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A water grid for the UK

By

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A Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Civil Engineering

March 2017

Newcastle-upon-Tyne

England

UK

Abstract

The water supply infrastructure systems of the UK depend on a number of sources of water vulnerable to the impacts of climate change; however, the extents of these impacts on the performance of the water supply infrastructure systems are highly uncertain. While contemporary analyses exist, they are inappropriate for the projection of impacts and the supporting of decision-making at large spatiotemporal scales.

This study appraises existing analyses of the impact of climate change on the water resources of the UK through a review of existing data and methods, addressing them via the development of a powerful probabilistic modelling framework. Consisting of models of climate variables, hydrology, and water supply infrastructure, the framework is suitable for the simulation of current and projected future water resource infrastructure systems under uncertain future conditions and at relevant strategic spatiotemporal scales. The study yields probabilistic projections of meteorological, hydrological and water resources drought severity, frequency and duration, and demonstrates the framework in a performance comparison between the existing configuration and the same system augmented with a ‘Water Grid’ facilitating the sharing of water resource.

This study makes several conclusions. Firstly, that existing models of the impacts of climate change on the water supply infrastructure system of the UK are inadequate, restricted in their fitness for purpose by their roles within the prevailing regulatory framework and the data and methods available. Secondly, the UK is likely to experience progressively fewer meteorological drought events of shorter duration and increased severity, resulting in substantial reductions in river flows both on average and at the 5th percentile, and leading to substantial increases in water resources drought severity and duration over the 21st Century not wholly mitigable in the east and south of England via inter-basin transfers from Wales and the midlands.

Acknowledgements

Firstly, I would like to thank Chris Kilsby for his supervision, support, and friendship throughout the accomplishment of this research, and Hayley Fowler for her involvement in the early months of my PhD.

Secondly, I would like to thank my family. Their extended love, emotional (and, occasionally, financial) support, patience, and understanding, gave me the strength to bear this Heraclean labour.

Finally, special thanks to Freya. Your grace illuminates me.

Statement of authentication

The work described in this thesis is my own; where I discuss the work of others, I have appropriately made reference to this. I would like to thank Vassilis Glenis for administering execution of the UKCP09 Weather Generator. I am the sole author of this thesis.

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Glossary of terms, abbreviations and acronyms

A priori	From before or from the former
Albedo	The diffuse reflectivity or reflecting power of a surface
AOGCM	Atmosphere-ocean GCM
ASCE	American Society of Civil Engineers
BGS	British Geological Survey
CCWater	Consumer Council for Water
CDF	Cumulative Distribution Function
Ceteris paribus	With all else remaining constant
DEFRA	Department for Food, Agriculture & Rural Affairs
Dry year	A period of low rainfall and unconstrained demand, after Environment Agency *et al.* (2012)
DSI(m)	The m-month index of drought severity
DWI	Drinking Water Inspectorate
EA	Environment Agency of England & Wales
Et alia (*et al.*)	And others
FDC	Flow Duration Curve
GA	Genetic Algorithm
GB	Great Britain
GCM	General Circulation Model *or* General Climate Model
GHG	Greenhouse Gas
IBT	Inter-basin transfer
ICE	Institution of Civil Engineers
IPCC	Intergovernmental Panel on Climate Change
MAM(d)	The mean of the d-day annual minima
MCDM	Multi-Criteria Decision Making
MCMC	Markov-chain Monte-Carlo
MME	Multi-model Ensemble
NRFA	National River Flow Archive
NWL	Northumbrian Water Limited
Ofwat	Water Services Regulation Authority
PDF	Probability Distribution Function
PPE	Perturbed Physics Ensemble
PWS	Public Water Supply
Q(95)	The discharge exceeded by 95% of observations, i.e. the 5th percentile
Q(99)	The discharge exceeded by 99% of observations, i.e. the 1st percentile
RCM	Regional Climate Model
SAAR	Standard Average Annual Rainfall
SEPA	Scottish Environment Protection Agency
SRES	Special Report on Emissions Scenarios
SW	Scottish Water
Target headroom	A buffer between water supply and demand designed to

	encapsulate specific uncertainties, after Lawson *et al.* (1998), Carnell *et al.* (1999) and Chadwick and Thomas (2002)
TWL	Thames Water Limited
UK	The United Kingdom of Great Britain and Northern Ireland
UKCP	United Kingdom Climate Impacts Project
UKMO	United Kingdom Met Office
UU	United Utilities

1 Introduction

1.1 Chapter outline

This chapter introduces the theme of this thesis, and summarises its aims and objectives.

