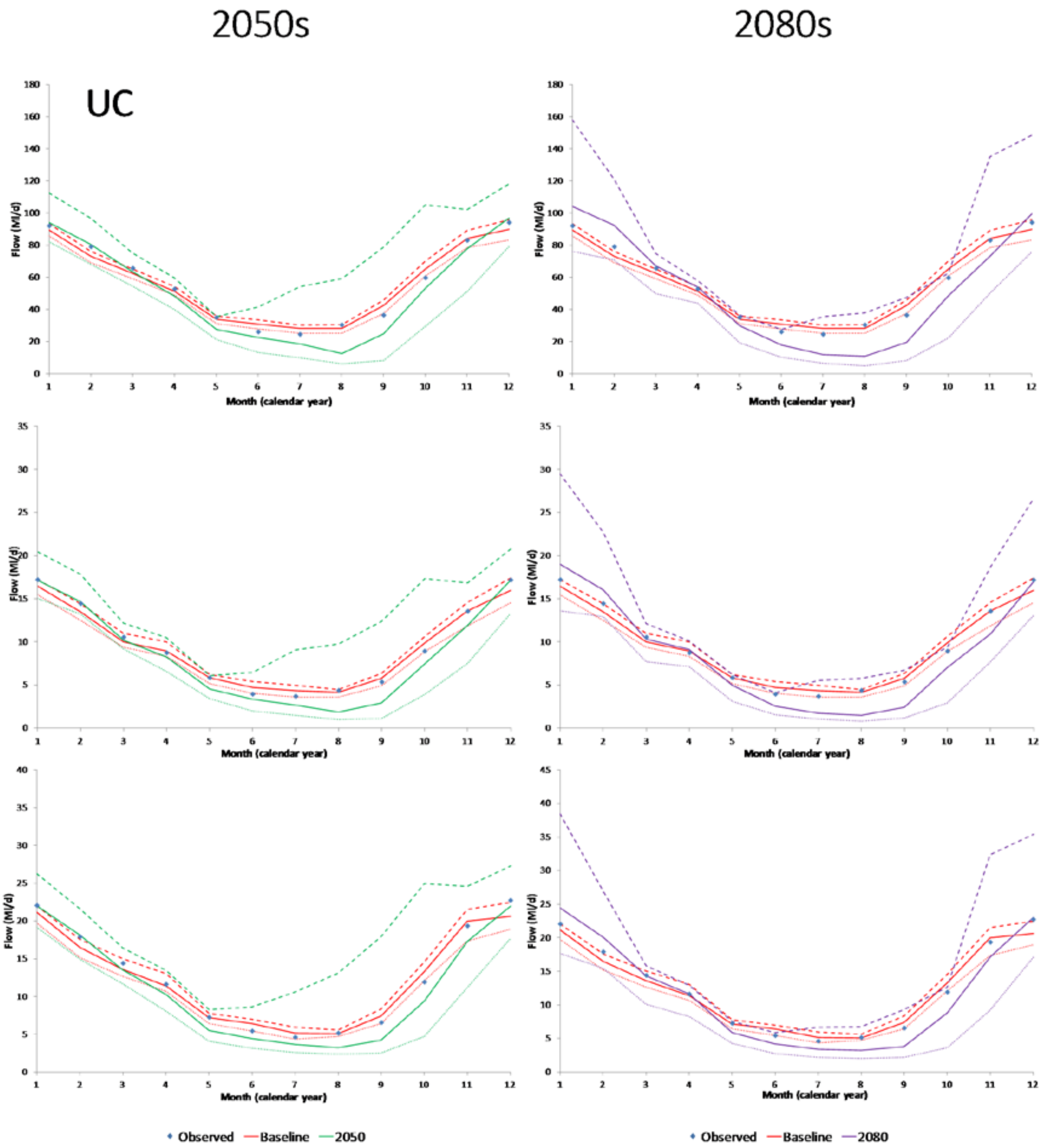


Figure 5.12. Continued from previous page

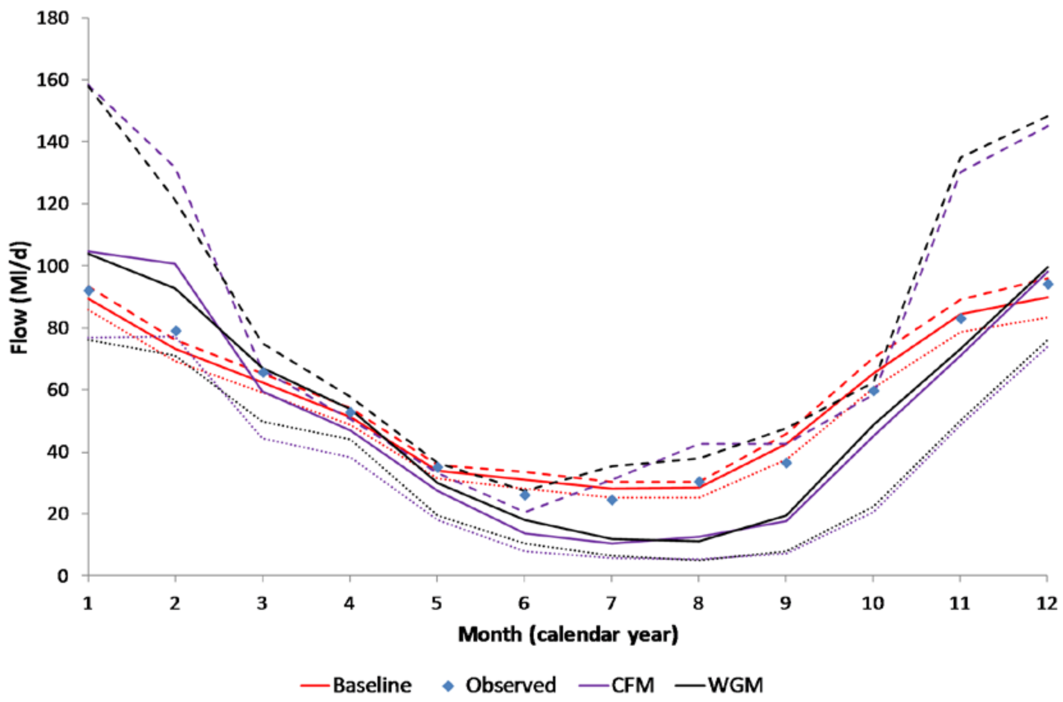


Figure 5.13. Baseline average flow per month at UC validated against instrumental data (blue rhombi), with changes to those statistics in the 2080s using the CFM and WGM overlain. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively.

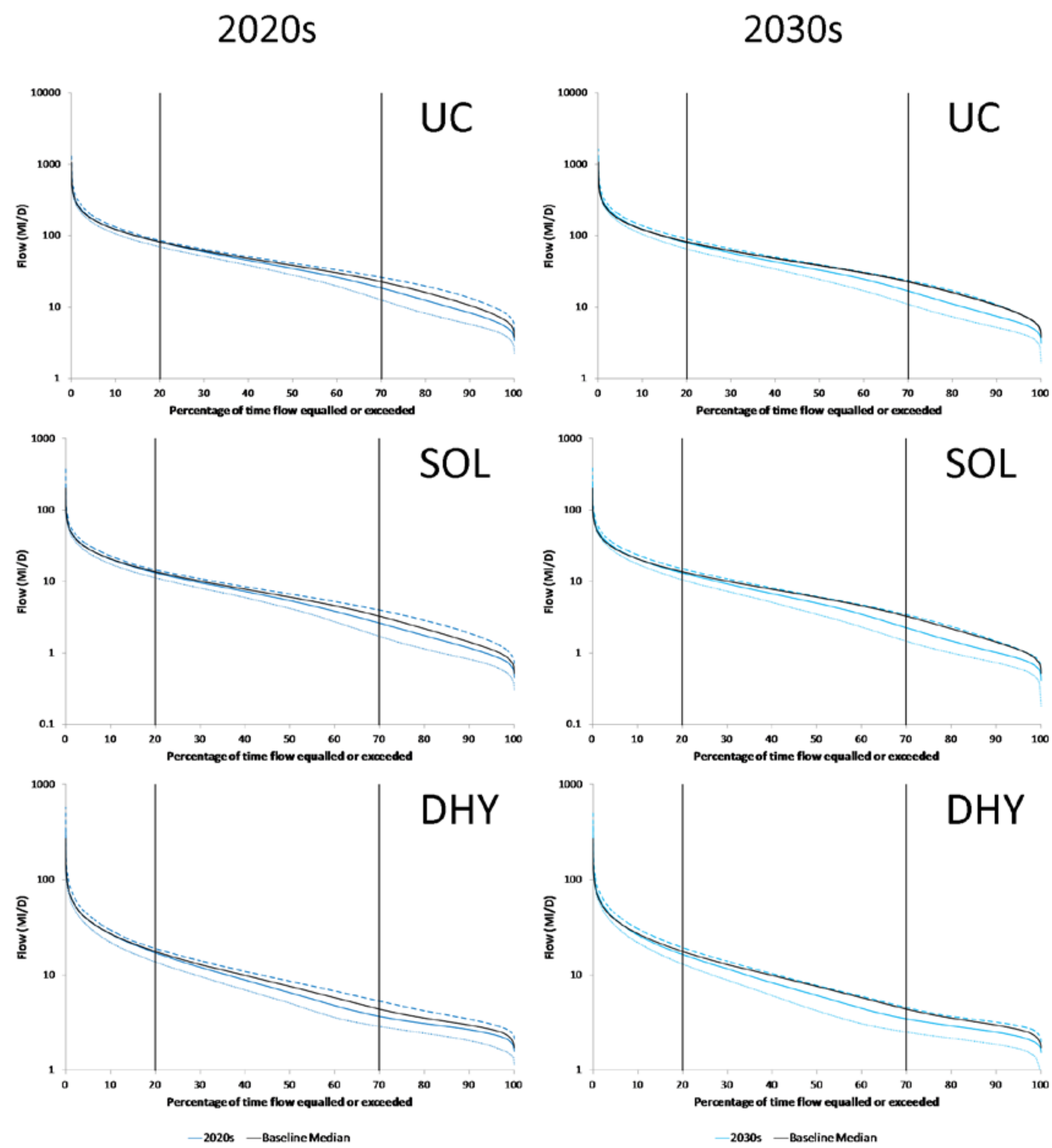
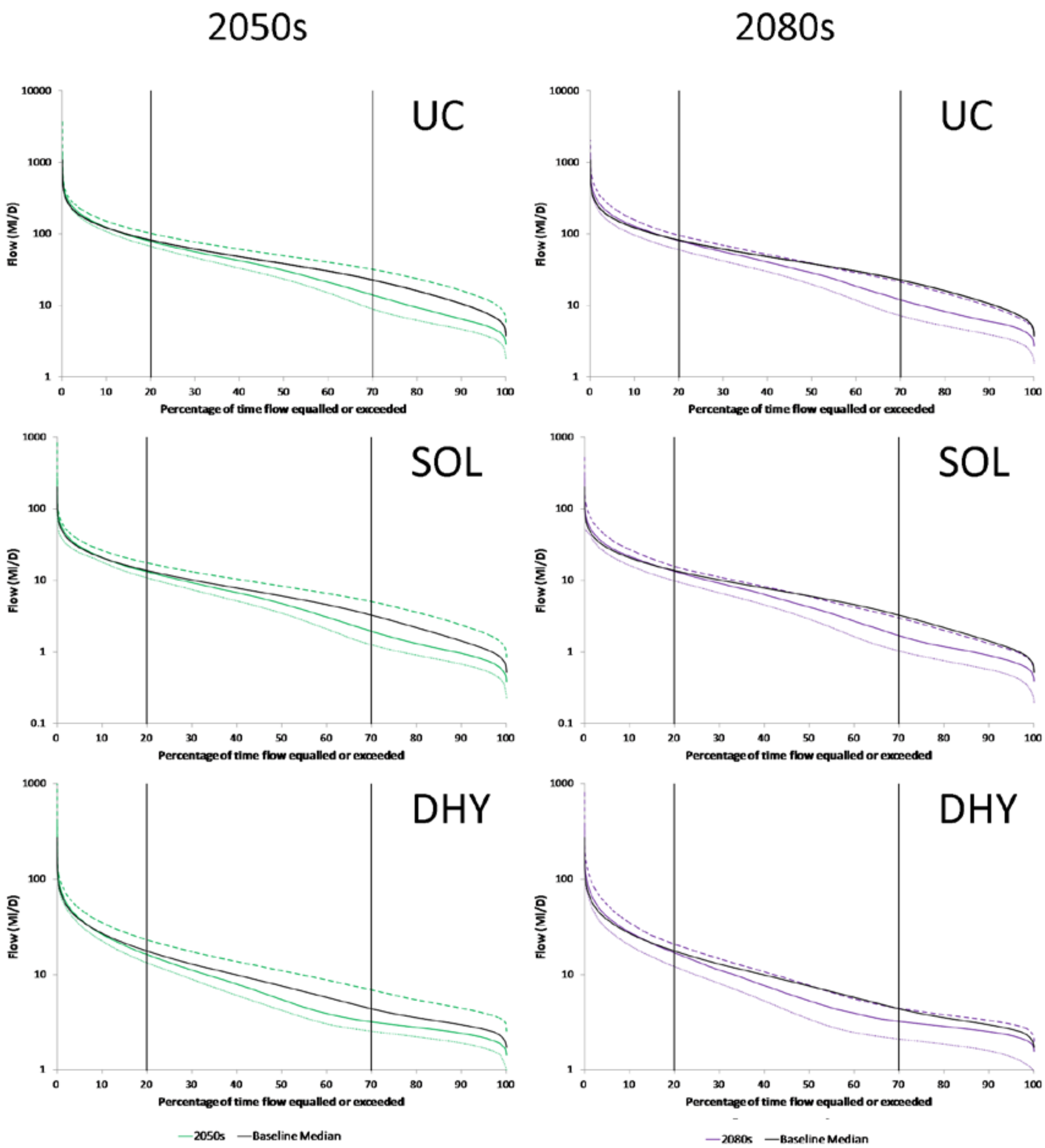


Figure 5.14. Annual FDCs for Upper Churnet (top), Solomon's Hollow (middle) and Deep Hayes (bottom) in the 2020s, 2030s (this page), 2050s and 2080s (overleaf) using the WGM. Solid lines: simulation range median; dashed lines: simulation range maximum; dotted lines: simulation range minimum (all in terms of the low -flow section of the FDC (probability of exceedance >70%)). Vertical lines split the plots into high (<20%), medium (20% - 70%) and low (>70%) flows (after Yilmaz *et al.*, 2008)



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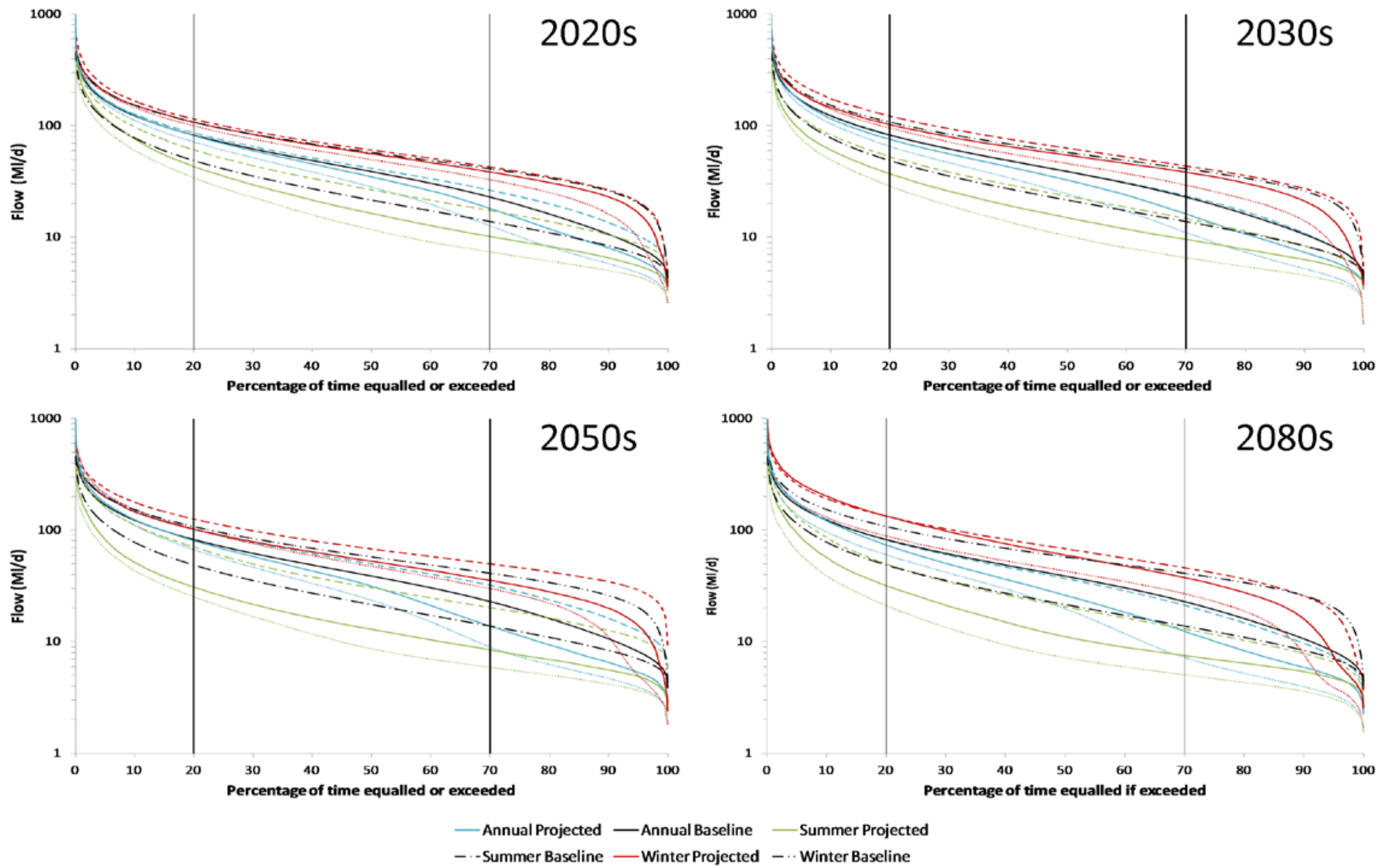

Figure 5.15. Annual, summer half-years (AMJJAS) and winter half-years (ONDJFM) FDCs for Upper Churnet in the 2020s, 2030s, 2050s and 2080s compared to the baseline medians. Solid coloured lines represent the simulation range median, dotted coloured lines represent the simulation range minimum, and dashed coloured lines represent the simulation range maximum (all in terms of the low flow section of the FDC (probability exceedance >70%). Vertical lines split the plots into high (<20%), medium (20—70%) and low (>70%) flows (after Yilmaz *et al.*, 2008)

Table 5.4 (a). Percentage changes of average flow/day at UC in each month in the future time-slices from the baseline median. The minimum, median and maximum of the simulation range is given in each case. Red/orange boxes denote less flow compared to the baseline and blue more, with the strength of colour denoting the scale of that change. The colouring is based on the median simulation in each future time-slice.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January	-13.8	-2.1	26.7	-11.4	6	27.6	-7.1	5.2	24.8	-15.1	16.1	76.6
February	-6.8	2.7	18.2	-9.1	11.2	26.1	-6.7	10.6	31.6	-3.1	26.4	65.5
March	-13.2	-2.8	15.9	-13.9	-2.2	19.1	-12.4	2.5	22.4	-20.1	7.8	20.1
April	-15.9	4.5	24.1	-11.1	2.5	25	-21.7	-5.3	16	-14.5	5	12.5
May	-24.3	2.8	37.8	-26.3	-2.4	25	-35	-18	5.4	-43	-11.7	7.6
June	-41.3	-19.7	44.2	-47.1	-20.3	36.3	-57.7	-27	31	-66.5	-42.1	-11.2
July	-64.8	-27	97.2	-64.5	-38.3	28.3	-64.7	-33.9	89.7	-77.3	-57.9	25.8
August	-65.1	-25.5	16.9	-68.2	-42.2	1.7	-78.7	-55.6	106.3	-82.9	-61.1	33.1
September	-59.9	-17.4	32.3	-55.8	-29.2	2.8	-81	-42.9	81.4	-81	-53.7	12
October	-38.8	-15	12.4	-41.7	-11.1	18.1	-54.5	-19.6	60.5	-66	-25.6	-4.3
November	-34.4	-3	21.5	-41.3	-4.3	36.5	-38.5	-7.2	19.9	-40.6	-13.1	60.2
December	-8	2.4	24.6	-12.6	6	17.7	-12.2	8.2	30.5	-15.4	10.8	65.3

Table 5.4 (b). Median percentage changes of average flow/day at UC in each month in the future time-slices from the baseline. Red/orange boxes denote less flow compared to the baseline and blue more, with the strength of colour denoting the scale of that change. The size of the font describes the percentage of the simulation range that agrees on the signage of change. Underlined font denotes 100% agreement on the signage of change.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January		-2.1			6			5.2			16.1	
February		2.7			11.2			10.6			26.4	
March		-2.8			-2.2			2.5			7.8	
April		4.5			2.5			-5.3			5	
May		2.8			-2.4			-18			-11.7	
June		-19.7			-20.3			-27			<u>-42.1</u>	
July		-27			-38.3			-33.9			-57.9	
August		-25.4			-42.2			-55.6			-61.1	
September		-17.4			-22.2			-42.9			-53.7	
October		-15			-11.1			-19.6			<u>-25.6</u>	
November		-3			-4.3			-7.2			-13.1	
December		2.4			6			8.2			10.8	

5.9 Conclusions

A comprehensive assessment of future climatic and hydrological conditions in the North Staffordshire WRZ is carried out using sub-sampled UKCP09WG information. The core outcomes of the study are:

- The simulations unanimously agree on the signage of monthly precipitation change on only two occasions, December in the 2050s and 2080s. In all other cases, at least some of the range of simulations projects a change in the opposite direction to the median simulation (Table 5.1(b)).
- A majority of the simulations show a movement towards greater seasonality, with wetter winters and drier summers. The confidence with which this statement is made increases with more distant time horizons. There is little agreement on average rainfall trends in spring and autumn (Figure 5.1 and 5.3)
- More intense winter rainfall is likely in the future given greater average winter rainfall alongside largely unchanged amounts of dry days and increased rainfall variability (Figures 5.1, 5.4 and 5.5)
- Enhanced summer drying is likely as a result of decreased average rainfall, more frequent dry days and longer durations with <1mm rainfall for each more distant time horizon (Figure 5.5 and 5.11).
- PET and open water evaporation rates are very likely to increase, with median projections of 30-34% increases in summer by the 2080s. Consistency between simulations is reduced in the winter, but more modest increases are likely. Spring and

autumn show large increases in PET and open water evaporation, decreasing the amount of rainfall available for use as water supply (Table 5.3).

- A majority of simulations project decreased summer flows at the three sub-catchments by the 2020s, before steadily becoming further reduced as the century progresses (Figure 5.12)
- Median simulations suggest increases in winter flows, but the signage of change is not consistent across the simulations. Flows are likely to be reduced well into autumn and back below baseline levels in March, suggesting a shorter reservoir recharge period (Figure 5.12 and Table 5.4).
- The flow profile at each sub-catchment is progressively more extreme as the century progresses, with reductions to low-flow events indicating more frequent and intense episodes of hydrological drought, and larger winter high flow events evidencing more frequent heavy rainfall events (Figure 5.14).Summer low flows are reduced in all simulations by the 2080s, and most winter simulations are also reduced. Extreme low flows are substantially reduced in the half-year winters by the 2050s and 2080s (Figure 5.15), primarily due to lower flows in October (Table 5.4(a)).
- Using the CFM carries-over extreme multi-seasonal drought events from the historical record, thus producing periods of more extreme drought in the future projections than the WGM, which are manifested as reduced overall average flows in the analysis presented here. This effect is studied in more detail in Chapter 6 (Figure 5.13).

- A future that is likely to have enhanced single-season summer droughts accompanied by more extreme winter rainfall is indicated, suggesting a more challenging environment for water resource supply.

6 CLIMATE CHANGE IMPACTS ON WATER RESOURCE SHORTAGES

6.1 Introduction

This section of the research project focuses on translating the climate change-influenced simulations of relevant hydroclimatological variables into probabilistic distributions of water shortage that can be adopted into a WRZ robustness assessment. The resultant cumulative distribution functions (CDFs) of water shortage probability at various severities in future time periods can be used as the baselines against which a potentially infinite number of adaptation options can be applied, testing the extent to which they keep the water supply system at the required Levels of Service (LoS) throughout the future over a pre-determined amount of the uncertainty range.

The chapter begins by providing an overview of the data and models that are used in this phase of the modelling process (discussed in more detail in Chapter 3), before outlining how this approach is different to the literature reviewed in Chapter 2. The core results of this phase of the project are then split into the impact of climate change on raw water storage at Tittesworth Reservoir (Section 6.4), and the resultant future water shortage metrics for the North Staffordshire Water Resource Zone (WRZ) (Section 6.5). Throughout both of those sections the differences between the weather generator method (WGM) and the change factor method (CFM) are discussed, before conclusions are drawn in Section 6.6.

6.2 Data sources and models used

The information analysed in this section consists of the flow, daily rainfall and open water evaporation sequences produced in Chapter 5. The flow and rainfall sequences from both the WGM and CFM are at a daily time-step, whilst the open water evaporation data is daily for the WGM and monthly for the CFM.

40 temporally-consistent simulations for flow at Upper Churnet (UC), Solomon's Hollow (SOL) and Deep Hayes (DHY), as well as direct rainfall and open water evaporation at Tittesworth Reservoir, are used for each of the four future time-slices that represent the 2020s, 2030s, 2050s and 2080s. Of those 40, 20 are created using the WGM and thus have independent temporal sequencing and climate variability but reduced representation of the most extreme dry events (Jones *et al.*, 2009), and 20 are created using the CFM, so produce extreme events but have temporal sequencing identical to the instrumental record.

The research in this chapter relates to the areas of the flow diagram (Figure 3.1) shaded blue. The North Staffordshire WRZ Aquator water resource model is used to produce probabilities of water shortage conditions in a calendar year in each of those future simulations, based on the infrastructure and operational conditions of the area. At this stage of the project, the model assumes all processes within the North Staffordshire WRZ are kept stationary at 2012 conditions, including abstraction licenses, reservoir control curves, capacities of water treatment works (WTWs) and linkages, demand profiles and compensation requirements. All of these parameters are provided by Severn Trent Water (STW).

6.3 Differences to cited literature

With the increased complexity that climate change uncertainty brings to decision-making in the water sector, replicable tools that balance scientific rigour and usability are required (Arnell, 2011(b)). Provided here is an approach for determining climate change impacts on water supply shortage in the North Staffordshire WRZ that aims to meet the requirements of industry whilst taking climate change uncertainty into account. In a water resources context, a robustness analysis approach involves taking multiple views of the future and evaluating a set of potential decisions or actions in their ability to maintain a given standard of supply (as a result of the negative and positive impacts of climate change) using an iterative computational modelling analysis (Lempert and Groves, 2010). It is proposed that using such an approach can produce greater confidence in making investments in the UK water industry based on climate change information, as the uncertain information can be distilled to a quantitative assessment of whether a water supply system can be considered robust to a pre-determined standard over a given time period. This section focuses on the 'baseline' conditions against which those adaptation options can be tested, and thus constitutes a risk-based climate change impact assessment.

Having easily communicable climate change impact information is crucial to the water resource planner not only in providing external assessments to customers and shareholders but also internally by providing traction in the boardroom. The methodology provided here allows for the uncertain simulated futures to inform decision-making by providing the water resource manager with yes-or-no type answers based on satisfying an acceptable risk of some unwanted outcome at a defined point in the future.

6.4 Projections of change to raw water storage at Tittesworth Reservoir

6.4.1 Weather generator method

An assessment of how the profile of raw water storage at Tittesworth Reservoir is projected to change over the course of the 21st century using the WGM is provided in Figures 6.1(a) and 6.2. Various trends in Figure 6.1(a) and Table 6.1 can be seen:

1. Late-winter to early spring (FMA) average raw water storage remains very high across the simulation range, with only the most extreme simulations projecting a noticeable reduction in the latter-half of the 21st century.
2. Late autumn to early winter (ONDJ) raw water storage is reduced in nearly all simulations across the various time horizons. Table 6.1(b) indicates that there is 95%+ agreement on the negative signage of storage change in October, November and December from the 2030s onwards, and 85%+ agreement from June through to January from the 2030s onwards. By the 2080s, a reduction in storage in November is agreed across the entire simulations range.
3. Summer half-year (AMJJAS) reductions in average raw water storage at Tittesworth Reservoir are widely projected across the uncertainty range, the severity of which increase over time (Figure 6.2, Table 6.1(a)).
4. Annual lows of mean storage at Tittesworth Reservoir are progressively moved deeper into autumn as the century progresses. In the baseline period, September fill is lower than August, which is lower than October. In the 2020s median simulation, mean October storage equals August, and is lower by the 2050s. In the 2080s median

simulation, October has only slightly higher mean storage than September in the median simulation and lower in the most extreme dry simulations. However, heavier rainfall in the winter months produces mean water storage values in February and March only slightly reduced from the baseline in the median simulations of all future time horizons (Table 6.1(a) and Figure 6.2).

5. There are three winter months in which the median raw water storage average is increased across all four future time periods (April and May in the 2020s, and May in the 2030s). The increase is slight, is primarily due to the large volume of water in the reservoir in the baseline simulations, and agreement between simulations is poor (Figure 6.1(b)).

6. The period of significant reservoir recharge is reduced and shifted further into winter form the baseline period.

7. In a majority of the simulations the more extreme high winter rainfall and associated flows are able to restore Tittesworth Reservoir to similar average volumes in the spring to the baseline period following greater draw-down in the summer months. This indicates that a majority of the simulation range points towards increased single-season summer hydrological droughts.

Figure 6.3(a) shows the mean Tittesworth Reservoir storage through an annual profile in each of the 2020 weather generator (WG) simulations. It can be seen by eye how a normal distribution is evident in terms of water storage, with the extreme tails of the distribution manifested as extremely low and high mean reservoir storage and a clustering of simulations in the centre (this is also evident in the rainfall and flow data, but is not shown here). This is seen even more starkly in the 2080s, where the cascade of uncertainty increases.

Seeing as the methodology for providing adaptation measures for a water resource system robust to climate change takes into account 80% of the uncertainty range (Figure 3.16), the extreme low storage simulations seen in Figure 6.3(a) would inevitably be discounted in decision-making. This occurs as a result of striking a balance in industry between taking into account as much of the uncertainty as possible and making decisions based on a future that is unlikely to be realised. Figure 6.3(a) expresses more uniform annual profiles than the same plots for average rainfall (Figure 5.3), although a divergence between the profiles can be seen in terms of many of the simulations projecting greater water stress showing the nadir of mean water storage in October, and all of those suggesting less-extreme water stresses suggesting the minimum values will be in September.

6.4.2 **Change factor method**

Figure 6.1(b) and Table 6.2 provide an assessment of future raw water storage at Tittesworth Reservoir according to the CFM. Figure 6.1(b) shows future projections of water storage as delta values from the 1920-2010 instrumental record rather than a simulated baseline period (as was the case with Figure 6.1(a)), as this longer period forms the basis of the perturbation approach. The simulated 1961-1990 baseline has higher summer average storage than the 1920-2010 instrumental record (as shown in

Figure 6.4), so although the delta changes appear similar (Figure 6.1; Table 6.1), the actual raw storage values for two approaches are in fact different (Figure 6.4). The following trends are seen in the CFM data:

1. There are no significant changes in JFMA raw water storage. The sign of change in winter storage does not show good agreement across the range of simulations (Table 6.2(b)).
2. 90% of the simulation range projects decreased summer storage from the instrumental average in late summer (JASO) from the 2030s onwards. There is less agreement over trends in the 2020s (Table 6.2(b)). On only one occasion is there unanimous agreement between simulations on the signage of raw water resources (June in the 2080s).
3. Summer reductions in water storage are substantially reduced in the median simulations, and very rarely show an increase across the entire dataset. The shift towards reduced storage is generally constant throughout time, but varies slightly between months. Median reductions from the baseline in the present storage nadir month of September are 6.7%, 11.3%, 15.5% and 21.2% in the 2020s, 2030s, 2050s and 2080s, respectively, whilst October reductions are 6.6%, 8.4%, 14.7% and 21.8%, showing an acceleration in the latter half of the century that leads to the annual low storage month moving later in the year towards October by the 2080s (Figure 6.3(b)), particularly in the 'drier' simulations in the range.

6.4.3 **Differences between the two downscaling approaches in terms of raw water storage**

Comparing the WGM and the CFM shows that:

1. The patterns of raw water storage are broadly similar, and show the same trends in relation to their respective baselines. There is greater agreement on the signage of change in the WG simulations than the CFM simulations (Tables 6.1(b) and 6.2(b))
2. Both approaches suggest that winter water resources are likely to remain at high levels, with slight increases on a small number of occasions.
3. There is agreement between the two approaches that September and October see the greatest decreases to water resources at Tittesworth Reservoir over time (Figure 6.1; Tables 6.1(b) and 6.2(b)). The median decreases (in relation to the respective baselines) are greater in the WGM than the CFM. By the 2080s, the median summer nadir of reservoir capacity is similar across both approaches despite the median baseline WG capacity being significantly higher than the 1920-2010 instrumental record (Figure 6.4).
4. The annual nadir of water storage is moved back into October in many simulations of both approaches, particularly those at the drier end of the range (Figure 6.3).
5. As a result of the fixed temporal sequencing, the CFM approach produces simulations where the reservoir is not replenished in almost every spring, as occurs using the WGM. As a result, even though normal or minor droughts conditions are reproduced well using the WGM (see Chapter 3), the lack of major multi-seasonal

drought events accounts for the differences between the two methodologies in terms of average raw water storage (and temporary use ban (TUB) events; see section 6.5).

6. As the century progresses, the climatic variability in the WGM allows for more dry summers than in the CFM, so the average reservoir capacities of the two approaches become gradually more aligned (and therefore the decreases from the 1961-1990 baselines are greater than the CFM decreases from the 1920-2010 instrumental record) (Figure 6.4). This is caused by the lack of climatic variability in the CFM approach, with the static temporal sequence of drought years restricting the amount of drought years simulated.

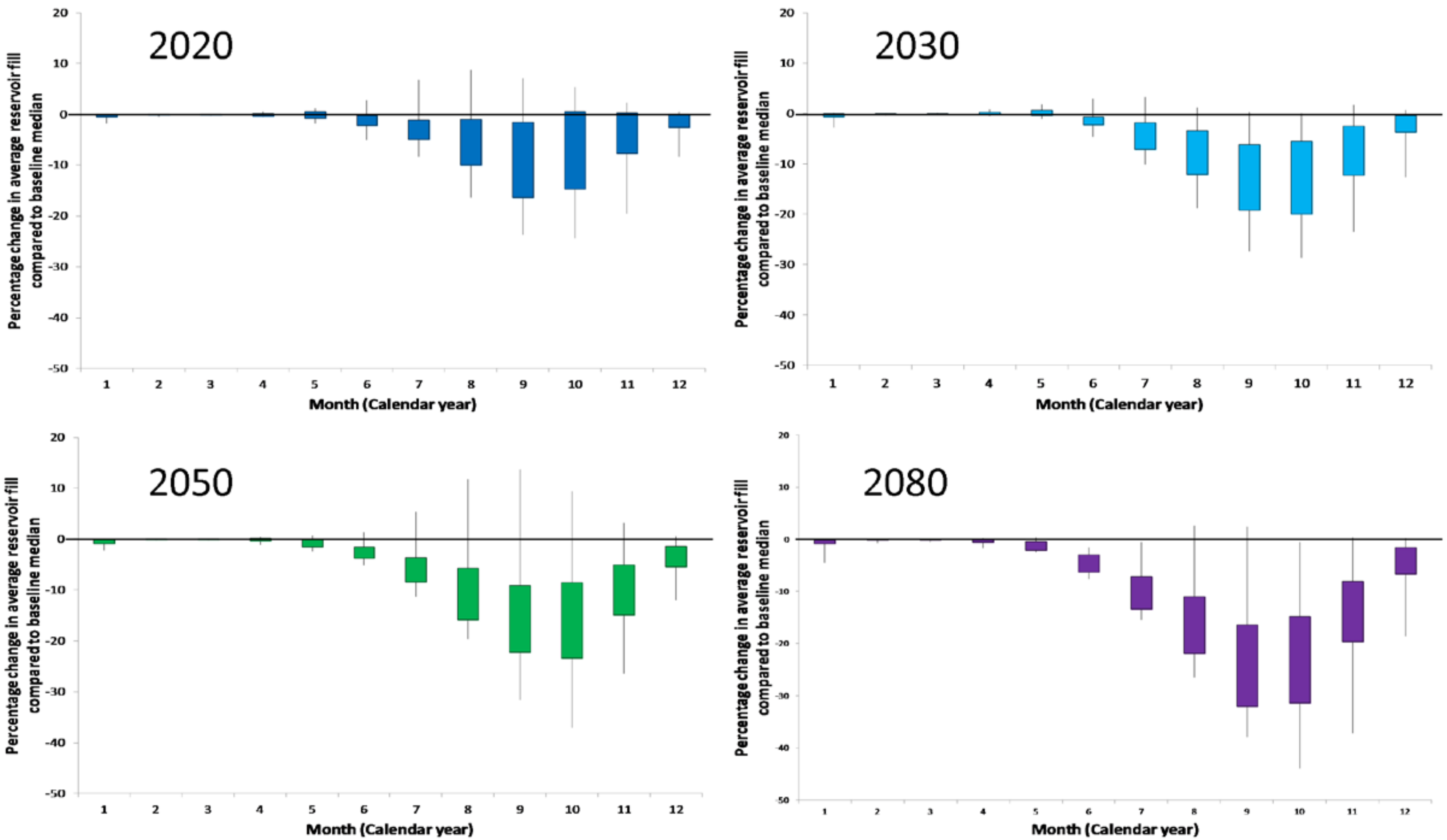

Figure 6.1(a). Box-and-whisker plots of percentage change in raw water storage at Tittesworth Reservoir in future time horizons across the range of uncertainty. The limits of the boxes represent 25-75% of the range, whilst the whiskers represent the full extent of the range. Future reservoir storage compared to the simulated baseline median (representative of 1961-1990) when the WGM is used.

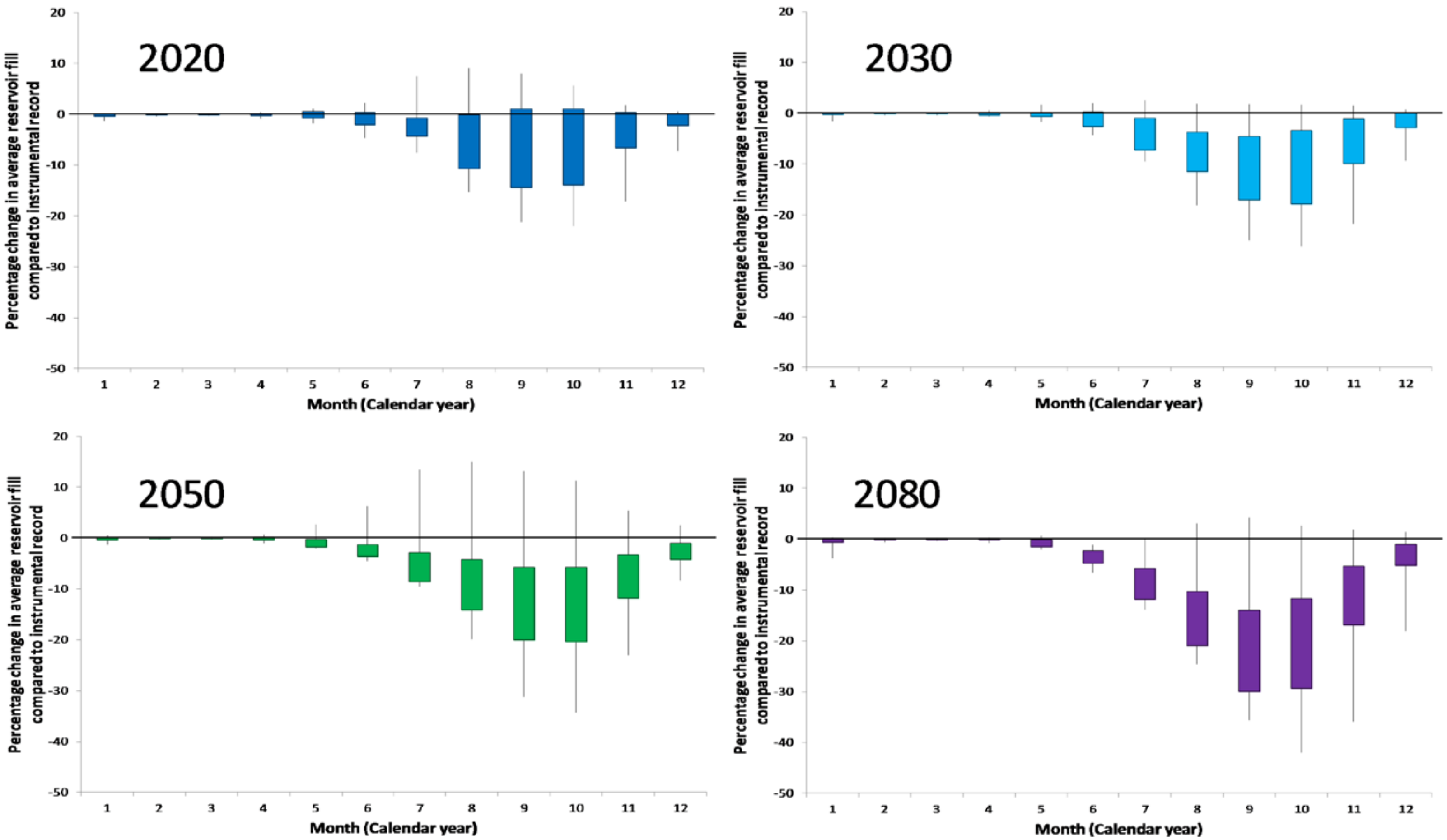

Figure 6.1(b). As Figure 6.1(a), but with future reservoir storage compared to the instrumental record (1920-2010) when the CFM is used.

Table 6.1(a). Percentage changes of raw water storage at Tittesworth Reservoir in each month in the future time-slices from the baseline median using the WGM. The minimum, median and maximum of the simulation range is given in each case. Red/orange boxes denote less raw water storage compared to the baseline/instrumental record and blue more, with the strength of colour denoting the scale of that change. The colouring is based on the median simulation in each future time-slice.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January	-1.8	-0.2	0	-2.8	-0.3	0	-2.2	-0.4	0	-4.4	-0.5	-0
February	-0.5	-0	0	-0.4	-0	0	-0.3	-0	0	-0.6	-0	0
March	-0.2	-0	0.1	-0.1	-0	0	-0.3	-0	0.1	-0.5	-0	0
April	-0.4	0	0.5	-0.5	-0	0.7	-1.1	-0.1	0.4	-1.7	-0.2	0.2
May	-1.7	0	1.2	-1.1	0.1	1.9	-2.4	-1	0.7	-2.4	-1.2	0.3
June	-5	-0.9	2.8	-4.6	-1.7	2.9	-5.1	-3.3	1.3	-7.5	-4	-1.6
July	-8.3	-3.4	6.8	-10.1	-4	3.3	-11.3	-6.8	5.4	-15.5	-9.2	-0.6
August	-16.4	-5.8	8.7	-18.8	-9.4	1.1	-19.7	-11	11.8	-26.5	-15.7	2.7
September	-23.6	-7.2	7	-27.3	-13.3	0.3	-31.6	-18.4	13.6	-38	-23.8	2.3
October	-24.3	-6.4	5.4	-28.6	-10.7	-0	-37	-17.8	9.3	-43.9	-26.3	-0.5
November	-19.4	-3.4	2.2	-23.6	-6	1.7	-26.4	-10	3.1	-37.2	-14.5	0.3
December	-8.3	-0.9	0.6	-12.6	-2.5	0.6	-11.9	-3.5	0.5	-18.5	-3.9	0.3

Table 6.1(b). Median percentage changes of raw water storage at Tittesworth Reservoir in each month in the future time-slices from the baseline using the WGM. Red/orange boxes denote less rainfall compared to the baseline and blue more, with the strength of colour denoting the scale of that change. The size of the font describes the percentage of the simulation range that agrees on the signage of change. Underlined font denotes 100% agreement on the signage of change.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January		-0.2			-0.3			-0.4			-0.5	
February		-0			-0			-0			-0	
March		-0			-0			-0			-0	
April		0			-0			-0.1			-0.2	
May		0			0			-1			-1.2	
June		-0.9			-1.7			-3.3			-4	
July		-3.4			-4			-6.8			-9.3	
August		-5.8			-9.4			-11.1			-15.7	
September		-7.2			-13.3			-18.4			-23.8	
October		-6.4			-10.7			-17.8			-26.3	
November		-3.4			-6			-10			-14.5	
December		-0.9			-2.5			-3.5			-3.9	

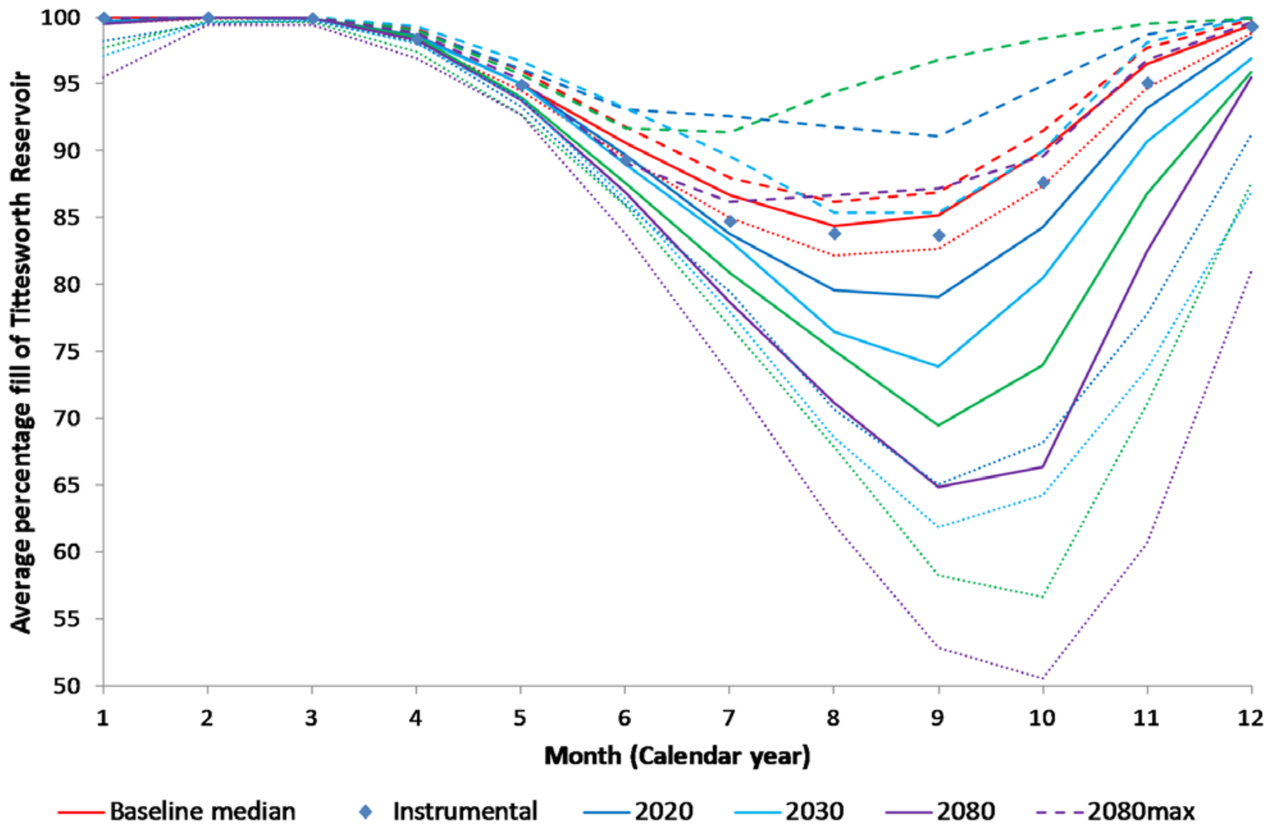

Figure 6.2. 1961-1990 simulated baseline average percentage fill at Tittesworth Reservoir per month (red lines) and 1961-1990 instrumental data (blue rhombi). Changes to those statistics using the WGM in the 2020s, 2030s, 2050s and 2080s are overlain. Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively.