1.2 Introduction

The UK possesses a complex network of interacting infrastructure systems that facilitates the impoundment, transport, appropriation and treatment of water for the purposes of public water supply (e.g. Ratnayaka *et al.*, 2009). It depends critically upon withdrawals from sources of freshwater, many of which are unsustainable or only marginally sustainable at current and projected future rates of consumption and availability (Environment Agency, 2008; Environment Agency, 2011a). Indeed, current trends imply a progressive diminution in the buffer between the demand for water services and the quantity of water available to meet that demand (the 'target headroom'): the annual average quantity of water available to meet supply in a period of low rainfall and unconstrained demand (a 'dry year' (Environment Agency *et al.*, 2012)) has fallen continually over the period 2005-2010 (HM Treasury and Infrastructure UK, 2011), and may reduce significantly under future climate conditions (Charlton and Arnell, 2011; Environment Agency, 2011a), while the population of the UK, and the corresponding demand for water services, may well increase under a range of plausible socio-economic scenarios (Environment Agency, 2011a; The Futures Company, 2012). Cave (2009) is among those authors (e.g. Environment Agency, 2011a; Institution of Civil Engineers, 2012) that suggest that, in the absence of wide-ranging changes to system configuration, operation, and/or regulation, this apparent imbalance between the quantity of water available to meet demand and the demand for water services may lead to an increase in the severity and frequency of water shortages, and a corresponding decrease in the reliability of the water supply infrastructure system and its resilience to water resource scarcity. The consequent competition for increasingly scarce water resources may also lead to exacerbated, possibly detrimental, wide-ranging stresses on the environment (Defra, 2012; Rance *et al.*, 2012).

At present, the impacts of "severe" water stress are limited to the south and east of England (Environment Agency and National Resources Wales, 2013); however, the

Environment Agency (2011a) and the Institution of Civil Engineers (2012) warn of similarly exacerbated water stress emergent in the north and southwest of England and the west of Wales by the 2050s. Together with the UK Government (2011), these parties recommend a coherent and scalable strategy to manage increasing water stress that combines measures that improve the efficiency of water use, and thus mitigate the impact of population growth on the demand for water services, with the development of new sources of water and more optimal redeployment of pre-existing water resources that increase the apparent quantity of water available for use in regions of severe water stress.

Opportunities for the development of new sources of water and the enhancement of existing resources are limited by hydrological and land-use constraints, while opportunities for optimal redeployment of water resource and improved strategic operational practices are limited by the composition of the water supply infrastructure system as a collection of distinct regional networks with limited and carefully regulated interconnections. Cave (2009), however, notes that the majority of consumers of water services depend on a minority of these regional networks, many of which are adjacent to one another, and highlights the consequent opportunity for greater integration of the water supply infrastructure system of the UK across the physical and organisational boundaries that separate adjacent regional water supply infrastructure networks.

Despite having long been considered a feasible mechanism for meeting anticipated growth in the demand for water services (National Rivers Authority, 1994; The Royal Academy of Engineering, 2011), there have been few incentives to encourage studies that suitably evaluate the impact of the widespread implementation of strategic, interconnected water transfers (a.k.a. a 'water grid') on the water security of the UK over an extended planning horizon (Cave, 2009), and the long-term costs and benefits of such transfers remain uncertain (Institution of Civil Engineers, 2012). The limitations of the few studies that do exist include representations of the relationships between climate and water resource that eschew simulation of physical processes for statistical proxies, under representation of the full range of uncertainties inherent in climate change projection, and short planning horizons (e.g. Environment Agency, 2006a; Environment Agency, 2011a; Rance *et al.*, 2012).

This investigation aims to address these limitations by constructing a coherent, nationally consistent model of the impact of climate change on water resources. It uses a chain of models that links probabilistic climate change projection outputs (Jones *et al.*, 2009b) to simulation models of water supply infrastructure systems by way of simulation of hydrological processes. This preserves the nonlinear effects of climate and weather on soil moisture, groundwater recharge, and, thus, the quantity of water available to meet demand as constrained by hydrology and infrastructure, such as reservoirs, whilst accounting for a broad range of uncertainties arising from climate change projection. By driving simulation models of hydrology and water resource with probabilistic climate change projection outputs, this methodology facilitates the compilation of probability distributions of metrics of meteorological, hydrological and water resources droughts over a forecast horizon representative of the 21st Century.

1.3 Aims and objectives of this thesis

1.3.1 Aims

A1. Quantify the impact of a water grid on the performance of the public water supply infrastructure of the UK in the context of an uncertain future climate, improving prevailing methodologies from the perspectives of climate model uncertainty and national-scale consistency.

A2. Quantify the impact of climate change on indicators of meteorological, hydrological and water-resources droughts in the context of methods and data arising from the pursuit of Aim A1.

1.3.2 Objectives

O1. Review existing relevant climate, hydrological and infrastructure data and methodologies and identify opportunities for improvement from the perspectives of climate model uncertainty and national-scale consistency.

O2. Design a modelling framework capable of representing the water supply infrastructure system of the UK, in consideration of the findings of the review.

O3. Implement the modelling framework such that it is representative of the public water supply infrastructure system of the UK, subject to the available data.

O4. Quantify and compare the impact of climate change on the performance of the public water supply infrastructure system of the UK in both the absence and presence of a water grid.

1.4 Scope and structure of this thesis

This thesis, while considering the water supply infrastructure system of the UK, and, in particular, the integration of some or all of this system via a 'water grid' does so to the exclusion of Northern Ireland. As it focuses solely on the UK, it will primarily review studies of historical and future climate, hydrology and water resources relevant to the UK.

It reviews the data and methods prevalent in the determination of the water available for use from the public water supply infrastructure system, identifies deficiencies in these data and methods as far as the modelling of inter-basin transfers and climate change are concerned, and proposes and executes a more suitable methodology.

This chapter introduced the theme of this study, and summarised its aims and objectives.

§2 reviews the historical records and future projections of climate variables, hydrology and water resources and public water supply infrastructure available in the UK and the methods used to construct them. This includes the organisational and physical structure of the public water supply infrastructure system, and the anticipated stresses on the system that result from changing demand and resource availability. The chapter concludes with the presentation of a methodology for the national-scale assessment of the impacts of climate change using probabilistic projections of climate variables.

§3 describes the construction of time-series of synthetic spatially coherent projections of climate variables.

§4 outlines the structure of a simple hydrological model suitable for simulation of mean daily discharge per unit area from the output from §3.

§5 presents a network model of the strategic assets of the water supply infrastructure system of the UK that has the capacity to represent major abstractions from rivers, groundwater and reservoirs, reservoir storage, desalination, effluent recycling, transfers and environmental flows.

§6 discusses the studies presented in §3, §4 and §5 holistically and in the context of the water supply infrastructure system of the UK as described in this section and the strengths and weaknesses of existing work summarised in §2.

2 Review

2.1 Chapter overview

This chapter presents a review of the climate, hydrological regimes and water supply infrastructure systems of the UK, the prevalent methods for the modelling of water supply in the United Kingdom, and emergent strategies.

It is specifically concerned with capturing and summarising knowledge on current and future patterns and trends across three domains: climate variables (non-extreme precipitation, temperature, and potential evapotranspiration), river flows, and water infrastructure. It focuses on spatial scales and resolutions most relevant in the determination of the water available to meet demand from the public water supply in the UK, and key water infrastructure such as abstractions, reservoirs, esoteric sources and demand.

By the end of this chapter, the reader should understand the methods used in the UK, the data available, the limitations of these methods and data, and persistent gaps in knowledge or methodology.

2.2 Climate

The UK is an archipelago situated off the western seaboard of continental Europe, between the latitudes of 50°N and 60°N, south of the polar jet stream. As such, it exhibits a typical temperate oceanic climate dominated by the prevailing westerly winds characteristic of the general atmospheric circulation at mid-latitudes, but influenced by the penetration of Arctic air into the mid-latitudes. This predominantly manifests in the migration of weather fronts across the north-western aspect of the country, and, coupled with the effects of orographic lifting and concomitant rain shadow in the leeward aspect of slopes, results in a mean precipitation gradient from the northwest of the country to the southeast, albeit with volatility and substantial seasonal variability.