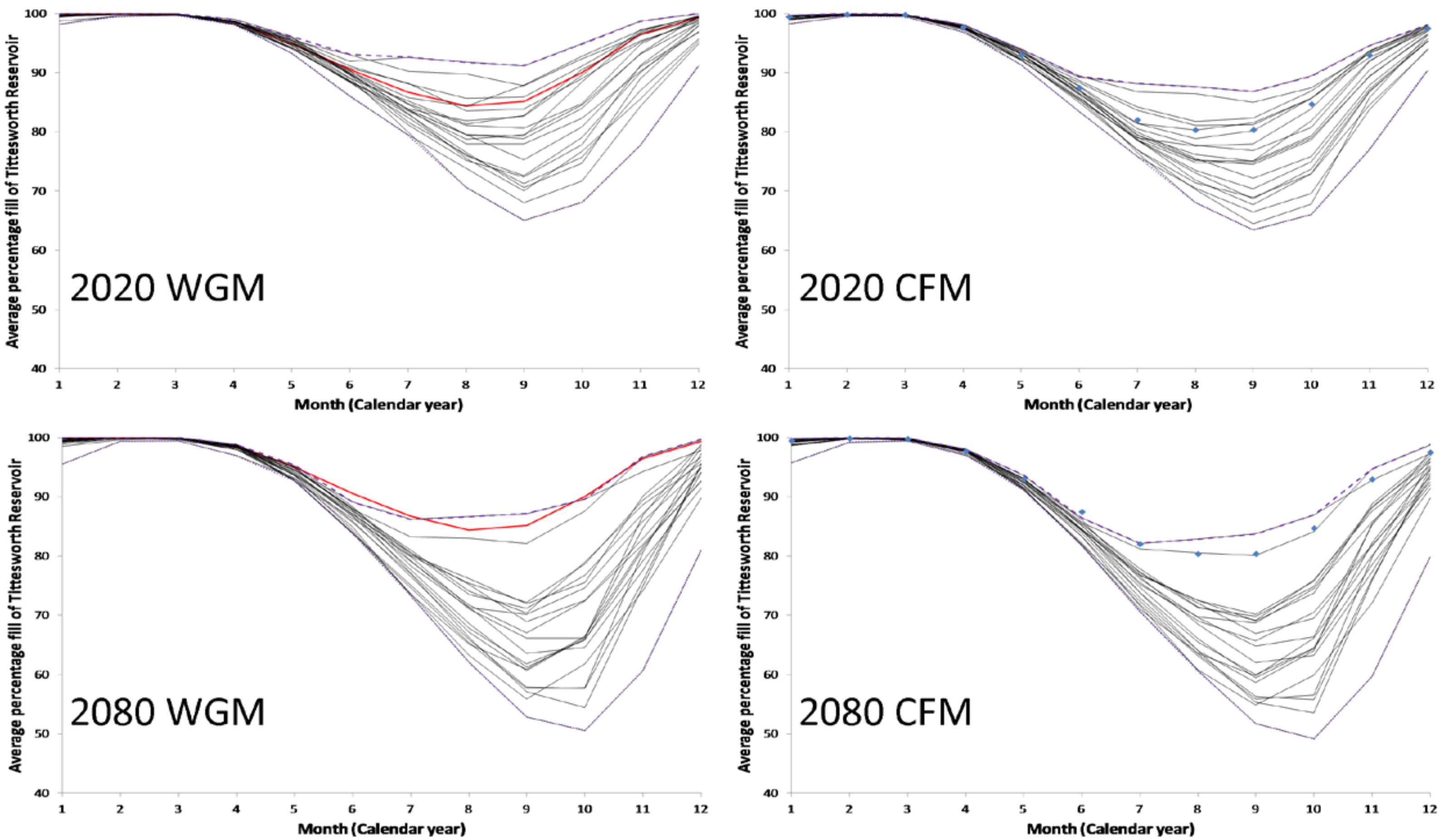

Figure 6.3. Average percentage fill at Tittesworth Reservoir per month for each of the sub-sampled simulations using the WGM in the 2020s and 2080s (left), and using the CFM in the 2020s and 2080s (right). Red line = baseline median; blue rhombi = instrumental data 1920-2010; dashed line = simulation maximum; dotted line = simulation minimum.

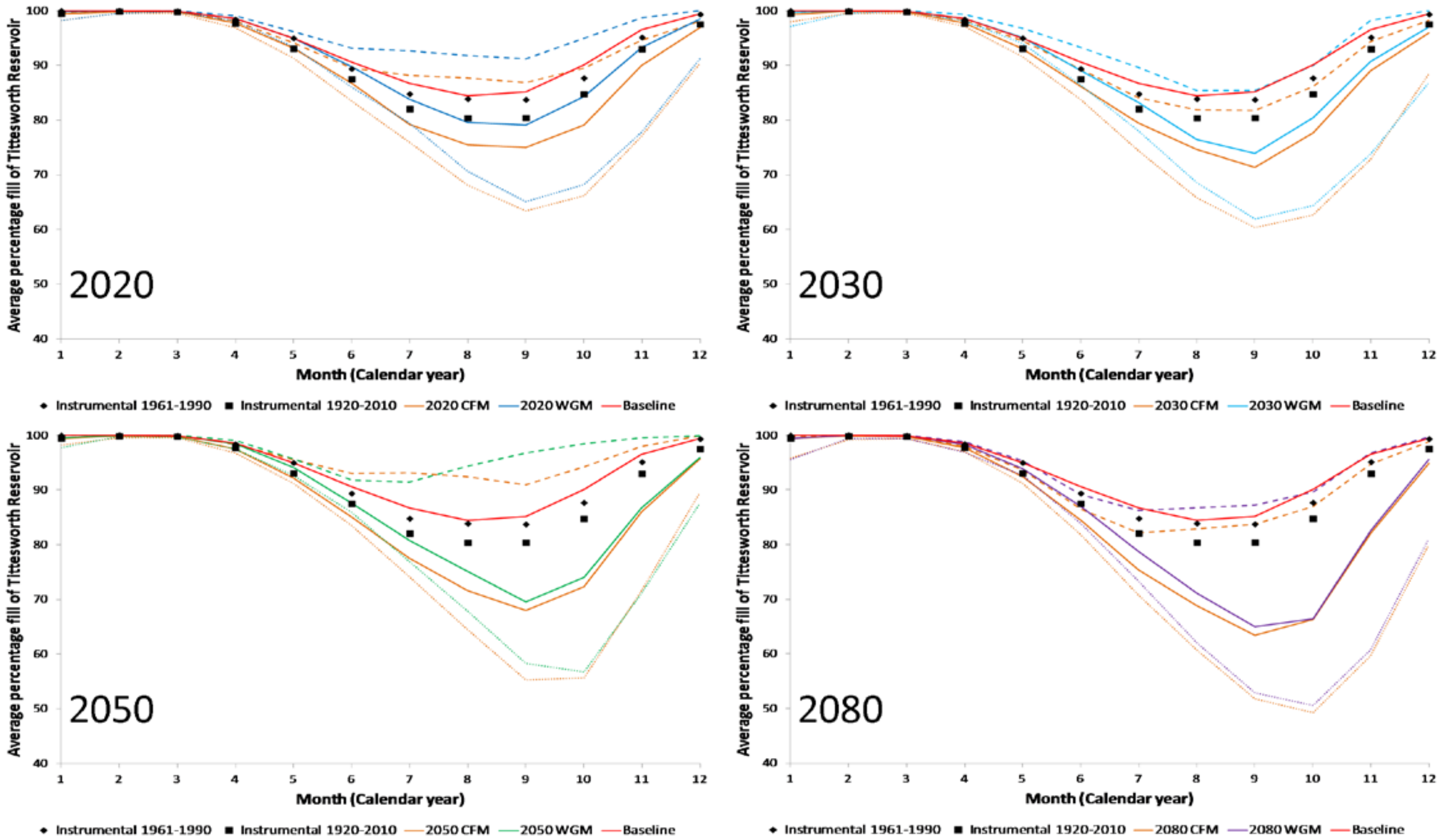

Figure 6.4. 1961-1990 simulated baseline average percentage fill at Tittesworth Reservoir per month (red lines) and 1961-1990 instrumental data (black rhombi) and 1920-2010 instrumental data (black squares). Changes to those statistics using the WG approach in the 2020s, 2030s, 2050s and 2080s are overlain on separate charts for each time-slice, along with CFM data for each time period (orange). Solid lines represent the simulation range median, whilst dashed and dotted lines show the maximum and minimum projections for each month, respectively.

Table 6.2(a). Percentage changes of raw water storage at Tittesworth Reservoir in each month in the future time-slices from the observed record using the CFM. The minimum, median and maximum of the simulation range is given in each case. Red/orange boxes denote less raw water storage compared to the baseline/instrumental record and blue more, with the strength of colour denoting the scale of that change. The colouring is based on the median simulation in each future time-slice.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January	-1.2	-0.6	0.2	-1.5	-0.1	0.2	-1.3	-0.1	0.5	-3.8	-0.1	0.3
February	-0.3	-0	0.1	-0.3	-0	0	-0.3	-0	0.1	-0.7	0	0.1
March	-0.3	-0	0.1	-0.3	-0	0.1	-0.3	-0	0.2	-0.4	0	0.1
April	-0.9	-0	0.4	-0.6	0	0.5	-1	-0.2	0.6	-0.8	-0	0.2
May	-1.9	0.1	1	-1.6	-0.1	1.6	-2	-0.9	2.7	-2.1	-0.7	0.6
June	-4.7	-0.9	2.2	-4.3	-1.5	2	-4.6	-2.8	6.3	-6.6	-3.5	-1.2
July	-7.5	-3.4	7.4	-9.4	-3.1	2.5	-9.6	-5.6	13.4	-13.8	-8.1	0
August	-15.3	-6.2	9	-18.1	-7.2	1.8	-19.9	-11	15	-24.6	-14.5	3.1
September	-21.1	-6.7	8	-25	-11.2	1.7	-31.3	-15.5	13.1	-35.7	-21.2	4.1
October	-22	-6.6	5.6	-26.1	-8.4	1.7	-34.3	-14.7	11.2	-42	-21.8	-2.6
November	-17.2	-3.2	1.7	-21.7	-4.3	1.5	-23.1	-7.6	5.4	-35.9	-11.8	-1.8
December	-7.3	-0.7	0.6	-9.4	-1.7	0.7	-8.3	-2	2.4	-18.1	-2.7	1.3

Table 6.2(b). Median percentage changes of raw water storage at Tittesworth Reservoir in each month in the future time-slices from the observed record using the CFM. Red/orange boxes denote less rainfall compared to the observed record and blue more, with the strength of colour denoting the scale of that change. The size of the font describes the percentage of the simulation range that agrees on the signage of change. Underlined font denotes 100% agreement on the signage of change.

	2020s			2030s			2050s			2080s		
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Min	Med	Max
January		-0.1			-0.1			-0.1			-0.1	
February		-0			-0			-0			0	
March		-0			-0			-0			0	
April		-0			0			-0.2			-0	
May		0.1			-0.1			-0.9			-0.7	
June		-0.9			-1.5			-2.8			-3.5	
July		-3.4			-3.1			-5.6			-8.1	
August		-6.2			-7.2			-11			-14.5	
September		-6.7			-11.3			-15.5			-21.2	
October		-6.6			-8.4			-14.7			-21.8	
November		-3.2			-4.3			-7.6			-11.8	
December		-0.7			-1.7			-2			-2.7	

6.5 Projections of change to water resource shortages

6.5.1 **Overview**

CDFs of water shortage risk in the North Staffs WRZ are presented using the approach outlined in Section 3.11. Using the labels described in Figure 3.14, acceptable risk *i* is maintained as 20% of the simulation range; that is, it is assumed that a system that satisfies LoS *x* in 80% of the simulation range would be an acceptable situation. This satisfaction of *x* is seen visually in the CDFs when the line emanating from the values for *i* intersects the distribution at or below or the line from *x* (i.e. $j \leq i$) (*x*, *j* and *i* are annotated on the first CDF for clarity (Figure 6.5)).

Figure 6.5 shows how water shortage risk in the North Staffs WRZ is altered purely as a result of changes to the climate, with no interventions to improve the system. This is, in effect, a baseline for each time-slice against which the effectiveness of adaptation measures can be measured. For each water shortage severity and downscaling approach used it is shown that the probability of a water shortage within a calendar year increases with more distant time horizons. Furthermore, in all cases the uncertainty involved with the projection of future water shortage probability widens with time.

6.5.2 **Weather generator method**

Figures 6.5(a) illustrates the changes to water resource shortage of varying severities in each of the WG simulations. For each severity of risk, defined as an LoS, there are significantly greater water shortage probabilities in the 2020s compared to the baseline period, with little further change in the 2030s. Figure 6.5(a) shows that in the 2020s, 62% of the simulations produce no TUB events, and in the 2030s, 48% of simulations do not produce a TUB event, compared to 78% of the baseline simulations (Figure 3.17). Deeper into the future, even as the trend moves towards increased TUB events, there are still simulations that suggest no severe shortages.

Assuming the values for *i* and *x* are constant throughout time (i.e. the level of acceptable risk and water supply standards remain the same), questions such as 'is the North Staffs WRZ system resilient to climate change in the 2020s based on the identified acceptable risks' can be answered with a simple 'yes' or 'no' (assuming the limitations and assumption involved with the data are acknowledged). Values for *j*, and a colour-coded yes/no of whether the system can be deemed robust are shown in Table 6.3.

Figure 6.5(a) makes it clear that climate change reduces the extent to which the North Staffs WRZ system would be able to efficiently operate in its current set-up. TUB risk is shown to be within the acceptable risk in the 2020s in the 2030s, before *j* becomes steadily further from *i* throughout the century (Figure 6.4(a)). For the drought warning trigger (DWT) the current system is just inside acceptable climate risk in the 2020, before moving beyond the 20% of the uncertainty range mark in more remote time horizons (Table 6.3), and for the storage alert line (SAL) the current system is outside of acceptable risk in the 2020s.

For each severity a large shift in the amount of the uncertainty range beyond the observed water shortage frequency is seen from the 2030s to the 2050s. By the end of the century, 81% and 84.5% of the uncertainty range represents simulations where the acceptable DWT and SAL water shortage probability is exceeded, and 56.5% of the range projects TUB events to be of a higher probability than the acceptable LoS (Figure 6.5(a), Table 6.3). This clearly implies that significant changes to the WRZ setup would be necessary for securing water resources to the acceptable risk over such timescales.

6.5.3 **Change factor method**

Figure 6.5(b) presents the water shortage probability derived from applying CFs to the instrumental data. Note that $x_{1920\text{-}2010}$ is shown in this case as the longest available record was needed against which to apply the perturbation technique (i.e. the CFM).

It is immediately clear that more TUB events are simulated using the CFM, as would be expected given the limitations of the WGM discussed earlier. However, the lack of alteration to variability means that there is no information on how the sequencing of events may change, as the order of rain-days remains the same in each simulation to the instrumental record. As a result, Figure 6.5(b) shows that there isn’t the capability for the most extreme wet projections to produce simulations with extremely few water shortage events, like there is using the WGM, as only in the most extreme severity event does the CDF approach a probability of 0 for any future simulation (barring one extremely wet outlier in the 2050s.

In the 2020s, the resilience of the system to water shortage events is reversed to that shown in the WGM, with $j>i$ for TUB events and $j<i$ for SAL events (Table 6.3). The resilience of the system to DWT events is consistent with that shown using the WGM. When the SAL metric is assessed, the system remains robust in the 2030s, but in all other post-2020s time-horizon/LoS severity combinations the WRZ is deemed vulnerable to climate change (Figure 6.5(b), Table 6.3).

6.5.4 **Comparison of the two approaches**

For the WGM, the probability of a TUB event is shown to be within acceptable risk in the 2020s and 2030s, before j becomes steadily further from i throughout the century, making the system resilience to climate change inadequate in terms of TUBs. In contrast, when the CFM is used, projections of future water shortage at this severity are notably more severe and the probability of a TUB event is outside of acceptable risk in the 2020s and 2030s.

The opposite is true for SAL events, with the WGM suggesting the system is not robust in the 2020s and 2030s, and the CFM projecting it is. Therefore, the only metric against which there is agreement in terms of the robustness of the system to 80% of the simulation range is DWT (Table 6.3). This highlights the limitations of each approach; the WGM does not produce the most extreme droughts adequately (thus reduced TUBs) and the CFM does not take into account climate variability and thus has a reduced range of uncertainty (thus fewer SALs). As a result, the CFM and WGMs agree on the robustness of the system to DWT events only (Table 6.3). Therefore, it can be said with reasonable confidence that the current system is robust to DWT events in the 2020s, but not so thereafter, and TUB/SAL analysis should be treated with extreme caution. Unless the study of a TUB or SAL event is explicitly necessary, the DWT should be focussed upon when both the WGM and CFM are used together.

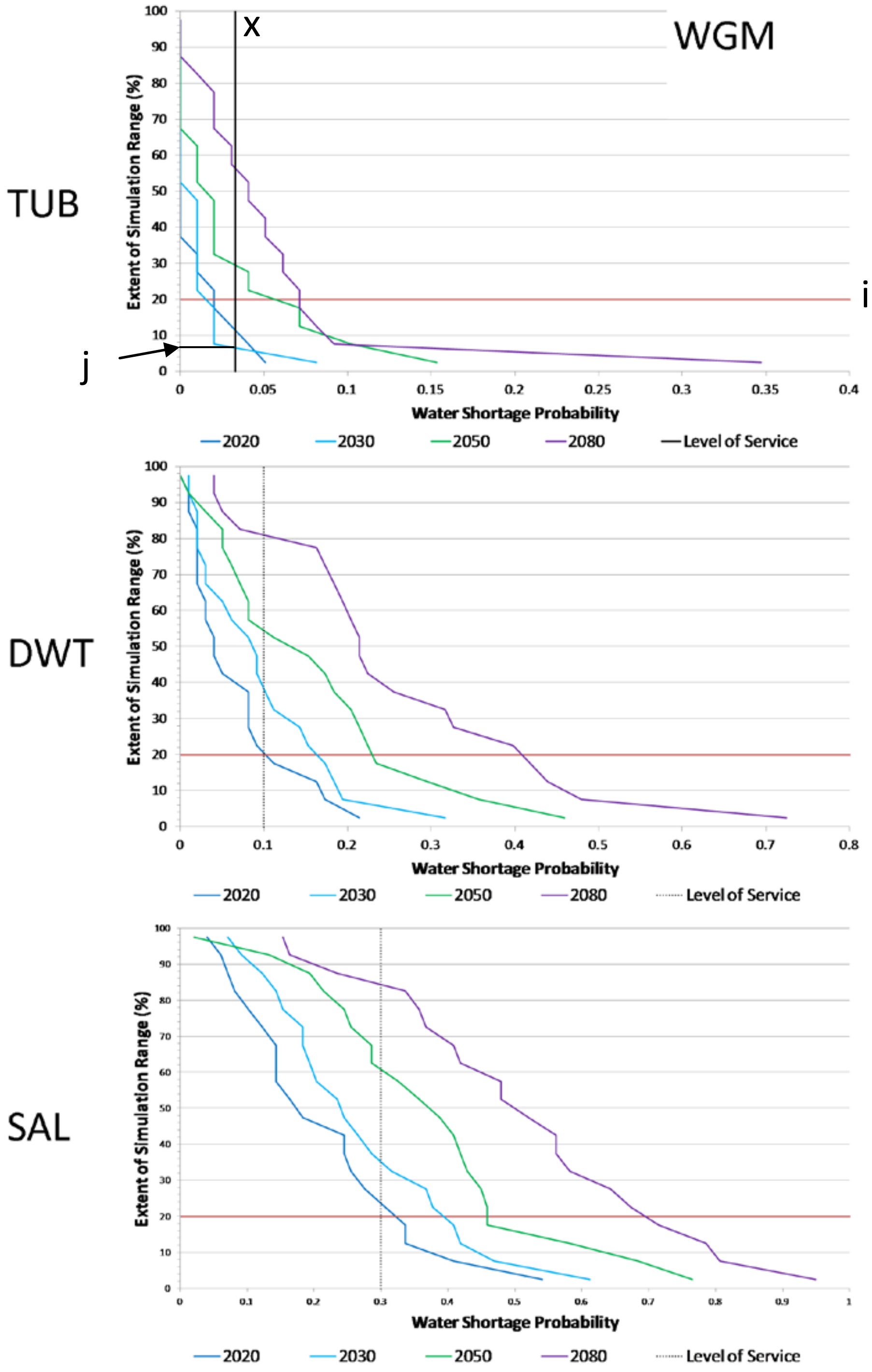

Figure 6.5a. CDFs of water shortage probability in the North Staffordshire WRZ for future time horizons using the WGM (this page) and the CFM (overleaf) when no adaptations are included in the Aquator model (i.e. current operational conditions). See Figure 3.16 for an explanation of the CDF plots.

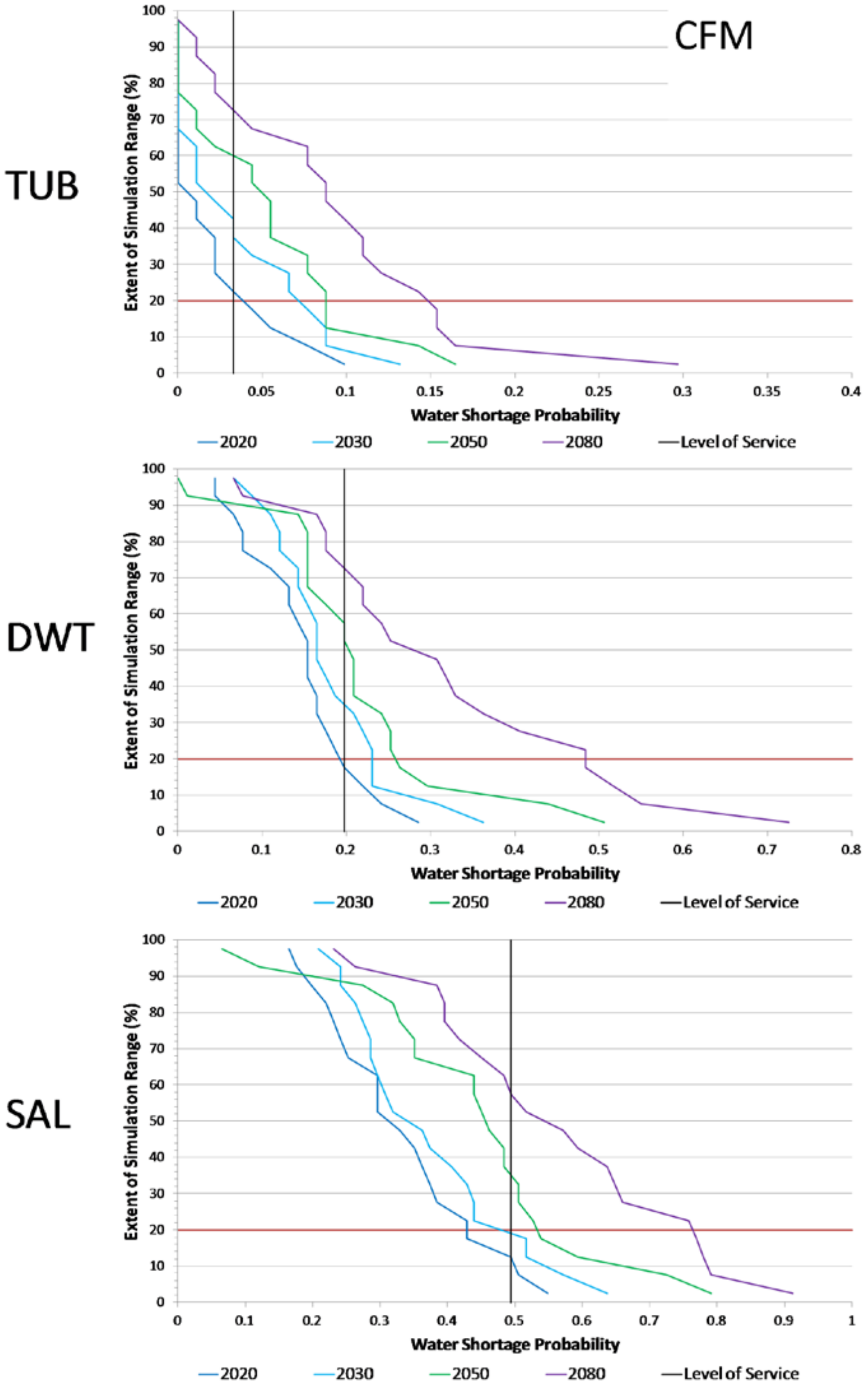

Figure 6.5b. As 6.5a, but for the CFM

Table 6.3. Matrix showing the percentage of the range of simulations that shows a probability of water shortage event below the acceptable LoS in each of the future time horizons. 1961-1990 LoS are used for the WG information, whilst 1920-2010 LoS are used for the CFM information, except for TUB where the company target of 3 in 100 years is used in both instances. Colouring denotes the satisfaction of acceptable risk (which is set at 20% of the simulation range); Green represents a system that can be deemed robust, while oranges show that more than 20% of the range does not meet expected LoS (the strength of hue illustrates the extent to which this target is missed), with reds representing more than 60% of the range.

	2020		2030		2050		2080	
	WGM	CFM	WGM	CFM	WGM	CFM	WGM	CFM
TUB	11%	22.5%	6.5%	37%	29%	60%	56.5%	72.5%
DWT	20%	18%	38%	35%	54.5%	52.5%	82%	72.5%
SAL	23.5%	13%	34.5%	19%	60.5%	35%	84.5%	58%

6.5.5 **Annual profile of water shortage risk**

Figure 6.6 shows the profile of DWT trigger conditions across the year for the range of simulations in each time-slice. DWT is focused upon for the reasons given in Section 6.5.4. It can be seen that the peak month for DWT events remains in October throughout all time horizons when either approach is used. This is in-line with the significant reductions to flows throughout the summer and the shortening of the reservoir recharge period (Figure 5.13 and Table 5.4) and the resultant gradual movement of minimum reservoir capacity towards October (Figure 6.2; 6.3); all of which acts to increase stress on the reservoir in the late summer/early autumn period.

A combination of the increased winter flow across much of the simulation range (Figure 5.13) and the inability of the WGM to produce multi-seasonal drought events mean that in each of the future time horizons there are few DWT events between February and

June (Figure 6.6(a)). The ability to turn down the reservoir output and eventually turn off output altogether in times of water stress is important for the recovery of the reservoir over spring, meaning that even in the CFM data, where more winter water shortage would be expected, DWT events are still extremely rare (Figure 6.6(b)). Further uncertainties added to the model, particularly with regards to the consistency of groundwater supply (which is assumed constant here), could create a situation with more DWT-severity events extending through the winter into the spring.

The pattern of annual DWT conditions remains similar throughout the progressing century, with a gradual exaggeration of the autumnal peak. This shows a picture of intensifying single-season summer drought in the WRZ, with heightened winter rainfall and flow compensating for summer drying, which enables the reservoir to recover by early spring in most simulations.

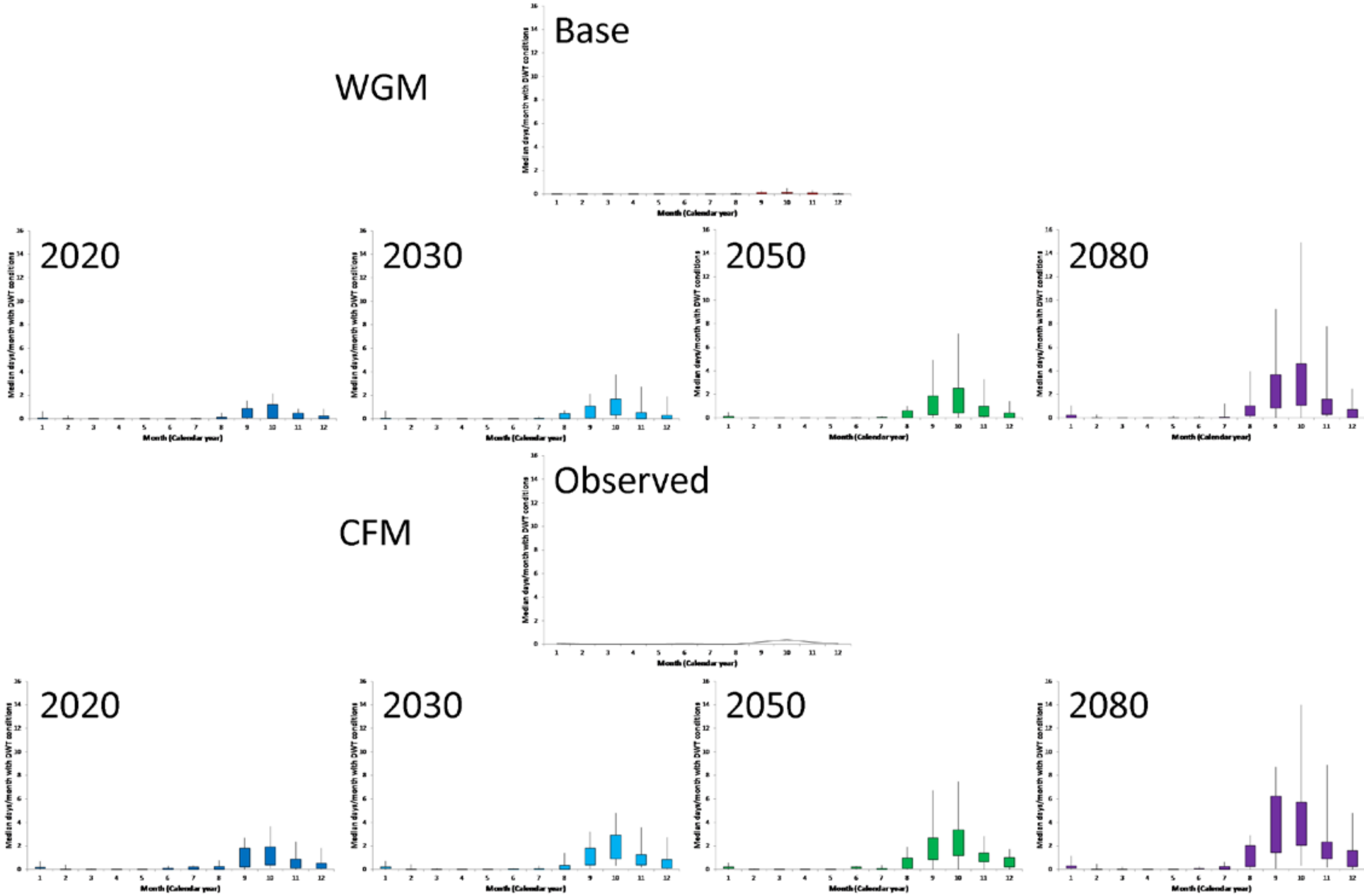

Figure 6.6. Box-whisker plots of days per month in which DWT conditions are triggered in each of the time-slices for the WGM (top) and CFM (bottom). Boxes represent 25-75% of the sub-sampled simulation range, whiskers show the extremes of the sub-sample.

6.6 Conclusions

The CDFs produced from the extensive flow, precipitation and PET datasets from UK Climate Projections 2009 weather generator (UKCP09WG) and HYSIM are useful for describing the ‘baseline’ conditions in the future against which adaptation processes can be tested. The approach used is original and represents an improvement over traditional communication of climate change impacts on WRZs. The limitations of the approaches used are known, and thus the results must be interpreted with caution. The key outputs of this phase of the modelling process are:

- Across a vast majority of the climate model uncertainty when using both the WGM and CFM, raw water storage at Tittesworth Reservoir is reduced from baseline (and observed, in the case of the CFM) conditions, particularly in the late summer/autumn (Figure 6.1).
- Using the WGM, annual mean low water storage at Tittesworth Reservoir is moved deeper into autumn as a result of more frequent and severe single-season summer droughts. (Figure 6.1(a)). Future median spring storage is not significantly changed to that in the baseline as a result of consistent re-filling of the reservoir due to the increased winter rainfall.
- Multi-seasonal droughts are not found in the WGM datasets due to limitations of the WG. As a result, Tittesworth Reservoir storage recovers in most winters despite the reduced summer storage in most future simulations years. (Figure 6.2). As a result of using the instrumental record as a basis for the dataset, the CFM produces multi-

seasonal droughts already found in the observed 1920-2010 sequence and therefore more extreme dry events and lower mean winter storage projections than the WGM (Figure 6.2). However, reductions from the respective reservoir capacity baselines of each approach are similar, particularly with regards to median values (Figure 6.1; Table 6.1(a) and 6.2(a)).

- Using both approaches the range of mean raw water storage varies significantly across the simulations, particularly in the summer, but discounting notably extreme wet or dry simulations produces a clearer picture of future storage (Figure 6.3). Omitting the most extreme simulations is acceptable given the use of the notion of acceptable risk (i.e. adaptation decision-making would not take into account the very driest projections).
- The CFM produces more TUB events than the WGM, which often produces no events in a simulation (Figure 6.5(a)), but produces a narrower range of uncertainty with regards to less extreme water shortage events (Figure 6.5(b)).
- Highest confidence can be assigned to the projections for DWT, where agreement between the two approaches on the robustness of the WRZ is consistent across in all future time horizons. In contrast, the WGM produces significantly less TUB events and significantly more SAL triggers events than the CFM, resulting in a disagreement on the robustness of the system in many cases (Table 6.3).
- Therefore, by analysing only the DWT, it can be said that the North Staffordshire WRZ is robust to the effects of climate change in the 2020s, but not so from the 2030s onwards (Figure 6.5; Table 6.3). Altering the conditions that constitute a

LoS or the percentage of the simulation range that is considered acceptable risk would cause changes to this conclusion.

- The annual profile of DWT events remains one of few in the late winter/spring with a peak in the late summer/autumn throughout the 21st century projections. The median simulation peak remains in October in all time horizons. As single-season summer droughts intensify in many of the simulations, the October peak is gradually increased with more remote time horizons and becomes significantly greater than the surrounding months, which is not the case in the baseline period (Figure 6.6).
- The reservoir trigger line metrics used in this research are useful to the water resource manager and are ideal for analysing uncertain climate change information as they are easily understandable and communicable (Hall *et al.*, 2012(a)), but are not the only relevant metric. The same methodology used here could, for example, be used to produce assessments of cost of supply or the exhaustion of a certain, or group of, groundwater license(s).

7 ADAPTATION OPTIONS ASSESSMENT

7.1 Introduction

With the climate change signal expected to increase relative to natural climate variability throughout the future (although much research aiming to ascertain the attribution of climate change signals in the instrumental record is on-going (e.g. Jones et al., 2013)), and the associated envelope of climate projection uncertainty expanding in tandem, securing water supply over any timescale now requires basing decisions on a number of potential futures (Dessai *et al*., 2009; Hall *et al*., 2012(a)). Therefore, a water resource system must be made flexible and adaptable to the point where it could still perform to pre-determined standards of supply across a vast range of potential futures. This represents an opportunity for the water industry. Through assessments of various potential climate change adaptation approaches across a probabilistic range of simulations, an incentive for incrementally increasing the robustness of a system is provided.

Described here is a first attempt to produce a robust approach (Groves and Lempert, 2007) to determining climate change impacts on water supply shortage in the North Staffordshire Water Resource Zone (WRZ) that aims to meet the requirements of industry, whilst taking climate change uncertainty into account. It is proposed that using such a methodology can produce greater confidence in basing investments in the UK water industry on climate change information, as the uncertain information can be distilled to provide a quantitative assessment of whether a water supply system can be considered robust over a given time period or not.

Adaptation strategies in the water sector range from those that are relatively insensitive to climate, such as smart metering, reducing leakages and increasing efficiencies, to approaches where the climatic conditions of the future are vital, such as developing, or acquiring licenses for, confined groundwater resources and surface water resources, or installing raw water transfers from other WRZs. However, producing strategies that create robust water resource systems as the range of uncertainty widens is not a case of simply picking those options that are effective in any climate. As a general rule, those that are more insensitive to climate generally have smaller volumes of water involved than those that are sensitive (for example, savings made by compulsory metering against the additional resource supplied by a reservoir). Furthermore, costs vary widely across the range of potential options; for example, desalinisation, although a relatively climate insensitive and high-yielding strategy in many cases, suffers from cripplingly high energy costs.

Whilst financial considerations are vital to water companies implementing Water Resource Management Plans (WRMPs), it is important to first know which adaptation strategies are likely to be successful across a broad range of feasible futures. This section of the project builds on the previous chapter by introducing a range of such strategies into the simulation set-up (termed as 'scenarios'), allowing an robust decision-making (RDM)-type analysis of their performance across the range of climate uncertainty to be carried out (Groves and Lempert, 2007).

This chapter begins by outlining the modelling framework used (which is described in detail in Chapter 3), before describing the nature of the adaptation options added to the model (Section 7.2) and the ways this approach differs from previous work on water resource management under climate forcings (Section 7.3). Results in terms of raw water storage at Tittesworth Reservoir (Section 7.4) and water shortage risk (Section 7.5) are described for both the weather generator method (WGM) and the change factor method (CFM), along with comparisons between the two. The annual profiles of the water shortage risk in the adaptation scenarios are shown, and conclusions are drawn (Section 7.6).

7.2 Data sources and models used

7.2.1 **Modelling framework**

The research carried out in this chapter concerns the green area of the overall methodology flow diagram (Figure 3.1), which essentially equates to processes of

Chapter 6 (shaded blue) being re-produced using the different adaptation options, which are modelled in Aquator. The 40 simulations of flow, open water evaporation and rainfall (20 from the WGM and 20 from the CFM) for each time-slice are re-modelled against a suite of adaptation strategies, in order to produce cumulative distribution functions (CDFs) for different scenarios that show how movement towards the satisfaction of acceptable risk can be achieved through applying interventions to the system.

The extent to which the risk-reducing effect of each scenario is diminished over time can be seen, leading to the 'building-up' of a portfolio of measures in order to maintain the satisfaction of a static acceptable risk as the stress from climate change changes throughout the century. This allows for adaptation to be flexible, to enable continual improvement and upgrading as more climate change information becomes available, rather than being fixed approaches which are more open to maladaptation (Hall *et al.*, 2012(b); Gersonius *et al.*, 2013)

7.2.2 **Selection of adaptation strategies**

Simulating climate change adaptation approaches in the North Staffs WRZ model enables the question, 'Is the North Staffs WRZ system robust to climate change in future periods given that adaptation measures *a, b* and/or *c* are introduced?' to be asked. Eight adaptation scenarios are introduced in this section to describe how the framework used here can be utilised to make decisions despite uncertainty (Table 7.1). Two areas of the model are focussed on, the demand factors (DFs)[13] at the various demand centres and the compensation requirement downstream of Tittesworth Reservoir for the River Churnet (that is, the guaranteed minimum discharge). Many other approaches to altering the model to simulate feasible adaptation options are possible, such as introducing new resources, altering abstraction licenses (see Manning *et al*., 2009 for an example of this), applying bulk water transfers, increasing pipe capacities and expanding surface reservoirs, but the two applied here are adequate to communicate the advantages of the RDM-type approach decision-makers.

[13] Demand factors are a tool used within the Aquator model to change the amount of water required across the WRZ. Water demands are given as monthly values at demand centre, so a demand factor would produce a percentage increase for each month at each demand centre simultaneously. At present they are used primarily to gradually increase the amount of water demanded by the system in order to ascertain Levels of Service (LoS).

Table 7.1. Descriptions of the nine scenarios simulated in the North Staffordshire WRZ Aquator model (including the current setup (scenario A), analysed in Chapter 6). The DF sets a level of demand across the model in relation to a present day value of 1. An = annual compensation requirement, Au = autumn, W = winter, and S = summer.

Label	Demand Factor (DF)	Compensation (megalitres per day)	Intervention Level
A	1	An = 14.8	None
B	0.95	An = 14.8	Low
C	0.95	An = 13.3	Low
D	0.95	Au/W = 14.8, S = 10	Medium
E	0.8	Au/W = 14.8, S = 10	Medium
F	0.8	An = 13.3	Low
G	0.95	Au/W = 14.8, S = 6.7	High
H	0.8	Au/W = 14.8, S = 6.7	High
I	0.8	An = 10	High

These measures are for illustration purposes only and are not necessarily representative of real-life plans for adaptation in the area. The adaptation strategies are chosen based on their ability to be modelled in Aquator and their obvious real-world application. They are all simplified in the model, losing the complex integration of competing factors that would be taken into account should they be applied in reality (e.g. ecosystem deterioration concerns regarding compensation flow decrease, unchanged annual future annual profile demand), and would not necessarily be physically or financially feasible (particularly significantly reduced compensation flows, which equates to reduced minimum flows being discharged from the reservoir into the upper

Churnet River, thus adversely impacting on ecosystem services). The DF 0.95 is chosen to be in line with Severn Trent Water company targets (Severn Trent Water, internal communication) over the current 25-year planning period, while the larger decrease to 0.8 of 2012 levels is an arbitrary figure. Solomon's Hollow (SOL) compensation of 13.3Ml/d (megalitres per day) represents a 10% decrease to compensation rates, while the further reductions are arbitrarily taken as 2.3Ml/d.

Compensation is required of STW in order to maintain water levels in the River Churnet downstream of Tittesworth Reservoir at acceptable levels. Alterations to the compensation levels are applied for in times of drought. The likelihood of such a large permanent reduction to compensation rates as described in the medium and high intervention scenarios (D, E, G, H and I) is, in the short time, low, as a result of the impact of local ecosystems. Reductions to demand (or increases to efficiencies) are a core thrust of water resource management practices by water companies across the UK. The 5% reductions in the low intervention scenarios (B, C and F) are in line with company targets over the water resource planning period (25 years), and the 20% reductions are a realistic aim thereafter.

Figure 3.2 shows the North Staffordshire WRZ, with the key areas at which the adaptation scenarios take effect. Stoke-on-Trent (which also includes Newcastle-Under-Lyme and various other small surrounding settlements) and Leek are the key demand centres that depend on Tittesworth Reservoir and surrounding groundwater sources (Leek and the smaller nearby settlements are denoted as 'Moorlands' in the Aquator model). These, as well as the adjoining demand centres of Stone and Market Drayton, which are supplied entirely by groundwater in the south of the WRZ, are influenced by the DFs shown in Table 7.1. The points marked * in Figure 3.2 represent the confluences of the streams from the Deep Hayes (DHY) (to the west) and the SOL (to the east) sub-catchments to the River Churnet. Inflows from these streams affect the reservoir upstream by determining the amount of compensation flow required to maintain the health of the River Churnet; reduced flows from SOL and DHY increase the amount of water required from the reservoir and vice-versa.

7.3 Differences to cited literature

The unique aspect of this section of the research is the development of a risk-based robustness assessment using UK Climate Projections 2009 (UKCP09) information for a WRZ, thus affording greater confidence in decision-making than current practices (Groves and Lempert, 2007) and challenging the standardized approach to climate change assessment in the England and Wales water industry (Arnell, 2011(b)). Metrics of water shortage risk in the form of crossing control curves are used to convey the impact of climate change on a WRZ (Brekke *et al*., 2009; Hall *et al*., 2012(a)), and a replicable, practical and unique approach for assessing the effect of adaptation measures to control, or reduce, that risk to an acceptable level is given. Work of this nature has not been carried out on STW resources before, and represents a basis for other WRZs that can facilitate changes to the way climate change impact assessment is handled in the water industry.

It is shown how probabilistic UKCP09 information can be presented and communicated effectively in order to aid decision-making within an organisation and customer understanding of climate change threats. This is achieved by introducing a methodology that uses tangible and easy-to-understand metrics that are already routinely used in industry but are also directly relatable to the customer, rather than more abject concepts such as deployable output (DO) (Hall *et al*., 2012(a)). Furthermore, despite inevitably increased computational modelling requirements, the methodology is designed to be practical for use in industry.

In this project, uncertainties beyond climate change are not searched for, so the robustness of a system to climate change is described rather than the actual robustness of the system as a whole. This is largely in order to keep modelling requirements practical for industrial use and to streamline the work towards legislative requirements on water companies to assess climate change as part of WRMPs.

7.4 Projections of change to raw water storage

7.4.1 Weather generator method

The effect of adaptation measures on water shortage is largely dependent on the amount of raw water available from Tittesworth, so the annual profile of storage is assessed before determining the updated metrics of shortage probability. In each case, the reservoir storage is given as a percentage of the total capacity of the reservoir (6440 Megalitres (Ml)). Figure 7.1 illustrates the varying influence that the adaptation options have on water resource fill at Tittesworth Reservoir when the WGM is used to simulate the conditions in the WRZ. Each time-slice in Figure 7.1 are split into two for clarity, but also split the more severe scenarios (top) from the less severe (bottom).

It can be seen that a small reduction in demand (scenario B) only slightly increases the average reservoir levels in the median simulation in each time-slice. Adding a small reduction to the required compensation downstream from the reservoir is more effective (scenario C), although it is still unable to raise reservoir levels in the 2020s back to those in the baseline period (Figure 7.1). Applying a more severe demand reduction (scenario F) enables reservoir levels in the 2020s to exceed the baseline period in the spring by reducing the drawdown necessary, but levels fall below the baseline by August and remain so until the average reservoir level is back to almost full in February and March. The minimum and maximum extreme simulations from the sub-sample show similar trends to the median 2020 simulations, although the increased effect of scenario F in the spring and early summer is more clearly visible.

The more severe alterations to the model, shown in the lower half of Figure 7.1, show that reservoir levels in the 2020 projections can be increased above baseline levels through interventions to demand and compensation requirements. Reducing summer demand to 10Ml/d (scenario D) produces increased median spring reservoir levels and similar summer/autumn levels compared to the baseline, whilst adding further demand restrictions or a further summer compensation reduction to 6.8Ml/d (scenarios E and G, respectively) produces significantly increased reservoir levels. However, even for scenario G there are significant proportions of the uncertainty range that project average summer resources will be reduced.

The patterns shown in the 2020s are repeated in the 2030s, 2050s and 2080s (Figure 7.1). It becomes increasingly clear throughout the century that scenarios B, C and F are unlikely to produce reservoir levels akin to the baseline period, with even the most extreme wet scenarios for the 2080s only marginally producing increased summer reservoir levels, and the median simulations significantly reduced. Therefore, it becomes clearer as the century progresses that the more severe scenarios (D, E, G, H and I) would be necessary to maintain reservoir capacities at similar levels to the baseline period (scenarios H and I are not simulated for the 2020s and 2030s).

Table 7.2 shows the results for the 2080s, and describes how gradually diminishing confidence in decreased summer/autumn resources is replaced by improved confidence in increased spring resources as more severe adaptation scenarios are introduced. As an example, when there is no intervention to the model (scenario A) the four occasions of universal agreement across the sub-sampled range indicate a reduction in resources, whilst the three occasions of total agreement when intervention is highest (scenario H) show increased resources. The general picture, when severe interventions are in place, is one of reduced draw-down of the reservoir in spring, leading to a situation where late summer/autumn raw water resource has less drastic reductions despite the increased frequency and magnitude of summer droughts (Figure 5.12).

7.4.2 **Change factor method**

Figure 7.2 and Table 7.3 show the same information for the CFM as Figure 7.1 and Table 7.2 do for the WGM. Whilst the similarities are noticeable, it should be considered that instrumental values replace the simulated baseline values, in-line with the rationale given in Chapter 3.This means that although reductions from the observed record are similar to those seen in the weather generator (WG) simulations from the 1961-1990 baseline simulations (i.e. Table 7.2 has similar delta values to Table 7.3), the actual values are lower, particularly earlier in the century.

Median simulations in the 2020s suggest that scenario F is sufficient to restore summer reservoir capacities to those in the 1920-2010 observed record, with spring capacities increased. Such conditions would point to reduced water shortage risk. In the 2030s, the less severe scenarios show heightened seasonality compared to the observed record, with significantly reduced late summer (JAS) resources but a slower draw-down in the spring to early summer (MAMJ) and a faster recovery in the late autumn and early winter (OND).

Median simulations for scenario H, the most severe intervention, produce resources in excess of the instrumental record throughout the year in the 2050s (whereas the 2050s scenario H WG median simulation does not reach the baseline value). Indeed, for much of the year the median scenario H simulation shows higher values in the 2080s, particularly during spring and early summer. As in the WGM, it is clear that the lesser adaptation options do not enable reservoir levels to recover to the instrumental levels by the latter half of the century.