Further climatic variability arises from a number of remote atmospheric drivers, including solar and volcanic forcing, the El Niño-Southern Oscillation (ENSO), the North Atlantic tripole sea-surface temperature (SST) pattern, the Quasi-Biennial Oscillation (QBO), and the Atlantic Multi-Decadal Oscillation (AMO) (e.g. Folland *et al.*, 2015). A related indicator long considered influential on UK rainfall, the North Atlantic Oscillation (NAO) is a metric of the relative strengths of the semi-permanent centres of low and high atmospheric pressure located over Iceland and the Azores, respectively, which influence the strength and direction of the mid-latitude westerlies. If the pressure difference is large (a 'positive' NAO), the westerlies are strengthened, which results in cool summers and mild, cloudy, wet winters in the UK. If the pressure difference is small (a 'negative' NAO), the influence of westerly airflows is lessened, resulting in increased volatility arising from conflux between dry air from Eurasia travelling from east to west over northern Europe and moist air from the Atlantic Ocean, including the formation of anticyclones that 'block' the motion of weather systems, leading to long dry periods. Either state can persist for many months. As such, the 'negative' phase of the NAO has been linked with drought events observed in the UK and northwest Europe; however, direct attribution of droughts to NAO and/or other atmospheric drivers is challenging (Todd *et al.*, 2013).

The remainder of this section focuses on a description of climate variables most pertinent to water resource, available data, historical trends, and future projections. For more detailed description of the climate of the UK in the context of the global climate system, see, for example, Barrow and Hulme (2014) or Mayes (2013); see also Hurrell (2003) for a more detailed analysis of the NAO.

2.2.1 Historical

On average, the UK receives some 263 400 $\times 10^6$ m^3 of precipitation each year, equivalent to around 1 080 mm per unit area, of which some 60%, or 157 550$\times 10^6$ m^3, leaves the land surface as runoff (Centre for Ecology and Hydrology (Wallingford) (CEH), 2004; Centre for Ecology and Hydrology (Wallingford) (CEH), 2007). There is a considerable precipitation gradient from the northwest to the southeast in response to orographic forcing and prevailing climate conditions: Wales, western Scotland, northwest England and southwest England receive very much more precipitation than the rest of the country: mean annual precipitation, for example, ranges from 500 mm to 4 000 mm (Jenkins *et al.*, 2008).

The United Kingdom possesses a substantial network of meteorological instrumentation that records observations of a number of climate variables (UK Meteorological Office, 2012). Despite being the principal source of information about climate and weather in the UK, inconsistencies in measurement between stations over time limit the usefulness of comparison of observations between sites (Perry and Hollis, 2005b; Perry *et al.*, 2009). The Met Office therefore produces several value-added products derived from the raw data that provide a quality-assured, homogeneous basis from which to proceed.

Computed from a subset of stations representative of nine sub-regions of the UK (Alexander and Jones, 2001), or, more recently, gridded observations (Simpson and Jones, 2012), HadUKP focuses on providing a long baseline for the analysis of monthly precipitation for England and Wales from 1766, sub-regions of England and Wales from 1873, and sub-regions of Scotland and Northern Ireland from 1931. Jenkins *et al.* (2008) apply linear regression and the Mann-Kendall tau test (Sneyers, 1990) to these data to analyse long-term trends in precipitation across the UK, and, in agreement with Jones and Conway (1997), conclude that there has been no significant change in annual average precipitation across England and Wales for the period 1766-2006, but, while winter precipitation increased in all regions of the UK, summer precipitation decreased in all regions except northern Scotland and northeast England. A complementary study by Mills (2005) also echoed the findings of trends towards wetter winters and drier summers; however, the low spatiotemporal resolution and poorly defined spatial representation of HadUKP limit the suitability of these data to studies at sub-regional scale.

Similarly, the Met Office Historical Central England Temperature (HadCET) dataset (Parker *et al.*, 1992) uses observations of air temperature from a different subset of weather stations to provide a long baseline for the analysis of monthly mean temperature and daily mean temperature. Although this dataset provides daily observations from 1772 to the present and monthly observations from 1659 to the present, the observations are valid only for a triangle enclosed by Lancashire, London, and Bristol, and require further transformation to be applicable elsewhere. Despite this limitation, Jenkins *et al.* (2008) use HadCET and a dataset derived from Jones and Lister (2004) to demonstrate a positive trend in mean annual temperature across central England, Scotland, and Northern Ireland.