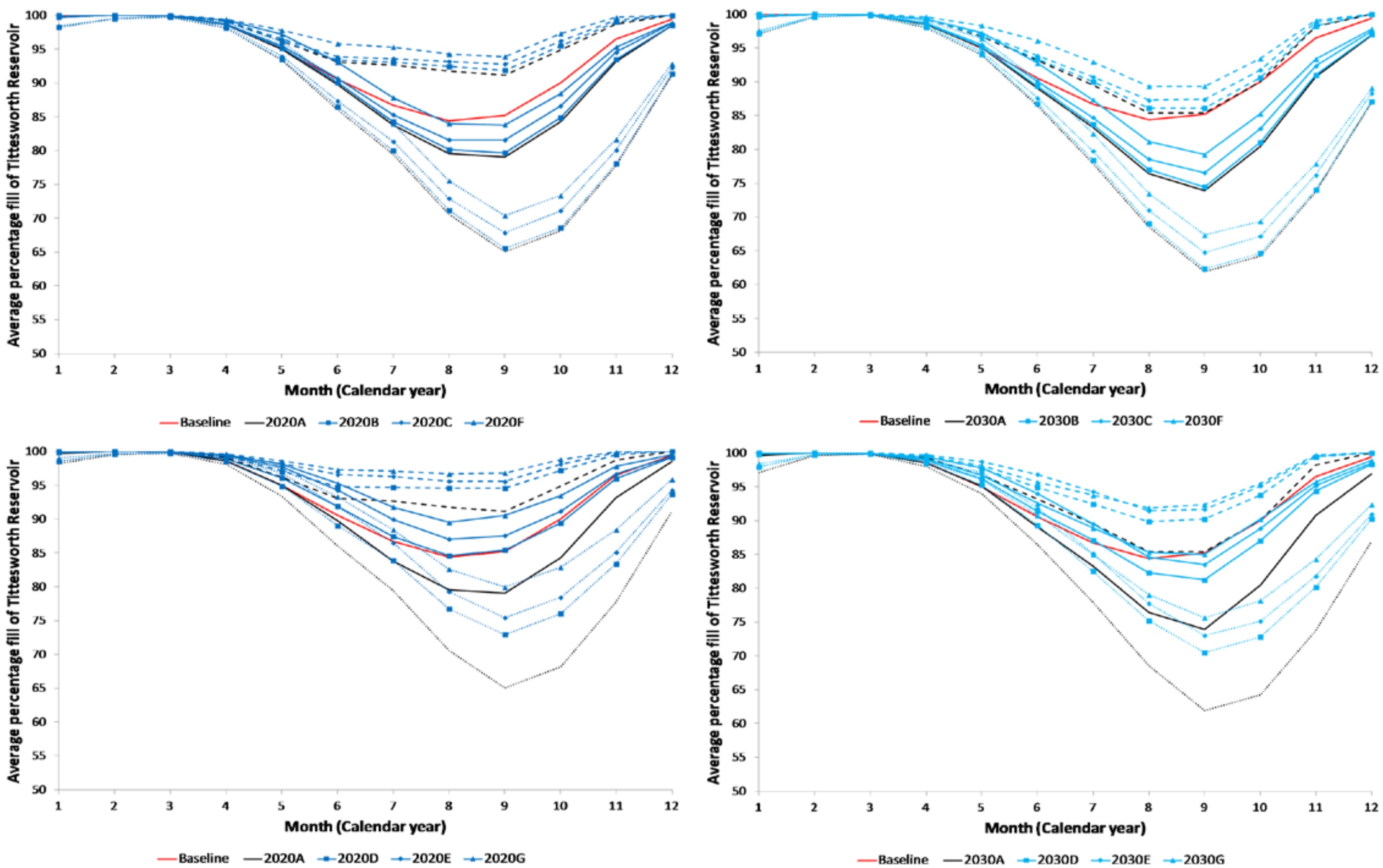

Figure 7.1. 1961-1990 simulated baseline average percentage fill at Tittesworth Reservoir per month (red lines), with changes to those statistics as a result of adaptation measures in the: 2020s, 2030s (this page), 2050s and 2080s (overleaf) overlain. All simulations use the WGM. Upper and lower boundaries of scenario A are shown as black dashed and dotted lines, respectively. Explanations of the scenarios used are found in Table 7.1.

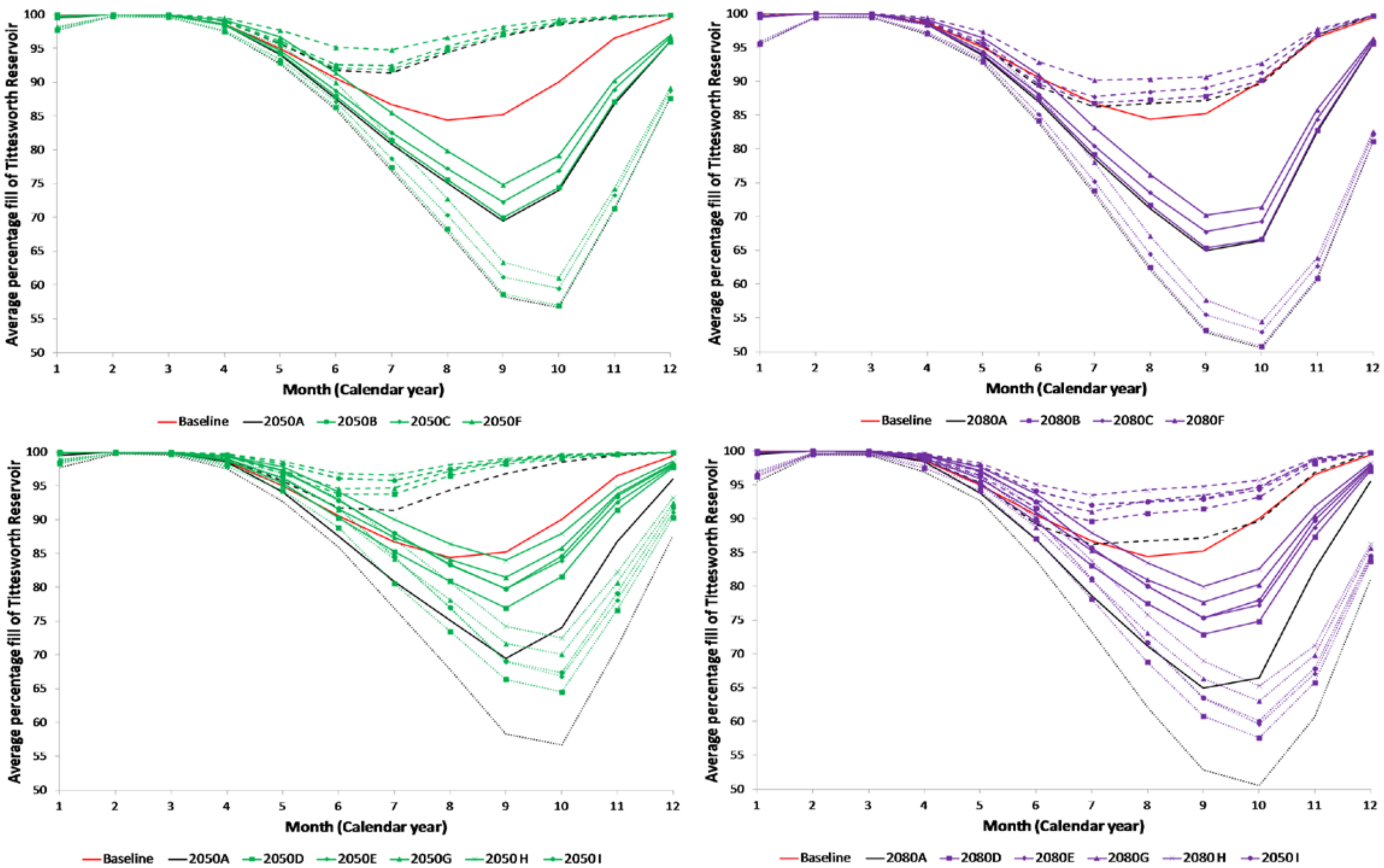

Figure 7.1. Continued from previous page

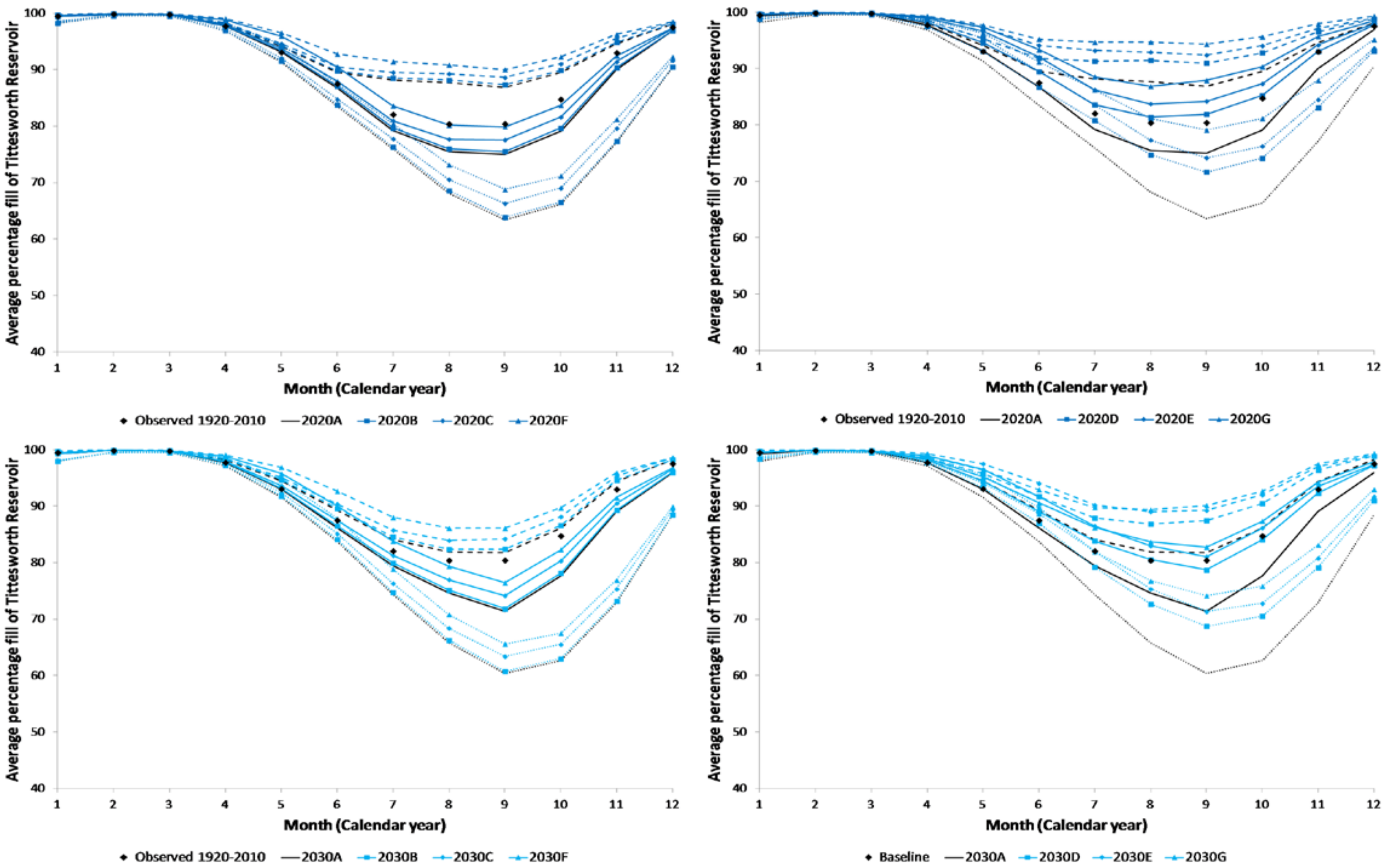

Figure 7.2. 1920-2010 observed average percentage fill at Tittesworth Reservoir per month, with changes to those statistics as a result of adaptation measures in the: 2020s, 2030s (this page), 2050s and 2080s (overleaf) overlain. All simulations use the CFM. Upper and lower boundaries of the scenario A are shown as dashed and dotted lines, respectively. Explanations of the scenarios used are found in Table 7.1.

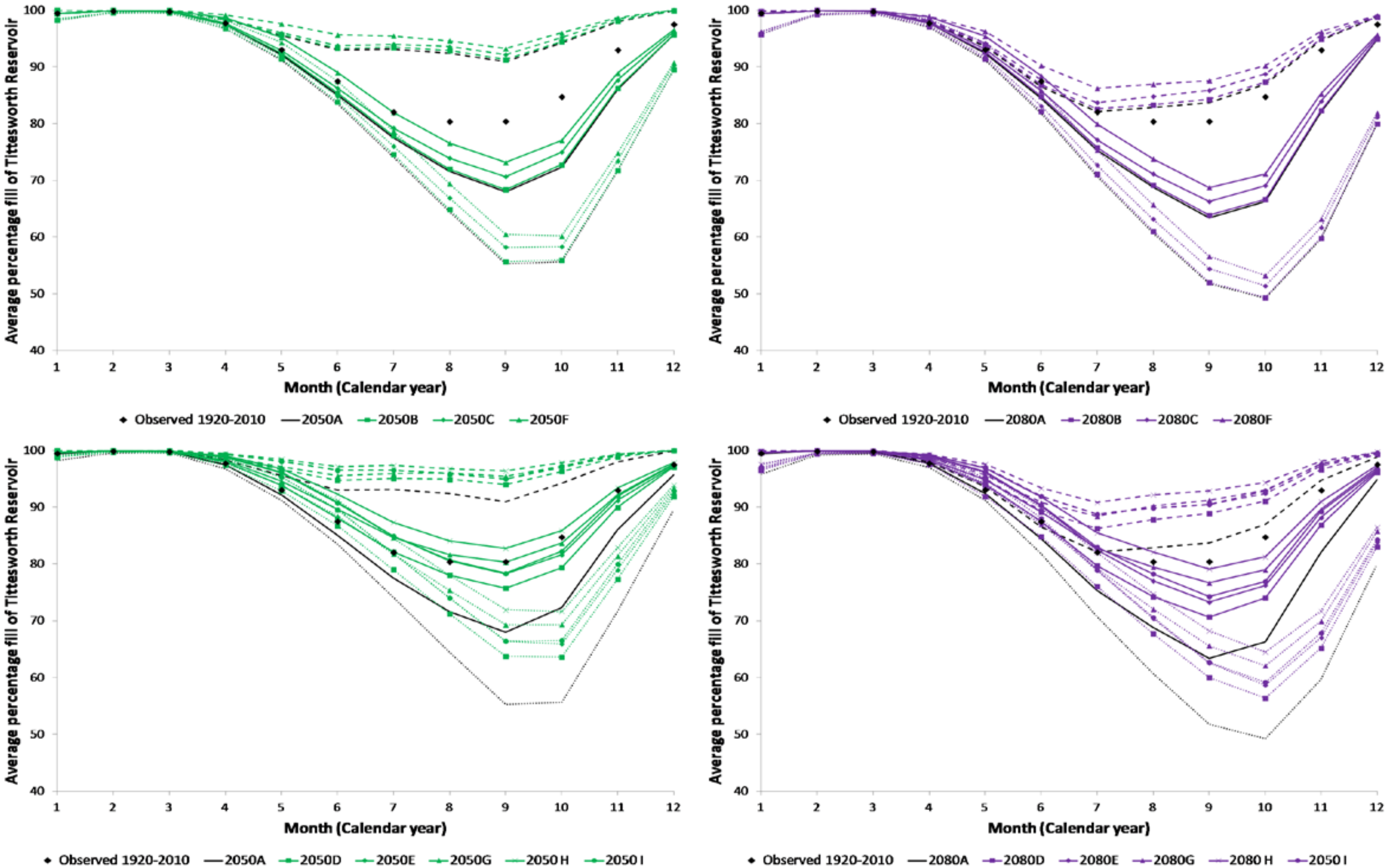

Figure 7.2. Continued from previous page

Table 7.2 Agreement on the signage of monthly raw water storage at Tittesworth Reservoir/day change (as a percentage of total capacity) in the 2080s compared to the baseline (1961-1990) median simulation with different adaptation scenarios applied using the WGM.

	A	B	C	D	E	F	G	H	I
January	-0.5	-0.5	-0.4	-0.3	-0.3	-0.3	-0.2	-0.2	-0.2
February	-0	-0	0	-0	-0	0	-0	-0	0
March	-0	-0	-0	-0	-0	-0	-0	-0	0
April	-0.2	-0.2	-0	0.2	0.7	0.6	0.4	0.9	0.8
May	1.2	-1	-0.6	0.2	2.2	1.5	1	2.7	2.2
June	-4	-3.6	-2.8	-1.1	2.1	0.4	0.4	3.4	2.1
July	-9.3	-8.7	-7.3	-4.2	-1.1	-4.1	-1.6	1.4	-1.1
August	-15.7	-15.1	-12.9	-8.3	-5.2	-9.8	-4	-1.2	-5.2
September	-23.8	-23.3	-20.5	-14.5	-11.5	-17.6	-8.9	-6.2	-11.5
October	-26.3	-26	-23.1	-16.9	-14.2	-20.7	-10.9	-8.3	-13.5
November	-14.5	-14.2	-12.6	-9.5	-8.1	-11.1	-6.3	-4.9	-7
December	-3.9	-3.9	-3.4	-2.4	-2	-3.1	-1.5	-1.2	-1.7

Table 7.3. Agreement on the signage of monthly raw water storage at Tittesworth Reservoir/day change (as a percentage of total capacity) in the 2080s compared to the observed record (1920-2010) with different adaptation scenarios applied using the CFM.

	A	B	C	D	E	F	G	H	I
January	-0.1	-0.1	-0	0	0	-0	0.1	0.2	0.1
February	0	0	0	0.1	0.1	0.1	0.1	0.1	0.1
March	0	0	0	0.1	0.1	0.1	0.1	0.1	0.2
April	-0	0	0.2	0.4	1.2	1.1	0.7	1.4	1.3
May	-0.7	-0.5	0	1	3.4	2.5	1.8	4.1	3.4
June	-3.5	-3	-2.1	-0.1	3.1	1.1	1.8	4.9	3.2
July	-8.1	-7.7	-6	-2.9	0.6	-2.6	0.8	4.2	1.1
August	-14.5	-14	-11.5	-7.7	-4.2	-8.2	-1.2	2.1	-2.7
September	-21.2	-20.6	-17.6	-12.1	-8.9	-14.5	-4.7	-1.6	-7.6
October	-21.8	-21.4	-18.5	-12.7	-10	-16.1	-6.9	-4.2	-9.3
November	-11.8	-11.5	-9.7	-6.6	-5.2	-8.3	-3.7	-2.2	-4
December	-2.7	-2.7	-2.2	-1.4	-1.1	-1.9	-0.5	-0.2	-0.9

7.4.3 **Differences between the two approaches in terms of raw water storage**

Table 7.3 suggests that using the CFM approach produces less confidence in drier summers and more confidence in wetter springs in the 2080s than the WGM (Table 7.2). With little to no intervention (scenarios A, B and C) the decrease to water resources overall from the observed record remains, but is not predicted as confidently as the reduction from the 1961-1990 baseline in the WG simulations. Similarly, when intervention to the system is greatest (scenarios E, G, H and I), the CFM approach predicts very little summer/autumn resource reduction with poor confidence (65-90% agreement on scenario I from August to December, with a peak 9.3% median decrease) and large spring resource increases with good confidence (95-100% agreement on scenario I from March to June, with a peak 3.4% median increase), whilst the WGM is still predicting summer/autumn resource reductions with reasonable confidence (85-95% agreement on scenario I from August to December, with a peak 13.5% median decrease) and spring increases less so (40-100% agreement on scenario I from March to June, with a peak 2.2% median increase).

In terms of absolute values of raw water storage, the CFM projects lower median levels at the reservoir in all of the scenarios, although the extent to which this is the case reduces with further afield time horizons, as described in Section 6.4.3. Both approaches project that the peak resource minima shifts from August in the baseline and observed record to September in the median simulations, for each scenario. However, the lack of temporal rain-day variability in the CFM dampens any alteration to seasonality, so only in the WGM is a further shift of resource minima to October evident in the dry end of the simulation range (observable from the 2050s onwards). The choice of scenario rarely alters the annual profile of average water resources significantly, although on those occasions where there is a change (scenario I, for example), it is seen in both the WG and CFM datasets.

7.5 Projections of change to water shortage risk

7.5.1 Overview

CDFs of water shortage probability under various adaptation scenarios are presented based on the methodology outlined in Figure 3.16. The plots shown in Figures 7.3, 7.4 and 7.5, and the information in Table 7.4, use the current conditions for each future time-slice that were developed in Section 6.5 and illustrated in Figure 6.5 as ‘baselines’ against which the adaptation options are tested. As in Figure 6.5, current Levels of Service (LoS) are taken as the company standard for the temporary use ban (TUB) events (3 in 100 years) and the derived values from the observed 1961-1990 maximum DO simulation for the drought warning trigger (DWT) and the storage alert line (SAL).

7.5.2 Weather generator method

In the 2020s, it can be seen that applying demand saving only to the model has a relatively minor effect on the CDFs (scenario B), although a reasonable reduction in SAL events is seen (Figures 7.3, 7.4 and 7.5). Small alterations to the summer compensation flow requirements from Tittesworth Reservoir of 10% are sufficient to satisfy acceptable risk in the 2020s (scenario C) across all severities. Applying further scenarios would constitute maladaptation as the target acceptable risk is already achieved, but their ability to reduce water shortage risk still further is evident.

Baseline (scenario A) water shortage risk is increased in the 2030s, and scenarios B and C are no longer adequate to produce a robust system across each of the severity ranges. Scenario F, which maintains compensation rates at a 10% reduction from Scenario A and reduces the DF to 0.8, and scenario D, which maintains the DF at 0.95 and reduces summer compensation rates to 10Ml/d, both produce a robust WRZ for the 2030s across all three water shortage severities. This constitutes a situation in which further metrics, such as cost, would be useful to the resource decision-maker in order to make the most strategic decision on adaptation when building-up a portfolio of measures to counter increased water shortage risk over time. All further Scenarios would again surmount to maladaptation, or over-engineering.

In the 2050s, scenario F (in which summer compensation flow remains at 13.3Ml/d and the DF is reduced to 0.8) is no longer robust to the range of feasible futures, but scenario D (where the compensation is reduced and the DF stays static) is. If it is assumed that scenario F is cheaper to introduce than scenario D, in an adaptive learning process, where the best approach is selected at the time and adaptation portfolios are built up, it follows that scenario F would be introduced to satisfy acceptable risk in the 2030s so scenario E (summer compensation flow of 10Ml/d and DF of 0.8) could be introduced in the 2050s. In reality, the summer compensation flow value would be optimised, or found using trial-and-error (rather than jumping arbitrarily from 13.3Ml/d to 10Ml/d), but the principle of the technique advocated here remains sound.

By the 2080s, scenarios D and E are no longer adequate to produce a robust WRZ, so more extreme reductions in compensation flow are necessary (scenario I, where a year-round compensation flow of 13. 3Ml/d is introduced), is close to satisfying acceptable risk but is not quite within the target probability for SAL events. As a result, in terms of the strategies included in this research, a drop to 6.7Ml/d summer flow compensation would be needed, although again the optimal amount would be searched for in a practical application. With such a drastic reduction in summer compensation flow, the difference between the higher DF (scenario G) and the lower DF (scenario H) is minimal.

7.5.3 **Change factor method**

Figures 7.3, 7.4, 7.5 and Table 7.4 present the results of the CFM-based simulations of the adaptation scenarios. The results are broadly similar to those for the WGM, but differ somewhat for the TUB and SAL severities for the reasons described in Section 7.5.4. Assuming acceptable risk at all three severities must be satisfied, scenario C must be introduced in the 2020s for the WRZ to be deemed robust, as is the case with the WGM. However, in the 2030s scenario C continues to be adequate, with the further reductions in demand (scenario F) or compensation flow (scenario D) unnecessary, as is the case for the WGM.

Conclusions for the 2050s and 2080s using the CFM are similar to those for the WGM when the DWT is assessed. However, they are significantly different when only the

TUB or SAL are analysed, for the reasons given in Section 7.5.4. Should all the metrics need to be satisfied in order to achieve acceptable risk, scenario D would be necessary by the 2050s, and the most severe interventions (scenario G and H) would be needed by the 2080s.

7.5.4 **Comparison of the two approaches and revised results**

There are significant differences between the approaches, which are to be expected given the limitations of each. Table 7.4 shows that the WGM produces less water shortage risk than the CFM at the most extreme severity (TUB), resulting in a total of seven disagreements as to whether the system is deemed robust or not (2020s and 2030s scenarios A and B, 2080s scenarios D, E and I). Given that the company LoS of 3 TUBs in 100 years is used, it is expected that the WG would not produce the most extreme dry events as frequently as the CFM. However, this is a necessity as there are no TUB events in the instrumental record during the WG validation period (1961-1990), so results would be heavily skewed. In all but the 2050s, the TUB shows the greatest divergence between the two approaches for any of the severity levels (Table 7.5).

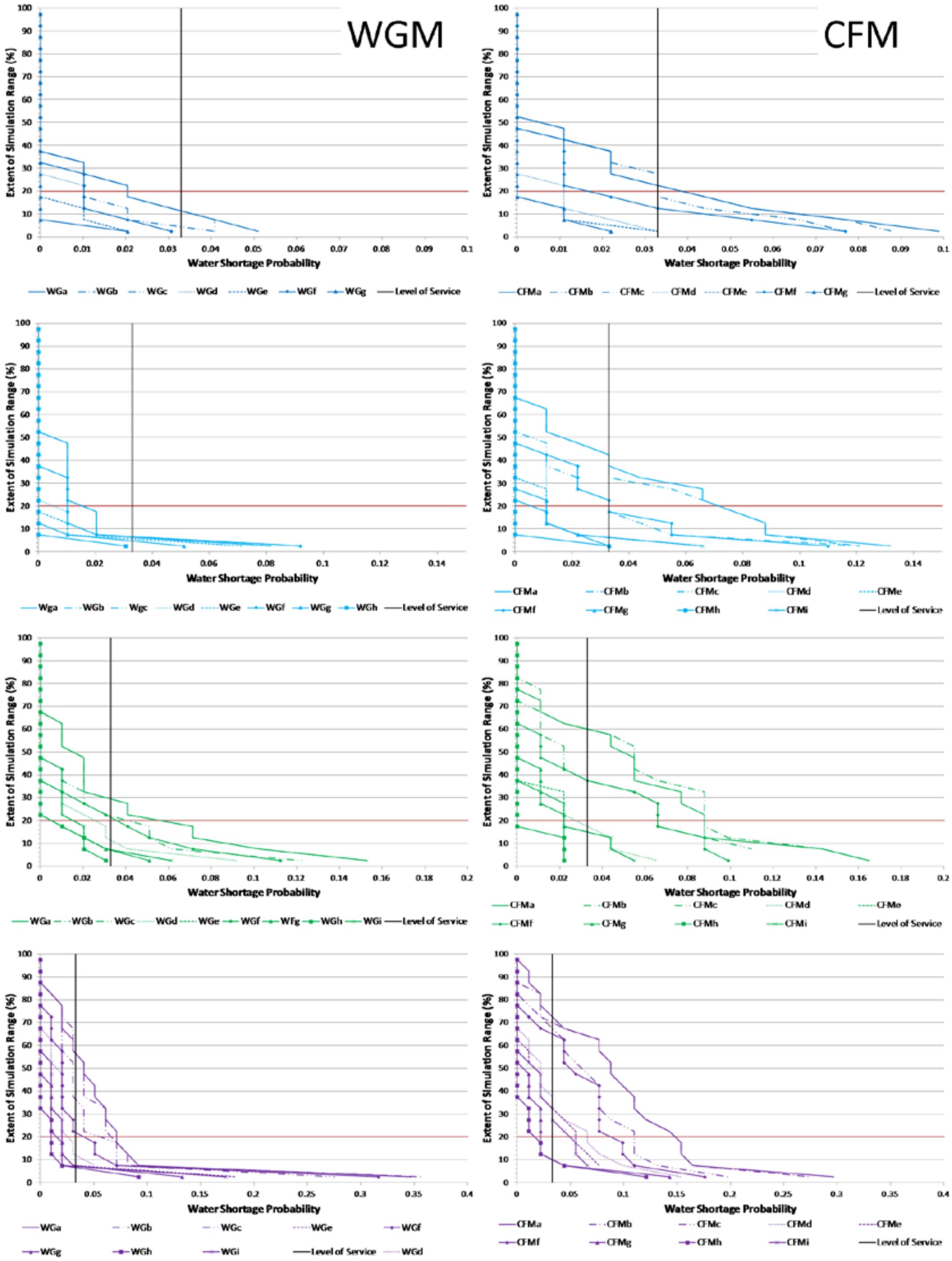

Figure 7.3. CDFs of water shortage probability at the TUB (high) severity in the North Staffordshire WRZ for future time horizons when various adaptation measures are modelled. Left: WGM, right: CFM. From top to bottom: 2020s, 2030s, 2050s and 2080s

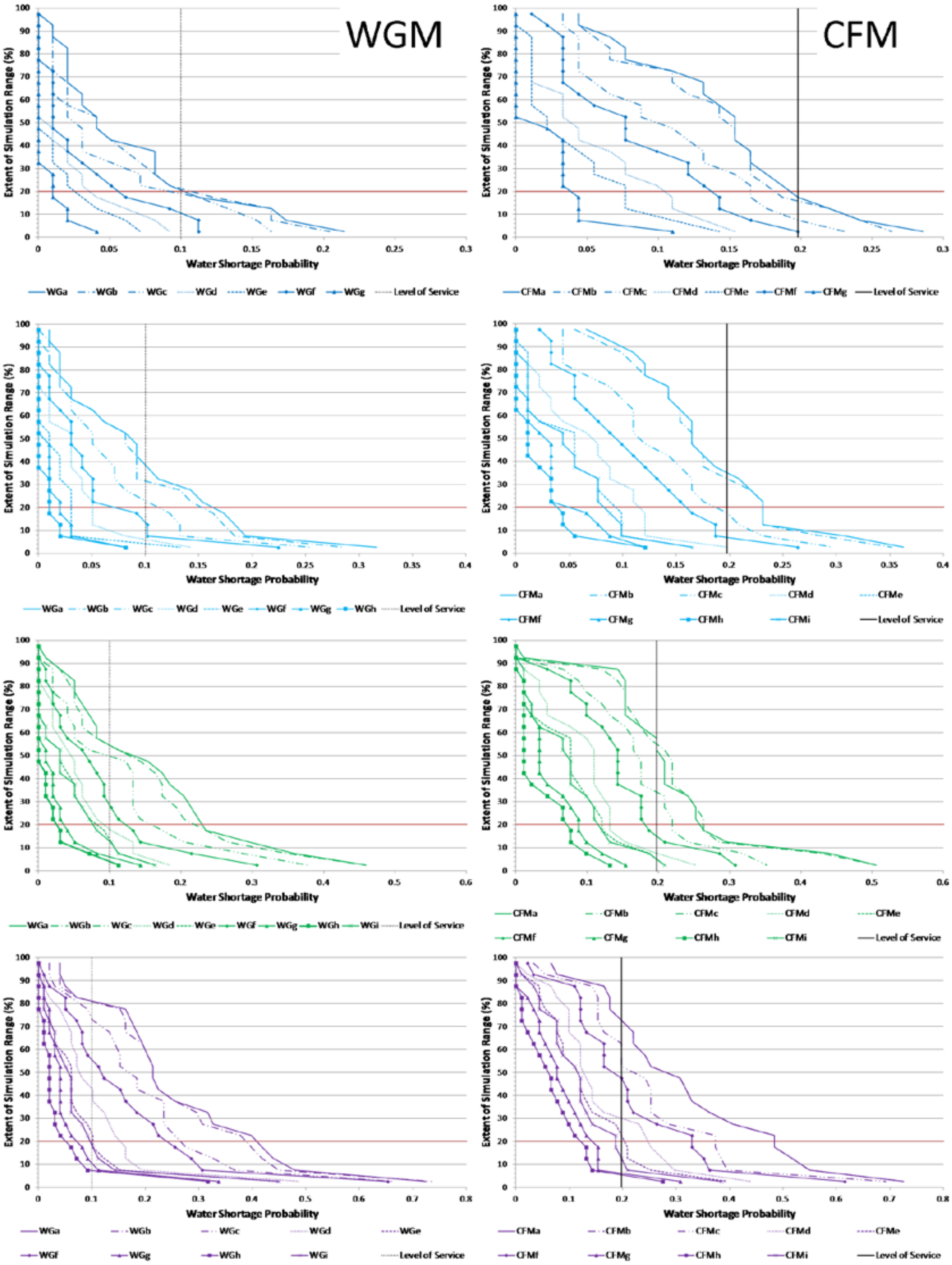

Figure 7.4. CDFs of water shortage probability at the DWT (medium) severity in the North Staffordshire WRZ for future time horizons when various adaptation measures are modelled. Left: WGM, right: CFM. From top to bottom: 2020s, 2030s, 2050s and 2080s.

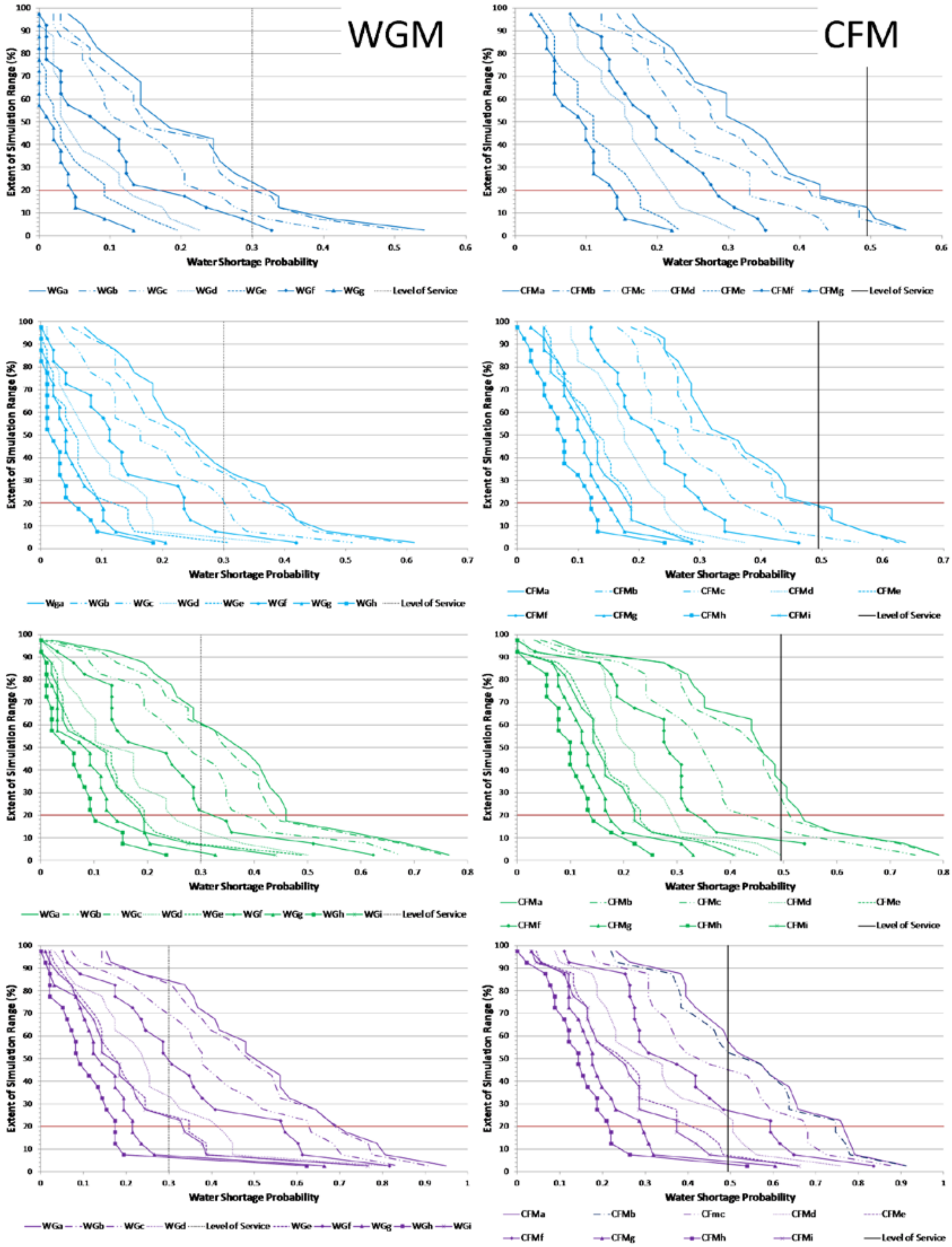

Figure 7.5. CDFs of water shortage probability at the SAL (low) severity in the North Staffordshire WRZ for future time horizons when various adaptation measures are modelled. Left: WGM, right: CFM. From top to bottom: 2020s, 2030s, 2050s and 2080s.

Table 7.4. Matrices of water resource robustness in the North Staffordshire WRZ at three levels of severity in the 2020s, 2030s, 2050s and 2080s with different adaptation scenarios applied using the WGM and CFM. Percentages relate to the amount of the UKCP09 sub-sampled simulation range that conforms to each LoS (as described in Figure 3.14). Green values are within LoS, oranges to reds do not.

	2020s		2030s		2050s		2080s	
TUB	WGM	CFM	WGM	CFM	WGM	CFM	WGM	CFM
A	11%	22.5%	6.5%	37%	29%	60%	56.5%	72.5%
B	11%	22.5%	6.5%	32.5%	29%	60%	56.5%	69.5%
C	4%	17%	6.5%	17%	22%	37.5%	36%	67%
D	0%	2.5%	6.5%	6%	11%	17.5%	12%	32.5%
E	0%	2.5%	6%	6%	7%	15%	7%	32.5%
F	0%	12%	6.5%	17%	21.5%	37.5%	22%	65%
G	0%	0%	2%	2%	7%	0%	7%	10%
H	0%	0%	0%	2%	0%	0%	6.5%	10%
I	0%	0%	0%	2%	7%	15%	7%	27.5%

DWT	WG	CFM	WG	CFM	WG	CFM	WG	CFM
A	20%	18%	38%	35%	54.5%	52.5%	81%	72.5%
B	21%	16%	31.5%	33%	54.5%	55%	81%	72.5%
C	19%	7.5%	23%	17.5%	50%	34%	73%	52.5%
D	0%	0%	6%	2.5%	18%	7.5%	43%	30%
E	0%	0%	4%	0%	13.5%	5%	23.5%	23%
F	10.5%	2.5%	13.5%	7%	29%	15%	55.5%	48%
G	0%	0%	0%	0%	6%	0%	10.5%	6%
H	0%	0%	0%	0%	4%	0%	7%	5.5%
I	0%	0%	0%	0%	14%	5%	18%	13%

SAL	WG	CFM	WG	CFM	WG	CFM	WG	CFM
A	23.5%	13%	34.5%	19%	60.5%	35%	84.5%	58%
B	20%	7%	33.5%	18.5%	60%	28%	83%	52.5%
C	9.5%	0%	20.5%	5.5%	46%	14%	69.5%	45%
D	0%	0%	4.5%	0%	13%	2.5%	33%	24.5%
E	0%	0%	3%	0%	7%	0%	25%	7.5%
F	6%	0%	7%	0%	22%	9%	49%	27%
G	0%	0%	0%	0%	3.5%	0%	7%	4.5%
H	0%	0%	0%	0%	0%	0%	6%	3.5%
I	0%	0%	0%	0%	7%	0%	24%	8.5%

Conversely, when the less-severe SAL is assessed, the CFM produces significantly reduced water shortage risk than the WGM, causing disagreement on system robustness on eight occasions (2020s scenario A, 2030s scenarios A, B and C, 2050s scenarios C and F, and 2080s scenario E and I). This is due to the lack of any alteration to climate variability in the CFM which makes it unlikely that a substantial deviation from the set amount of drought years in the instrumental period will exist in the future simulation. As the WGM is able to produce events of this extremity (unlike the TUB) and has the ability to change climate variability from the past, the spread of SAL events per simulation across the UKCP09 is much greater, causing acceptable risk to not be satisfied more often. The reduced spread of water shortage probabilities in the CFM simulations compared to those produced by the WGM (and vice-versa for the TUB) can be seen by eye in Figures 7.3, 7.4 and 7.5.

Therefore, the medium-severity metric of water shortage risk, the probability of crossing the DWT in a given year, produces the most useful results for informing decision-making on water resources, as was suggested in Section 6.5.4. There is better agreement on system robustness between the WGM and CFM, with no disagreement at all in scenario A (Table 7.4 and 7.5). Although there are three examples of disagreement (2020s scenario B, 2030s scenario C and 2050s scenario F), only the latter is beyond a borderline call, and the average percentage difference between the approaches for each time-slice is far lower for the DWT than the TUB or SAL (Table 7.5). It is therefore clear, given the relevance of the DWT metric to industry planners (see Section 8.4) and the substantially improved agreement between the approaches that this severity of water shortage should be focussed on in any further industrial application of the concepts explored in this research.

Table 7.5. Mean percentage differences between the extents of the simulation range conforming to LoS in the WGM and CFM for each severity level and time horizon. The number of occasions on which the two approaches disagree as to whether the acceptable risk of 20% of the simulation range is satisfied is also shown.

	2020s	**2030s**	**2050s**	**2080s**	**Disagreements**
TUB	5.9%	9.2%	13.7%	19.6%	7 / 36
DWT	2.9%	2.7%	7.8%	7.7%	3 / 36
SAL	4.3%	6.7%	14.5%	16.7%	8 / 36

By taking only DWT events into account, results can be drawn with greater confidence. The current system (scenario A) can be deemed robust to future climate change in the 2020s. In the 2030s, adaptations are necessary. There is disagreement between the WGM and CFM as to whether scenario C is sufficient to satisfy acceptable risk, but scenario F is certainly adequate. Moving beyond normal WRMP horizons, the 2050s would require scenario D (assuming the uncertainty involved with scenario F is too great). Finally, deep into the century more drastic changes to the WRZ would be necessary, with scenario G, H or I necessary to maintain a robust system. In an industrial application of this process, the scenarios would be more nuanced; not containing the substantial leaps in compensation flows in evidence here, for example. They would also be focussed on the WRMP time-scales, which at present would mean not moving beyond projections for the 2030 time-slice. However, the case study provided here clearly shows how the RDM-type approach can be implemented in a WRZ, and concise conclusions can be drawn from uncertain information.

7.5.5 **Annual profile of adaptation effects**

Figure 7.6 shows the profile of DWT trigger conditions across the year for the range of simulations in each scenario in the 2080s when the WGM is used. DWT is focussed upon for the reasons given in Section 6.5.4. Scenario A is shown in Figure 6.6, and is similar to scenario B.

The DWT event profile described in Section 6.5.5 - with a peak in October and limited or no drought conditions in spring - remains in all of the less-severe strategies (B, C, F), as well as D, whilst when more substantial interventions are introduced (scenarios E, G, H and I), the drought event peak is generally pushed back to November (both in terms of median and maximum simulations). The shift is evident in scenarios in which a reduction to summer compensation is focussed on, rather than annual compensation (E and I), as well as when a severe reduction to demand is introduced (E, H and I). It can clearly be seen how progressively more sizable adaptations produce markedly reduced peak and median number of days with drought events in the late summer, whilst the smaller amount of winter drought days remains comparatively intact.

The similarity between scenarios E and I shows that reducing compensation flows across the whole year rather than just the summer months does not produce a markedly different profile, which is intuitive given the trend towards single-season summer drought in the future (see Section 6.4.1). However, despite the similar annual profiles, the reductions across the whole year acts to bring scenario I within acceptable water shortage risk in the 2080s when scenario E is not (Table 7.4).

With the exception of scenarios B and C, where little change to the annual profile is seen, September becomes relatively less drought-prone than November, as more significant adaptations are modelled. This occurs as the increased winter flows projected across much of the simulation range do not come into effect until December (Table 5.4), after which a rapid recovery of raw water resources is seen through to March. Therefore, this effect is primarily caused by the control curves for the reservoir reflecting current (2012) conditions, rather than the potential inflow conditions of the 2080s, meaning that too much flow is ‘expected’ in November rather than December, January and February, thus producing exaggerated drought events in that month.

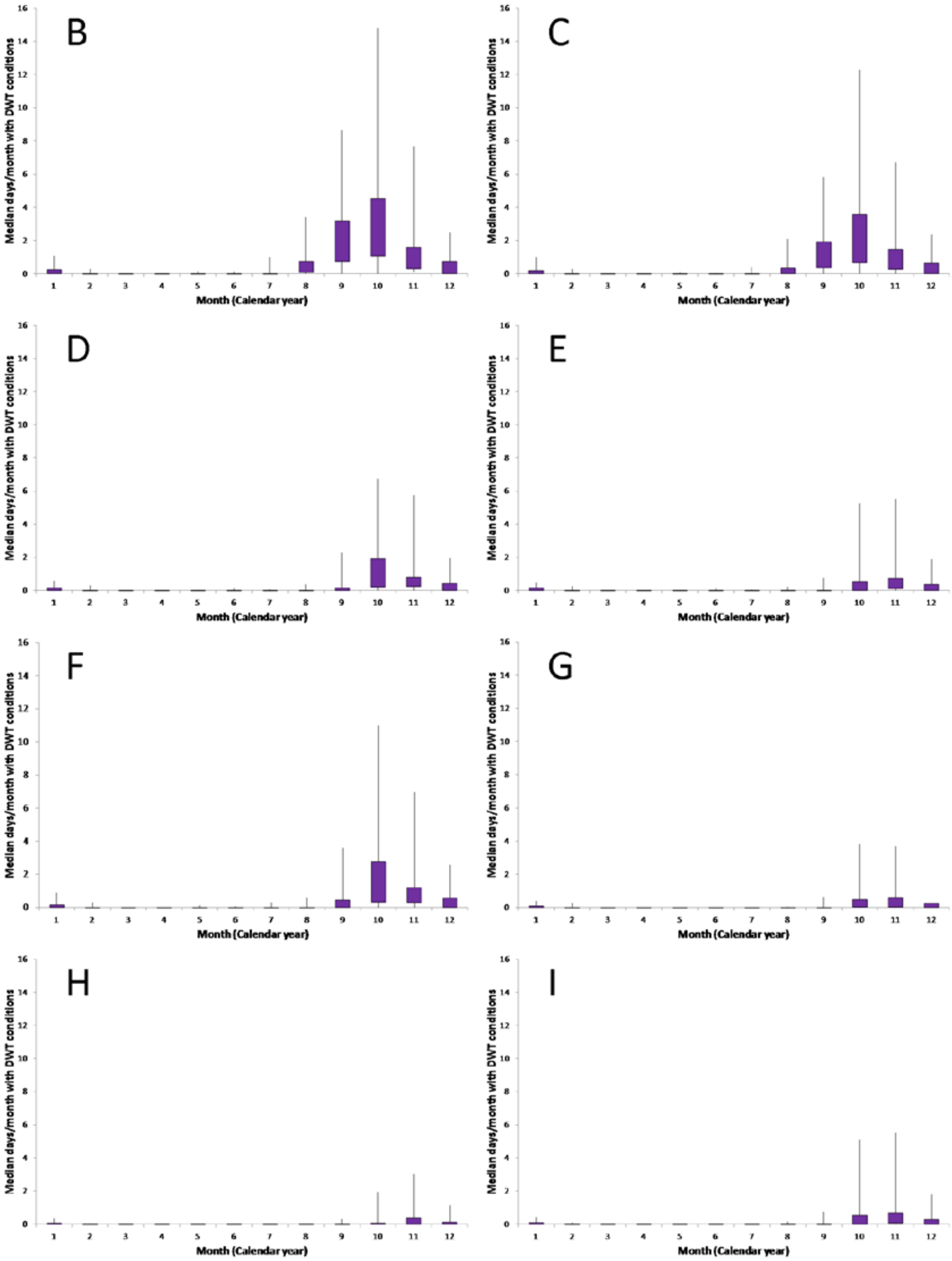

Figure 7.6. Box-whisker plots of average days per month in which DWT conditions are triggered in the 2080s for different adaptation scenarios using the WGM. Scenario A can be seen in Figure 6.6.

7.6 Conclusions of adaptation options assessment

The case study developed in the previous chapters is built on to show how the performance of eight adaptation scenarios added to the North Staffordshire WRZ model can be measured and assessed using an innovative robustness assessment technique. It is found that the WRZ can be made more robust to climate change-induced water shortage risk when interventions are gradually introduced over time, although some measures are more effective than others. The case study used here clearly shows the potential for this type of assessment to be of use to the water industry. Although the logical extension of this work is to integrate the climate change information with further socio-economic pressures on the system, the importance of analysing climate change-only information is important, given the legislative requirement of UK water companies to provide Climate Change Risk Assessments (CCRAs). Employing RDM-type approaches, such as the one described here, is a useful approach for the UK water sector to take, and represents a much-needed de-standardisation of the way UKCP09 information is used in industry (Arnell, 2011(b)). Although the adaptation scenarios used here are rather arbitrary, they do enable a case study of how the methodology can be used effectively, and the results gathered are summed up below.