The interpolation of observations of climate variables to a regular grid (Perry and Hollis, 2005b; Perry and Hollis, 2005a; Perry *et al.*, 2009) provides the most flexible and consistent basis for the use of observations of climate variables recorded by the UK Met Office meteorological instrumentation network. Perry (2006) and Jenkins *et al.* (2008) use these data to examine spatiotemporal trends in a range of climate variables for the periods 1914-2004 and 1914-2006, respectively. They reach broad agreement with Jones and Conway (1997) that there has been no statistically significant change in average annual precipitation, but that some seasonal changes, such as decreases in summer precipitation, increases in spring precipitation in West Scotland, and increases in winter rainfall since 1961, are significant. Both studies also exhibit similar trends and significance of trends in maximum, minimum, and mean daily temperature, finding increases in these quantities over the study period that are of particular significance towards the end of the 20th Century. Both Perry (2006) and Jenkins *et al.* (2008) report mostly statistically significant decreases in air frost across the UK, the former also showing more variably significant decrease in snow cover, as well as spatially variable increases in sunshine and vapour pressure, this being concomitant with changes in relative humidity presented by Jenkins *et al.* (2008). Both studies show little to no change in mean sea level pressure. Finally, the National River Flow Archive adapts these data to maintain a database of monthly rainfall totals averaged for each river catchment monitored by the organisation (Centre for Ecology & Hydrology). While suitable for use in the context of hydrological studies, the spatial coverage of these data limit their use in more general studies. In addition, the only variable available from this source is precipitation: thus, additional transformation would be necessary to use these data with other sources on a consistent spatial resolution.

2.2.2 Future

Global Climate Models or General Circulation Models (GCMs) resolve known interactions within the atmosphere and between the atmosphere and the Earth's surface, and are the principal source of information about the possible future states of climate variables. Simulation of future climate states using a GCM requires assumption of a scenario of GHG emissions, typically associated with specific trajectories of socioeconomic development (e.g. Nakicenovic *et al.*, 2000) and their execution is computationally expensive, necessitating management of the parameterisations, spatiotemporal resolutions and domains of GCMs in order to facilitate the computation of sufficiently informative ensembles of models exploring multiple possible futures on limited computing resources and in timely fashion. However, ensembles of GCMs tend to consist of relatively few members, giving rise to significant uncertainty in model structure, GHG emissions, and natural variability. In addition, GCMs are typically unable to reproduce regional-scale phenomena, meaning that their outputs are unsuitable for direct application in the assessment of the impact of climate change on water resource at sub-continental scales without further transformation, which entrains further uncertainty (e.g. Fowler *et al.*, 2007; Maraun *et al.*, 2010). Soundharajan *et al.* (2016) and Peel *et al.* (2014) are among those authors using ensembles of GCM outputs to project the impacts of climate change on water resource system performance, albeit on very different spatial scales to those relevant to the UK, such as global-scale.

UKCP09 (Murphy *et al.*, 2009) is a suite of data products that facilitates detailed climate-change impact assessment in the UK at high spatiotemporal resolution. The methodology quantifies uncertainties arising from natural variability, GCM structure and future GHG emissions probabilistically, which is to say that it assigns a probability to possible climate futures in order to facilitate inference of the probability of climate change being more or less than a specified value. As such, it is a significant improvement over its predecessor, UKCIP02 (Hulme *et al.*, 2002), which, being built upon an ‘ensemble of opportunity’, offers a more limited treatment of uncertainty. The UKCP09 weather generator (Jones *et al.*, 2009a) is an interface to the probabilistic data product that synthesises statistically plausible daily time-series of precipitation and climate variables correlated with precipitation, such as maximum air temperature, minimum air temperature, and potential evapotranspiration. Series are consistent with underlying climate projections whilst preserving relationships between climate variables established from historical observations. The weather generator has the capability to generate statistically equivalent daily time-series of length 30-100 years centred on a quasi-stationary multi-decadal average for a point location assumed representative of both a 5 km cell located on a graticule aligned with the OSGB National Grid and/or a contiguous set of up to 40 such cells. Each series uses information from only 100 of 10 000 model variants comprising the probabilistic projections (note that this number of model variants differs from the maximum stated in Jones *et al.* (2009a), which describes the publically available interface to the weather generator). A large number of series are therefore necessary to obtain a fully representative sample of the variability; however, each sample is independent. Adaptation of the UKCP09 methodology is therefore necessary for use of the weather generator to synthesise series of climate variables at multiple locations with spatial consistency.