- The DWT severity of water shortage is the most useful metric for decision-makers, as the limitations of each of the approaches is reduced compared to the TUB and SAL severities (Table 7.5). Therefore, a WG-based exploration of water shortage risks in a WRZ is feasible as long as the most extreme severities are not searched for.

Given the advantages of projecting DWT events rather than TUB events in a practical sense (Section 8.4), this is not a limiting factor of the methodology developed.

- It can be said with reasonable confidence that the current system (scenario A) is robust to DWT events in the 2020s, but not so thereafter. Substantial demand-saving or efficiency measures to reduce demand alone are not able to make the North Staffordshire WRZ robust to an acceptable level of risk, but progressively more severe reductions to the compensation requirements would be sufficient.
- Relatively small alterations to the compensation requirements from Tittesworth Reservoir of 10% are borderline sufficient to satisfy acceptable risk in the 2030s (scenario C). Further reducing demand to 80% of current levels ensures the system is robust in the 2030s (scenario F).
- There is disagreement between the WGM and the CFM as to whether scenario F is sufficient in the 2050s, but reducing summer compensation to 10Ml/d (scenarios D, E and I) enables the system to cope regardless of the extent to which demand reductions/efficiency gains are implemented.
- In the 2080s, only by reducing summer compensation to 6.8Ml/d can the system be made robust to the range of uncertainty (scenarios G and H). With such a drastic compensation reduction in place, the lowering of demand is negligible (scenarios G and H).
- Using the WGM, some of the more severe adaptation interventions (particularly E, G, H and I) act to reduce the October peak drought event to an extent that November becomes the peak drought month in the 2080s across much of the uncertainty range (Figure 7.6). Each of these scenarios sees either the most extreme demand reduction

and/or the most drastic reduction in summer compensation flows. September drought events are comparatively reduced. The number of winter drought events remains relatively unchanged compared to the late summer (JA) and autumn (SON), regardless of which scenario is introduced to the model.

- Most of the scenarios act to decrease the rate of draw-down at the reservoir compared to the baseline (or observed record when the CFM is used). Alongside the later water resource minima caused by increased summer drought (Figure 6.1), this creates altered annual profiles of water resource availability, thus making it difficult to make decisions using this metric. Much of the change in monthly water resources may be as a result of the control curves for the reservoir reflecting current (2012) conditions rather than the future conditions they are subjected to in the Aquator model.
- The quantifications of the satisfaction of an acceptable probability of DWT-severity drought events shown in Figure 7.4 and Table 7.4 show how uncertain climate change information can be reduced to a simple yes or no assessment of adaptation approaches. The values and scenarios involved in this study are useful as a case-study, while they do not necessarily reflect real-life plans; they do show how the techniques put forward here can be used in an industrial application.

8 DISCUSSION

8.1 Overview

This section brings together the results from the Chapters 4, 5 6, and 7 and provides a discussion of how and why they constitute a progression on previous research into robust water resource management under climate change. The success of the approaches taken to address the issues and challenges highlighted in the Literature Review (Chapter 2) are assessed and the extent to which the objectives laid out in Section 1.2 are satisfied is considered.

8.2 Facilitating the improved use of uncertain climate change information in the England and Wales water sector

Using an innovative approach that enables risk-based assessments to be made based on uncertain information; climate change is shown to significantly exacerbate water shortage stress in the North Staffordshire Water Resource Zone (WRZ). This novel method for producing quantitative assessments as to whether a WRZ can be considered robust to climate change given the application of adaptations scenarios constitutes a step-forward for the analysis of water resource robustness, as previous 'traditional' predict-then-manage approaches are shown to be incompatible with probabilistic UK Climate Projections 2009 (UKCP09) information. The methodology provided here enables potentially limitless numbers of adaptation scenarios to be tested for robustness against any number of metrics of risk, not only in the water sector, but in any area susceptible to climate change in which the suitable models exist. Furthermore, overlooking abstract concepts such as deployable output (DO) in favour of more tangible metrics such as reservoir levels and associated Levels of Service (LoS) enables better communication of climate change threats. Similarly, headroom, which assigns arbitrary levels volumes of water to a supply to account for uncertainty, is not used in this approach as it is not suitable to take into account the extent of uncertainty involved with climate projections.

However, significant barriers to the uptake of such a radical approach exist, and the streamlining of decision-making in this style into industry is not straightforward. Procedures within the water industry are ingrained and moving to a bottom-up risk-based approach requires a paradigm shift in the way resource managers assess climate change impacts on company assets (Hall and Murphy, 2012). Using probabilistic UKCP09 information with approaches more suited to precise datasets (such as the observed record, or a single perturbation thereof) has understandably led to disappointing results. This study provides evidence of an applicable and replicable approach to using UKCP09 information to assess options across uncertain futures, and thus constitutes a significant advance to the uptake of climate change as a driver of investment in the England and Wales the water sector.

For significant investment to be made to counter the threat of climate change in the water sector, a significant shift in perceptions of risk must be made. The study here shows how uncertain information can be used to provide quantitative assessments as to whether a system is robust to future change, even if those conclusions are based on arbitrary decisions as to what constitutes ‘acceptable risk’. Until there is a movement to a more risk-averse outlook on climate change, where the possibility of vastly increased water shortage probabilities are seen as a bigger risk than over expenditure, it is doubtful that progress can be made (Gerst *et al.*, 2013). Similarly, the timescales on which water resource management is based need to be restructured before an approach such as this can make an impact on expenditure, as the dominance of 5-year Asset Management Plan (AMP) cycles limits the importance that can be placed on longer-term, but extremely significant, climate change impacts.

As time-slices are used, rather than transient series in which the climate changes over time, it must be assumed that a scenario that has been enacted in one time-slice (such as the 2020s) is still in operation in a more distant one (such as the 2030s). This enables combinations of scenarios to be built up over time. ‘Learning’ adaptation should be employed, where new information on climate change is continually added to the framework when it becomes available (Hall *et al.*, 2012c). This limits the extent to which long-term and relatively inflexible adaptations such as alterations to, or the development of new, reservoir storage is useful to the planner. In an approach such as that advocated in this research, ‘quick win’ options such as demand reductions and flexible, retractable options such as altering licenses and increasing connectivity are more appealing. This is at odds with the normal industry position of focusing on hard, large-scale supply side engineering works such as surface storage expansion, and therefore requires a significant conceptual change amongst water resource managers (Charlton and Arnell, 2011).

8.3 Climate change impacts on North Staffordshire Water Resource Zone

As well as providing a replicable framework for improving the use of climate change information in the England and Wales water sector as a whole, this research produces an in-depth analysis of the robustness of the North Staffordshire WRZ for the first time. It is therefore important to assess what climate change means for this region, and what the best approaches to counter any threat that exists are.

Assuming a pre-determined acceptable risk of 20% of the modelled range able to be below a LoS, and the most reliable water shortage metric being the drought warning trigger (DWT), it can be said that the WRZ is vulnerable to climate change-induced increased water shortage from the 2030s onwards. As the threshold representing a DWT event remains static through time and the probability of those events occurring increases throughout the century across the uncertainty range, the water shortage risk in the sub-catchment can be said to substantially heighten as a result of climate change (Figure 6.5).

It is shown that substantial demand-saving measures alone are unable to satisfy acceptable risk of water shortages in the 2030s. Reducing compensation flows to the River Churnet is shown to be a more effective means of increasing robustness (Figure 7.4; Table 7.4). Using the change factor method (CFM), reducing compensation by 10% from current levels is sufficient for the 2030s, whereas using the weather generator method (WGM) a further reduction in demand or compensation is required. This is one of only three future adaptation scenarios (out of a total of 32) in which the downscaling approaches disagree on whether the WRZ is robust to climate change according to the DWT metric (Table 7.4).

Beyond the 25-year Water Resource Management Plan (WRMP) period, the necessary alterations to demand and compensation required to maintain the robustness of the WRZ become more severe. By the 2080s, year-round compensation reductions of 32.5% and demand reductions of 20% are needed to satisfy acceptable risk (Figure 7.4; Table 7.3). This constitutes a robust approach for identifying effective scenarios that make the North Staffordshire WRZ robust to uncertain climate change impacts. Using cumulative distribution functions (CDFs) (Figures 7.3, 7.4 and 7.5) and water shortage risk matrices (Table 7.4) is a major improvement on previous approaches to communicate the impact of climate change on water resources, allowing for quick decisions to be made on whether robustness is achieved given any number of scenarios or conditions applied to the model.

Climate change is considered here in isolation and all other influencing factors are assumed to remain constant, allowing an explicit investigation of climate change impacts on water resource shortage. However it should be remembered when analysing datasets such as those shown here that climate change impact on water supply is only one of a suite of stressors that act upon the UK water industry, now and in the future. Incorporating the effects of temperature change on demand, taking land-use change into account, groundwater infiltration and irrigation demands are some of the further criteria that could be added to the data used in this study in order to produce an integrated assessment of future water shortage risk.

8.4 Applicability to the water sector

Delivering a replicable and applicable approach to using climate change information in the England and Wales water sector was a key objective of this research, and the approach taken has been developed to maintain the user-friendly, computationally efficient and uniform downscaling fundamentals of UKCP09. This represents an important aspect of the work, as it ensures it is a viable alternative to using UKCP09 information to that used in the 2013 draft WRMPs, which is based on DO (Severn Trent Water, 2013). As well as benefitting from the web-based interface employed by UKCP09, the additional elements of the approach used here, such as sub-sampling, z-transform scaling and the uncertainty assessments, do not add inhibitive computational or time expenses. As a result, the methodology is applicable to industry assessments, enabling a more complete exploration of probabilistic climate change projections. The inclusion of other aspects of water resource management such as groundwater models would be warranted in further applications of the approaches described here.

Section 6.5.4 describes how the highest confidence in the results from the modelling carried out in this research can be taken from the DWT, or medium, severity events. The fact that more severe and potentially more costly temporary usage ban (TUB) water shortage events are projected with lessened confidence may at first glance seem a limiting factor of this research, but this is in reality not the case. In a practical sense, crossing the DWT effectively defines the amount of time is spent in the boardroom making decisions on what to do about the reservoir; it makes water resource managers concerned about the water situation and can set in motion a plethora of potential operational changes, some of which are triggered automatically in the Aquator model (e.g. a reduction in Tittesworth Reservoir output) and some of which need to be manually modelled (e.g. demand saving). It is, then, the ‘first step’ of decision-making during a dry period. The TUB, on the other hand, is the last-resort; it is the final decision at the end of a long cascade of decisions. Before reaching a TUB event a multitude of decisions will have been made by resource managers that are not automatically triggered in the Aquator model. It is therefore more useful for the water company to know how frequently a situation in which resource managers must devote time, energy and capital resources to a water shortage event will occur (i.e. the triggering of a DWT) than the probability of a hypothetical TUB event that occurs under a set of conditions within the Aquator model without any input from a resource manager. It could be argued that the storage alert line (SAL) is even further towards the beginning of the decision chain than the DWT, but in a practical sense the consequences of crossing a SAL are very small in the North Staffordshire WRZ.

8.5 Extension of concepts explored

The control curve triggers used in this research project are one of many metrics that could be employed to communicate the state of the North Staffordshire WRZ within the context of a robust decision-making (RDM)-type approach. By extending the study produced here to include other metrics with their associated thresholds to denote an unwanted outcome that reduces the robustness of the system, such as the probability of having to use the maximum licensed groundwater abstraction on a given number of days within a year or turning off supply from Tittesworth to the water treatment works (WTW) by a certain time in the year, the scenarios can produce results across a range of criteria which increases the depth of data supplied. Combinations of such metrics can form an RDM approach in the way proposed by Lempert and Groves (2010). With such information, decisions can be made based on any number of criteria. For example, in the dataset for the 2080s, three scenarios (G, H and I) satisfy acceptable risk at the DWT severity (Table 7.4), so all are equally effective in terms of achieving the target set in this project. However, there is no indication of the cost of each to implement, nor is there an understanding of the cost of supplying water in each scenario. Therefore it is easy to see how such scenarios that have shown their effectiveness in reducing water shortage risk to acceptable levels could be ranked based on cost, but introducing other valuable metrics that are important to the water resource planner can increase the depth of understanding before a decision is made.

It is suggested that a decision could be made on a step-by-step basis, with scenarios being discarded when they fail to satisfy a threshold at any stage. This also allows the decision-maker to prioritise which criteria are of most importance by the order in which they test for them. If a number of scenarios are produced for the WRZ at the end of the current planning period (the 2030s) which aim to (primarily) adhere to LoS, at (secondarily) least-cost whilst (thirdly) minimising the amount of times a groundwater license is maximised, the scenarios which satisfy the LoS to an acceptable risk would then go on to be tested against an acceptable probability of exceeding a pre-determined cost, and then on to being tested against an acceptable probability of a maximised groundwater license, and so on. In a real-world application, mitigating factors such as satisfying environmental flow indicators for the River Churnet would necessarily need to be the primary metric. The research carried out here does not extend to provide case studies of such metrics, but the advantages of such extensions from a management point-of-view are clear.

Finally, it is clear that significant possibilities for producing a similar RDM-type assessment outside of the water sector exist as well; train buckling events, slope failures, flooding events or customer delays as a result of climate change would be useful to a train infrastructure manager, the probability of a flooded road or a bridge closure due to high winds could be of use to a road infrastructure manager, and crop yields or pest proliferation would be useful to the agriculture sector. Assuming probabilistic climate data for the area is available, the relevant variables can be downscaled as necessary (this would be an issue in the case of high winds were UKCP09 information used) and the correct infrastructure-specific models exist, the overarching methodology used here is transferable to almost any sector that is influenced by a change in climate. Given such tools, the only remaining issue would be to develop or identify suitable metrics of risk against which to base decision-making, which would require significant stakeholder engagement.

8.6 Extension of uncertainty assessment to involve water shortage metrics

Given the advocacy in this research of moving towards using LoS as metrics of risk and building adaptation decisions using robustness assessments, it is intuitive that uncertainty assessments should be framed in the same way. Chapter 4 and Appendix A2 provide a novel approach to quantifying the uncertainties involved with climate change projections for a WRZ using the same principles as the main climate change impact assessment. This, to the authors' knowledge, is the first time that such an uncertainty assessment has been carried out. Expanding the approach to include further uncertainties such as hydrological modelling and potential evapotranspiration (PET) calculation is also possible.

The conclusions of Chapter 4 also clearly show the inadequacies of using precise projections of the future upon which to make decisions in terms of tangible metrics (i.e. the ability to satisfy key performance criteria such as LoS). Given the current practice of using the medium emissions scenario only for climate projections in the England and Wales water sector (after von Christierson *et al*., 2012), it is feasible that the projection ranges for the 2080s shown in Figure 4.5 are more directly relevant to industry than those detailed in Chapter 6. However, the rationale for using only the A1B scenario in industry guidance is not based on anything concrete as there is no 'correct' emissions scenario (or combination thereof) to use, so only using the A1B scenario for climate change projections is not necessarily best practice.

8.7 Uncertainties and limitations of the approaches used

Downscaling limitations

When the CFM approach is used, projections of future water shortage are notably more severe than the weather generator (WG) datasets for TUBs, similar for DWTs and less for SALs. This highlights the limitations of each approach; the WGM does not produce the most extreme droughts adequately (thus reduced TUBs) and the CFM does not take into account climate variability and as a result has a reduced range of uncertainty (thus fewer SALs). As a result, the CFM and WGM agree on the robustness of the system to DWT events only (Table 7.4).

Assigning the drought risk metric as the probability of a drought curve being triggered in a calendar year means that a) no information on the extent of those drought events is produced, and b) the succession of drought events from year-to-year is not identified. Point ‘a’ is deemed appropriate as the water shortage risk metric used must be usable, rather than endlessly detailed, given the large amount of simulations involved. Point ‘b’ is in principle more limiting, yet its effect in this case is dampened by the inability of UK Climate Projections 2009 weather generator (UKCP09WG) to produce multi-seasonal drought effectively, therefore reducing the probability of two or more exceptionally dry years in a row being as a result of anything more than statistical chance. Furthermore, heightened rainfall seasonality in the future is projected for the research area (Figure 5.1) increasing the likelihood of single-season summer droughts accounting for the majority of water shortage events. However, the two issues relating to point ‘b’ here remain the largest barriers to the effective use of UKCP09WG information for climate change adaptation decision-making.

As a result of spring reservoir levels being at ~100% in almost all simulations, it is suggested that the WGM is limited to studying the hydroclimatological effect of single-season summer drought, and cannot be extended to multi-seasonal drought assessment. In reality, the potential for large blocking systems that potentially produce winters with extreme low precipitation would increase as the century progresses due to the build up of energy in the climate system as a result of anthropogenic forcing. It is therefore intuitive that the WGM underestimates future extreme drought events (as shown by the reduced TUBs compared to the CFM, which includes perturbed versions of the multi-seasonal droughts in the observed record). Furthermore, there is no agreement across the UKCP09 perturbed physics ensemble (PPE) range with regards to changes in the position, and strength, of future storm tracks that greatly influence the UK climate, and the UKCP09 PPE range does not over a large amount of projections form other climate models (Jenkins et al., 2009).

As a result of these issues, the water shortage risk information provided by the WGM analyses are ‘semi-quantitative’ and the water shortage projections calculated here are chronically understated, particularly with regards to high severity events (thus the focus on medium severity events in the analysis of the adaptation measures). However, the ability to assess the performance of individual adaptation strategies using this dataset remains intact, although the values involved should not be taken as absolute. The introduction of an approach for producing relevant baselines against which to assess the WG output, described in Section 3.11, produces usable results for the water resource planner.

Hydrological modelling uncertainty

Uncertainties in the hydrological modelling phase of a hydroclimatological assessment are frequently represented within the literature as small in comparison to climate modelling and emissions scenarios (Wilby and Harris, 2006, Arnell, 2011(a); Teng *et al*., 2011). However, recent research assessing the practicality of assuming hydrological parameters remain constant in a calibration period different from the validation period challenges that view. Coron *et al.* (2012) follow on from work by Merz *et al*. (2011) to quantify the extrapolation capacity of a suite of hydrological models in differing climate conditions, finding that runoff can be significantly biased by precipitation differences between the validation and calibration periods. Wetter validation climates result in overestimation of runoff by as much as 20%, and vice-versa. The extent of the bias varies from basin-to-basin, but the validity of parameter transfer between differing climates is questioned, which raises questions when the same hydrological model for assessing current conditions and future climates in which mean annual precipitation, in particular, is changed (Coron *et al*., 2012).

These errors are not explicitly searched for in this research. Mean precipitation differences from the baseline period to the median A1B 2080 sequence are only +1.9%, but from the wider sub-sampled range in the A1B 2080 dataset, mean annual precipitation differences of up to -11% and +10.6% are seen. Substantial deviations in monthly average rainfall are simulated in the future as progressively drier summers with wetter winters occur (shown in Table 5.1). This potentially leads to a runoff overestimation bias in winter and runoff underestimation bias in summer. Further work would be necessary to ascertain the extent of this.

Re-framing uncertainty in the water industry

The data on various meteorological and hydrological parameters presented here highlights the difficulty that water resource decision-makers face when attempting to incorporate climate change information into decision-making using such metrics (Figures 5.1; 5.4; 5.5; 5.8; 5.9; 5.12). There are very few instances when the signage of change of any given water resource-influencing parameter is constant across the range of climate futures simulated using the UKCP09 data.

The outer boundaries of the uncertainty ranges must not be taken as concrete; there is no evidence to suggest that the low and high-end projections illustrated here are actually the outer limits of what should be expected in the future, they are merely adequate in representing a satisfactory range of what the technology in its current state of development is able to describe. Such approaches cannot be expected to describe the deep uncertainty of climate change. However, the way in which a technology or tool is used is more important than the proficiency of the technology itself (Howard *et al.*, 2010), and installing best practice in using climate projection uncertainty in order to make more robust plans for the future, such as the approach used in this project, is an objective worth pursuing.

With that in mind, ranges of future flows should only be used to attach likelihoods to changes to the hydroclimatological conditions within which the North Staffordshire WRZ will have to operate in the future. It is, for example, very likely that summer rainfall averages will reduce in July in the 2020s from the baseline conditions, but to say that that reduction will definitely be 7.5%, as projected by the median simulation, is invalid. Furthermore, given the inability of the WGM to incorporate multi-seasonal drought over multiple years and the uncertainty regarding non-linear climate change and ‘tipping points’, amongst other issues, it is certainly not wise to assume that a reduction of 39.2% in July average rainfall by the 2020s is the actual ‘worst-case’ scenario. A movement away from focusing on such statements in company reports is vital for effective understanding and communication of climate change impacts on the water industry. Original work such as this project shows how uncertain climate change can be presented in a more useful manner by water companies, focusing purely on water shortage risk and not considering changes to the superfluous parameters that cause that alteration to water shortage probability. Precipitation, flow and PET are clearly vital to water companies, but basing management decisions on, and communicating impacts using, future changes to them rather than the resource state they ultimately determine is not best practice.

9 CONCLUDING REMARKS AND RECOMMENDATIONS FOR FURTHER RESEARCH

9.1 Conclusions with respect to objectives

Objective 1: Develop a replicable and robust risk-based methodology for utilising UKCP09 data to inform decision-making, thus increasing the incentive to drive investment in the water sector based on climate change. The approach should provide a viable alternative approach to using UKCP09 information to that currently used by water companies.

Considerable work is carried out to provide a methodology that enables decisions to be made in the water industry using UK Climate Projections 2009 (UKCP09) information and further resources that are generally available to water companies. A study of the North Staffordshire Water Resource Zone (WRZ) shows that it is possible to produce a risk-based assessment of future water shortage using two downscaling approaches (weather generator method (WGM) and change factor method (CFM)), commercially available models (HYSIM and Aquator) and without excessive computational demands. Two innovative approaches used to produce a sub-sampled set of spatially-consistent WG simulations from the single-site range of 1000 UK Climate Change 2009 weather generator (UKCP09WG) simulations for each of the two emissions scenarios (a z-transform scaling procedure and United Nations Environment Programme aridity index (UNEP AI)-based sampling) are adequate if catchment-specific. Such additions to the UKCP09 data do not add excessive extra computational demand, and maintain the user-friendly ethos of the UKCP09 process.

The methodology used in the case study is geared towards the inclusion of probabilistic WG information in decision-making, and does not take into account 'predict-then-manage' approaches to water resource management. Therefore, adaptation decisions can be taken in greater confidence than when traditional predict-then-manage decision-making processes are used. Incorporating a potentially limitless number of different adaptation approaches into a modelling structure and testing them for robustness against one or more metric of risk takes advantage of data-rich probabilistic climate change projections, rather than treating the uncertainty as a negative. **From the results it is possible to make decisions on how the North Staffordshire WRZ can be made more robust to future conditions by identifying key metrics of risk, and applying an acceptable probability of not satisfying that metric of risk in the future.**

It is clear that an industrial application of such an approach, incorporating modelled versions of company adaptation options and further metrics of risk, could be produced based on the principles outlined here. **This represents a novel and applicable method for studying the impact of climate change on water resources.**

Objective 2: Produce an assessment of the impacts of climate change on water shortage risk in a catchment-specific study that is transferable to other regions, areas of risk to the water industry, and sectors.

Using the DWT as a metric of risk, **the North Staffordshire WRZ is considered robust to climate change in its current setup in the 2020s, but not so thereafter.** Conclusions such as this are specific to the metrics of risk used and the arbitrary quantification of what constitutes an acceptable risk of breaching a threshold value of that metric. This enables the production of quantitative assessments of future robustness to climate change from a probabilistic dataset and represents a major improvement on current assessments of climate change impact on water resources, highlighting the usefulness of the approaches used in this project.

Annual minima of raw water availability are reduced across 80% of the uncertainty range at Tittesworth Reservoir in the 2020s, and 95% in the 2080s.The extensive assessment of climate change impacts on the reservoir provided here represents a substantial increase to the pool of knowledge on how the North Staffordshire WRZ will be affected by future conditions. Such information is useful in the communication of climate change threats to stakeholders and customers.

Objective 3: Use robustness assessment approaches to identify effective adaptive responses to climate change in the WRZ in a way that is easily communicable and facilitates investment despite uncertainty.

By focussing on the drought warning trigger (DWT) as the metric of water shortage, the performance of a range of adaptation scenarios can be analysed as to the extent to which they make the North Staffordshire WRZ robust to climate change. Demand saving measures and reducing compensation flows are modelled to show how adaptation options influence the reservoir system. Applying adaptation options to the system in a risk-based approach such as this is a unique way of utilising UKCP09 information and represents an increase in the degree of confidence water resource planners can have when making decisions on uncertain futures.

The approach taken provides quantitative assessments of the extent to which a WRZ can be considered robust to climate change given the application of adaptations scenarios. By steering away from abstract terms such as deployable output (DO) and focusing on circumstances that affect customers (Levels of Service (LoS), reservoir levels), the results provided here are communicable and tangible. This represents an original way of communicating climate change impacts, and increases the possibility of justifying expenditure on adaptation in the water sector.

The outcomes of this section of the research form the basis of a research journal article, which is currently undergoing peer-review (Appendix A3).

Objective 4: Critically assess the performance of the UKCP09WG, discuss how the limitations of that and another downscaling approach, the CFM, inhibit the ability of the water industry to react to climate change, and map out the way forward for overcoming those issues.

Two downscaling approaches are used in the research in order to assess the advantages and limitations of each, and the role of weather generators (WGs) in climate change impacts on water resources is discussed in a journal article produced during the preparation of this thesis and published in *Meteorological Applications* (Impact Factor 1.318) (Appendix A1).

The production of robustness assessments of the North Staffordshire WRZ is hampered by the limitations of the WGM and CFM. The inability of UKCP09WG to describe long-term statistics that enable the simulation of multi-seasonal droughts means that extreme dry events are underestimated, and the CFM does not allow for changes to climate variability and thus cannot be considered to provide an extensive range of plausible climate futures. However, it is found that robust results can be obtained using UKCP09WG when the most extreme drought severity metric is not used. This is compatible with industry practice, where the DWT serves as the primary drought action trigger within STW. **Focussing on DWT as a metric of risk is therefore found to be advantageous both in terms of its suitability to the WGM and to company procedures, providing an innovative approach to overcoming limitations of the downscaling procedures.**

The approach taken in this project focuses on making use of the imperfect tools available to water resource managers and producing usable information from them. However, it is acknowledged that the progression of technology to overcome the limitations described here is important for the facilitation of better climate change adaptation.

Objective 5: Assess the relative scales of climate model uncertainty and emissions scenario uncertainty in terms of water shortage probability in the future.

A unique approach is described that quantifies the scales of two important uncertainty sources in hydroclimatological research- perturbed physics ensemble (PPE) uncertainty (which represents climate model uncertainty in a probabilistic projection range) and emissions scenario choice - in terms of water shortage probability for the first time. The approach taken enhances the canon of work on the extent to which each uncertainty source accounts for ranges of flows, but also takes that forward in order to quantify the extent to which each source accounts for ranges of water shortage probability. This section of the research forms the basis of a research journal article published in *Climatic Change* (Impact Factor 3.634) (Appendix A2).

PPE is shown to produce substantially more water shortage probability uncertainty than emissions scenario choice in the 2080s in the North Staffordshire WRZ. 45-55% (dependent on LoS choice) of the water shortage probability range described by PPE is outside the range described by emissions scenario choice. It is also shown qualitatively that similar conclusions can be drawn for precipitation and flow statistics and flows.

Objective 6: Facilitate the increased acceptance of climate change uncertainty into future water resource planning.

The uncertainty assessment described above highlights the importance of taking the fullest possible range of uncertainty into account, and shows that using precise projections of climate change (such as a mean UNEP AI simulation) cannot be assumed to be the 'most likely' outcome. **Building uncertainty into the adaptation assessment procedure enables water resource managers to be more confident that maladaptation will be avoided, thus improving the incentive for investment based on climate change information** (Figure 4.5).

It is found that problems regarding the use of UKCP09 information on which to base investment in the water industry are primarily as a result of using probabilistic data for purposes it is not suited for (such as predict-then-manage approaches). By adopting a bottom-up approach to assessing climate change risk (after initial top-down risk analyses to determine the key areas of concern) such as that proposed here, **water resource managers will be able to use the range of climate uncertainty to their advantage by testing the robustness of a number of adaptation options against a number of metrics of risk.**

Objective 7: Produce an assessment of the impact of climate change on hydrometeorological variables in the study catchment using a WG approach.

An extensive analysis of climate change impacts on hydrometeorological parameters in the North Staffordshire WRZ using the UKCP09WG is carried out at a greater level of detail than previously attempted. It is found that the full range of sub-sampled simulations agree on the signage of precipitation change in only 2 of the 48 future months modelled (December in the 2050s and 2080s). However, greater seasonality is suggested by a vast majority of the simulations, with more intense winter rainfall and reduced summer rainfall likely. This pattern becomes more pronounced as the century progresses, but individual models show distinct annual profiles of rainfall. Decreased summer flows are likely at each sub-catchment in the 2020s, with steadily increased reductions throughout the rest of the 21st century Increases to winter flows are also likely, but do not match the scale of the summer decreases, suggesting an overall drying of the sub-catchments across much of the simulation range.

Overall, a more challenging environment for water resource management is indicated by the hydrometeorological climate change impact assessment. Whether annual rainfall will reduce is unclear, but there is greater confidence in the movement to a more dichotomous seasonality of rainfall and increased overall aridity, meaning storing and using extreme winter rainfall is vital to water resource management in the WRZ as more frequent and intense single-season summer droughts occur.

9.2 Recommendations for further work

9.2.1 Extension beyond the current analysis

The clearest avenue for further work is to extend the robustness assessment beyond the borders of the North Staffordshire WRZ, which was chosen as the study site due to its problematic nature to Severn Trent Water (STW). Further work concerning assessments of the robustness of major water transfers from the STW Welsh reservoir system at Elan Valley to the Midlands has been proposed by the company. However, due to the issues with downscaling climate information, it is not a simple case of 'scaling-up' the processes described in this case study, with alternative approaches to producing spatial data and preserving low frequency variability required (see below).

9.2.2 Improvement of downscaling techniques

Due to the identified shortcomings in the downscaling approaches used in this project, there is a clear need for further research work to improve the performance of WG technology in terms of reproducing extreme dry events. It has been noted previously that there are limitations to all of the techniques that have been used to assess the impact of climate change on water resource supply, so producing definitive datasets that can be used to make decisions based on water resource scarcity metrics continues to prove difficult. As a result, much further work lies in progressing WG technology so that long-term statistics are included that make the framework for defining climate change impacts on water described here less susceptible to chronic under-representation of extreme drought events.

9.2.3 **Application to other sectors**

The largest scope for future work lies in expanding the concepts explored here to other areas that are at risk of being affected by climate change. Any sector where it is possible to apply future climate simulations of the relevant parameter(s) to a specialist model and define relevant metrics of risk is suitable for an application of robust adaptation assessment.

Within the water industry, flooding/inundation and water quality are the foremost impacts of climate change other than water shortage, as identified by the recent Climate Change Risk Assessments (CCRAs), and suitable metrics of risk can be produced (e.g. cost of insurance and failure to meet water quality standards or costs of treating water, respectively). Public health (heat mortality, spread of disease etc.), transport infrastructure (disruptions caused by track/road buckling, flooding, sea-level rise, slope failure, settlement of structures etc.), agriculture (crop yield, pest proliferation etc.) and coastal management (loss of property, insurance costs etc.) are examples of other areas in which the principals described here would aid decision-making on how to adapt to climate change.

9.2.4 **Expansion of uncertainty assessment**

Further research following this assessment could include considering other areas of uncertainty outlined by Bosshard *et al.* (2013) and Velazquez *et al.* (2013) (both of which focussed on runoff, rather than water resource shortage or risk), such as statistical post-processing techniques (e.g. comparing the UKCP09WG and CFM), hydrological models and potential evapotranspiration (PET) calculation (Bormann, 2011). It has been indicated that the prevalence of different sources changes over time (Bosshard *et al.*, 2013), so extending the uncertainty assessment to include less-distant time horizons would provide information directly relevant to a water company's Water Resource Management Plan (WRMP) timeline.

9.2.5 **Transient weather generators**

Further progress towards transient WG technology, such as that described by Blenkinsop *et al*. (2013), is also important. Moving away from the use of time-slices would enable the assessment of adaptation procedures in 'real-time' to better understand how a water supply system can change over time as the climate is altered. Particularly useful to the water industry would be a transient extension to the UKCP09 service (or as part of a similarly user-friendly interface).

Transient weather generation particularly lends itself to the 'roadmap' approach to considering adaptation scenarios (e.g. Haasnoot *et al*, 2012), where life cycles of different projects are seen in the changing climate signal. In a direct application of a probabilistic set of transient climate simulations to this project, it would be necessary to invert the cumulative distribution functions (CDFs) produced in this project so that they show the amount of simulations that have a water shortage event in each consecutive year (rather than the number of years in one simulation with a water shortage probability event). This would constitute a more direct application of the methodology proposed by Hall *et al*. (2012(a)).

9.2.6 Spatial weather generators

As has been discussed at length in this thesis, maintaining the spatio-temporal consistency of WG sequences is vitally important to the accurate modelling of catchments and WRZs under future climates. Should spatial weather generation (rather than just rainfall generation) become widely available in a user-friendly platform, the possibilities for hydroclimatological assessments (and the follow-on robustness assessments) over entire river basins or networks using fully synthetic daily sequences would be substantial (see Maraun *et al*. (2010) for a thorough review of the scope for improving spatial weather generation approaches). Such developments are well underway, and substantial research time is being afforded to make such tools a reality within hydrological assessments (e.g. Burton et al., 2010; can Vliet et al., 2012) and in other fields where the maintenance of spatial coherence is crucial, such as urban heat islands (e.g. Jenkins et al., 2014). It is clear, then, that a probabilistic, transient and spatially-consistent WG would be the ideal tool for the assessment of climate change impacts on a WRZ.

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APPENDIX A: PUBLISHED PAPERS

A1

METEOROLOGICAL APPLICATIONS
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RMetS
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Review

The use of probabilistic weather generator information for climate change adaptation in the UK water sector

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ABSTRACT: Adapting to climate change in the water sector requires abandoning two crucial assumptions. First, that the climate represented in the instrumental record is representative of the future. Instead, future water resource planning cannot be based on old measurements (or sequences derived from attaching change factors to instrumental data) and it should be recognized that stationarity is no longer viable, and, second, that climate modelling can be expected to give precise and certain predictions of the future. Instead, probabilistic projections of the future that take into account the full range of uncertainty should form the basis of robust climate change adaptation plans.

As a response to the first assumption, it is suggested that stochastic weather generators represent a particularly useful approach to understanding the impacts of future climate change on water resources at a catchment scale, particularly given the recent release of 'science-hidden' tools such as the UKCP09 weather generator. With regards to the second assumption, it is suggested that modelling activity should identify the range of plausible futures to develop probabilities of risk, using those robust decision-making techniques which can gauge the performance of potential adaptation strategies.

The best practice for delivering a replicable and practical hydroclimatological impact assessment for UK water resources at a catchment scale is identified, and an hypothetical example is outlined. It is suggested that although augmenting the resilience of water resources to climate change on a catchment scale is dependent on using the correct modelling tools, the robustness of the method with which that information is used to make adaptation decisions is equally as important. Copyright © 2012 Royal Meteorological Society

KEY WORDS statistical downscaling; risk; resilience; water resources; probabilistic decision making; hydroclimatology;

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Quantification of uncertainty sources in a probabilistic climate change assessment of future water shortages

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Abstract As the incorporation of probabilistic climate change information into UK water resource management gathers apace, understanding the relative scales of the uncertainty sources in projections of future water shortage metrics is necessary for the resultant information to be understood and used effectively. Utilising modified UKCP09 weather generator data and a multi-model approach, this paper represents a first attempt at extending an uncertainty assessment of future stream flows under forced climates to consider metrics of water shortage based on the triggering of reservoir control curves. It is found that the perturbed physics ensemble uncertainty, which describes climate model parameter error uncertainty, is the cause of a far greater proportion of both the overall flow and water shortage per year probability uncertainty than that caused by SRES emissions scenario choice in the 2080s. The methodology for producing metrics of future water shortage risk from UKCP09 weather generator information described here acts as the basis of a robustness analysis of the North Staffordshire WRZ to climate change, which provides an alternative approach for making decisions despite large uncertainties, which will follow.

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(Under peer review)

Climate change-induced future water shortages: Improving decision-making in an uncertain future

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Keywords: Water resources; climate change; probabilistic decision-making; risk; weather generator; robustness analysis

Abstract

An approach for facilitating better decision-making in the face of uncertain climate change information for the UK water industry is proposed. Using probabilistic UKCP09 datasets, a robust approach for translating uncertain information into a usable and

replicable risk-based climate change impacts assessment and decision-making exercise is described. With the crossing of control curves at a reservoir acting as the key metric of water shortage risk, it is shown in a case study of the North Staffordshire WRZ that in its current set-up, the system cannot be deemed robust to climate change from the 2050s onwards. Applying demand and supply-side adaptation options to the WRZ increases the robustness of the system to varying extents, and acts as an example to show how the framework described here can be used to build up portfolios of adaptation responses based on a potentially limitless number of modelled combinations. By communicating future simulations in the way described here, a combination of different metrics of risk, be they financial or environmental, can be used to assess the modelled adaptation options, allowing for optimisation of the WRZ. Although the next logical step from this research is to apply further socio-economic uncertainties to the modelling set-up, the assessment of climate change impacts on the robustness of water resources alone is crucial given the requirements made of England and Wales water companies to react to the threat of climate change explicitly.

APPENDIX B: SPATIALLY-AVERAGED UKCP09 DATA

Spatially-averaging the UKCP09WG data acts as a trade-off between increasing the amount of physical space represented by the information and the accuracy of that information. When selecting more than one grid square, or ‘point’, the group of squares selected are still considered as one point by taking the spatial averages of the means, standard deviations and inter-variable relationships of the individual grid squares (Jones *et al*., 2009). This clearly means that great care should be taken in interpreting these results should those averages be substantially different (i.e. climatological conditions are not homogeneous over the area that is selected).

Synthetic weather sequences for the entire North Staffordshire WRZ are not required as only the north-eastern section of the WRZ contains the sub-catchments that influence the reservoir (the area shaded purple in Figure 3.2), and the groundwater resources in the remainder of the WRZ are assumed to be impervious to drought conditions (Figure 3.11, a schematic of the WRZ, shows the approximate positions of these sites in relation to the reservoir and Stoke-on-Trent). Therefore the area selected as a ‘point’ for validation is shown in Figure B1. This selection is well within the 1000km^2 limit that is described in the UKCP09WG Online WG Report (Jones *et al*., 2009), yet is topographically heterogeneous so would be expected to have substantially differing precipitation regimes (Figure 3.3).

Figure B2 shows the validation of the spatially-averaged UKCP09WG simulations in terms of average rainfall, variability of rainfall and number of dry days per month. Being a spatially-averaged sequence, the simulated weather statistics at each catchment are identical, and therefore are shown only once, with the statistics from the relevant instrumental sequences overlain. It can be seen by the eye that the performance of the spatially-averaged WG baselines in reproducing past precipitation statistics is unsatisfactory. It is intuitive that the upland catchment, UC, is too dry, and the lowland catchment at DHY, too wet. Statistics at SOL are closer to the correct values by virtue of being between UC and DHY geographically, but remain unsatisfactory.

It is therefore clear that spatially-averaging the WG information across the three sub-catchments in the North Staffordshire WRZ does not provide a useful representation of the instrumental period. As a result, there would be no confidence in the future simulations, meaning a different approach must be sought (Section 3.6)

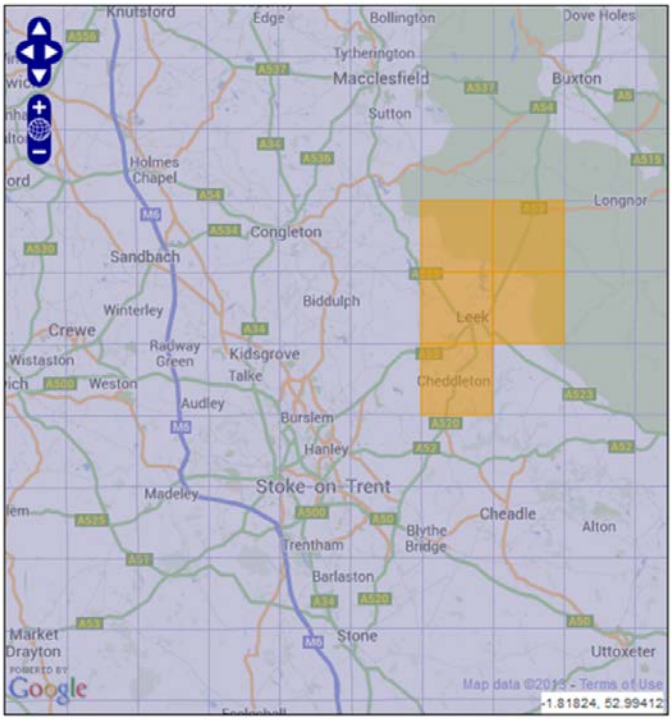

Figure B1. Screenshot from http://ukclimateprojections-ui.defra.gov.uk/ showing the grid-squares selected for the spatially-averaged WG simulations. Tittesworth Reservoir can be seen within the selected area.

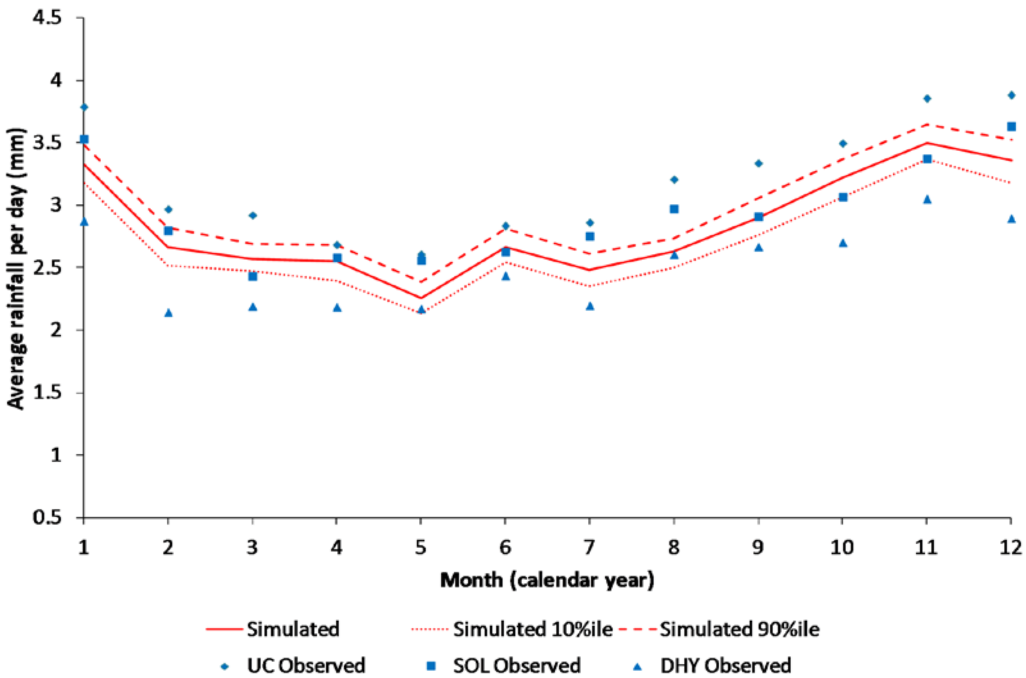

Figure B2. Average precipitation statistics for spatially-averaged WG baseline (1961-1990) simulation (red lines). Observed statistics for Upper Churnet, Solomon's Hollow, and Deep Hayes are overlain. It can be seen that spatially averaging UKCP09WG to cover all three sub-catchments produces unmanageable errors.

APPENDIX C: STANDARDISED PRECIPITATION-EVAPOTRANSPIRATION INDEX

The Standardised Precipitation-Evapotranspiration Index (SPEI), a drought monitoring tool based on climatic indices, is used to show the 12-month drought severity at Tittesworth Reservoir from 1902-2009 (Figure C1) (Vicente-Serrano *et al.*, 2010). The SPEI builds on the widely-used Standardised Precipitation Index (SPI; McKee *et al.*, 1993) by incorporating the influence of temperature on drought periods. This is clearly an important development given the increase in global temperature in the instrumental record and in projections for the future. The tool allows an entire time series to be normalised, so the extremity of each drought event can be analysed. Negative values indicate dry periods, whilst positive values show wet periods.

It can be seen that there is a movement towards more frequent 12-month drought events through the 20th and early 21st century at Tittesworth Reservoir. The 1961-1990 control period, highlighted in green, also shows a trend towards increased 12-month drought conditions. This departure can be explained by higher climate change-induced average temperatures increasing the possibility of large PET values that act to exacerbate a drought brought about by low precipitation rates.

The SPEI is not used in the analysis of future events as each UKCP09WG future time series is climatically stationary rather than transient (Jones *et al.*, 2009), so the monthly SPEI values are only useful in relation to the rest of that particular time series (where the climatic forces acting on temperature, PET and precipitation are consistent over time) rather than a baseline or other future time series. Instead, an overall aridity index is used to differentiate between the time series (see section 3.7). However, the SPEI remains a useful tool for analysing the extent to which the North Staffordshire WRZ has already been affected by changes to climate conditions, and such analyses can be used to judge the vulnerability of other WRZs in order to inform decisions on whether full climate change impact assessments are necessary. Should transient WG technology become readily available (such as Burton *et al.*, 2010; Blenkinsop *et al.*, 2013), the use of the SPEI and other such PET-inclusive drought metrics would become viable (or indeed ideal) for water shortage assessments such as this research.

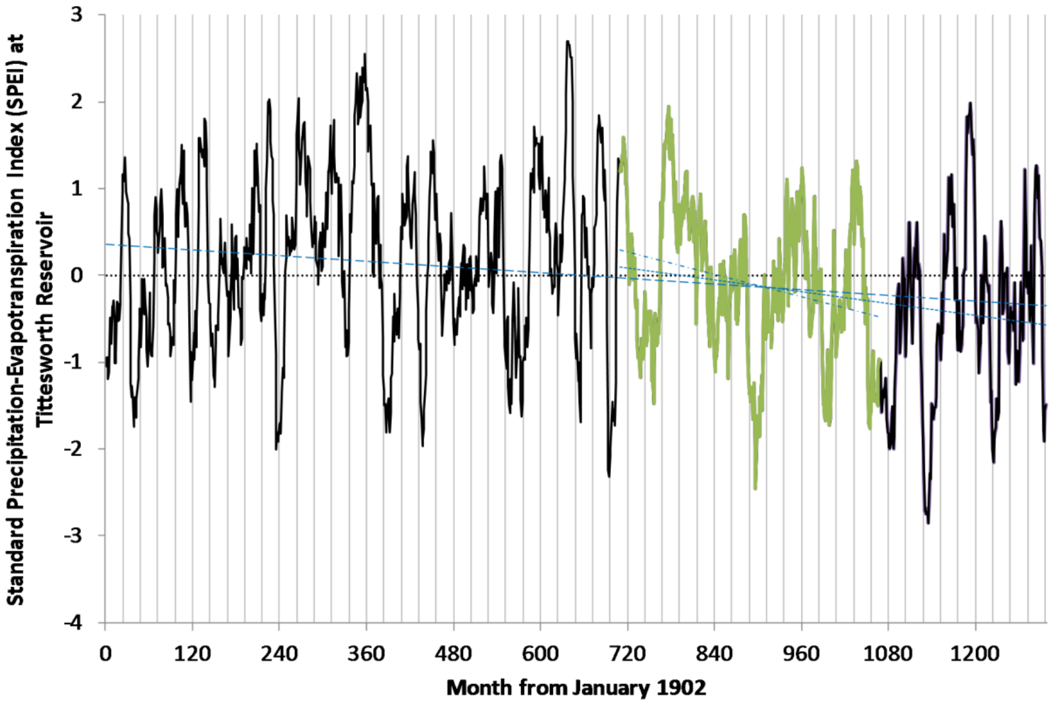

Figure C1. 12-month Standardised Precipitation-Evapotranspiration Index (SPEI) chart for Tittesworth Reservoir over the period of 1902-2009. A linear trend-line for the entire period shows a movement towards more frequent drought conditions over time (blue long-dashed line). Trend-lines showing increased aridity throughout the 1961-1990 baseline period (blue dash-dot line) and from 1961-2009 (blue short dash line) are also shown. The aridity trend for 1961-2009 is particularly relevant given the anthropogenically-influenced local and global temperature increases over this period.