It is important to note that UKCP09 uses the SRES GHG emissions scenarios (Nakicenovic *et al.*, 2000), which were superseded in part in 2013 by Representative Concentration Pathways (RCPs). RCPs disentangle scenarios of radiative forcing from scenarios of socio-economic growth (van Vuuren *et al.*, 2011). While this does not have dire implications for the validity of the scenarios underpinning UKCP09, the SRES A1B scenario mapping approximately to RCP6.0 and SSP2, for example (van Vuuren and Carter, 2014), it must be said that, despite being the most detailed suite of climate projections available for the UK during the construction of this study, UKCP09 cannot be said to be ‘up-to-date’ from this perspective.

A number of studies explore potential future changes in precipitation and drought. For example, Murphy *et al.* (2009) suggest that UKCP09 demonstrates little change in mean annual precipitation at the 50% level (under a medium emissions scenario), but find changes of up to -16% at the 10% level, and up to +14% at the 90% level by the 2050s, with no clear pattern emerging. Under the same conditions, these data suggest that changes in mean winter precipitation are very unlikely to be less than -11% and very unlikely to be more than 70%, while changes in mean summer precipitation are very unlikely to be less than -65% and very unlikely to be more than 10%. The largest increases in mean winter precipitation and the largest decreases in mean summer precipitation are located in the southeast and southwest of England. A number of authors make use of the HadRM3-PPE-UK 11-member RCM ensemble. Rahiz and New (2013), for example, found 'profound' and 'widespread' increases in drought characteristics in the 2050s and 2080s, with a tendency towards droughts of longer duration and an inverse relationship between drought frequency and drought duration. Burke and Brown (2010), similarly using HadRM3, reported increasing severity of drought in the latter half of the 21st Century, but that this was difficult to distinguish from natural variability. Finally, Burke *et al.* (2010) use a different treatment of the same climate model outputs to show an increasing drought occurrence throughout the 21st Century, depending on the drought index used, the HadRM3 ensemble member, and location. In their analysis of GCM outputs, Vidal and Wade (2009) focused on precipitation as an indicator of drought, and found an increase in short, severe droughts of three to six months' duration across the majority of the UK, and in long-term droughts in southeast England, but a decrease in long-term droughts in Scotland.

2.3 Hydrology and water resource

The UK is an island country, and, as such, does not receive runoff from any adjacent landmass. All naturally occurring freshwater in the rivers, lakes and groundwater in the UK therefore derives only from precipitation incident to the land surface, and the quantity of freshwater available to meet demand is equal to the volume of precipitation input less the volume of losses, which are determined by atmospheric energy budget, land-use, soil type and geology.

Characterisation of the historical and possible future distributions of the consequent hydrological regimes present in the UK has been, and continues to be, an active area of research. This section reviews the range of observations and measurements of hydrological behaviour and water resource available for the UK.

2.3.1 Historical

The UK has a dense network of hydrometric instrumentation measuring river flow and groundwater levels across the country (Marsh and Hannaford, 2008). The National River Flow Archive collates and archives data from this network, which suggest that the hydrologically effective rainfall that constitutes an input to rivers and groundwater is around 406×10^3 Ml/d annually (Centre for Ecology and Hydrology (Wallingford) (CEH), 2004), equivalent to some 7×10^3 l/h/d at 2010 population levels (ONS, 2011a), and that the spatial distribution of mean annual runoff broadly correlates with that of precipitation (European Environment Agency, 1999).

Hannaford and Marsh (2006) identified positive trends in observed runoff, most significantly in maritime catchments with a western aspect, with little evidence for change elsewhere. This is visualised by Stahl *et al.* (2010) who identified a tendency towards progressively greater winter river flow across the UK, partially offset by a negative trend in summer months and more variable change in spring and autumn months, leading to many catchments in the UK exhibiting a net positive change in runoff over the latter half of the 20th Century. Although cumulative deficits in precipitation, and concomitant droughts, have been infrequent during the period of available observations; however, there is a clear relationship between drought and low winter rainfall and/or groundwater recharge (Marsh *et al.*, 2007; Burke *et al.*, 2010).

Aggregated data from the Centre for Ecology and Hydrology (2004) suggest that the average proportion of incident precipitation lost through evapotranspiration is 50% in England and Wales, 30% in Scotland, and 40% on aggregate across the UK (Centre for Ecology and Hydrology (Wallingford) (CEH), 2004). Marsh and Hannaford (2008) summarise indicative losses in individual catchments that range from less than 10% of incident precipitation in the uplands of Wales, the Pennine Hills and Lake District of England and the highlands of Scotland, to over 90% of incident precipitation in the south and east of England, while Marsh and Anderson (2002) suggest that evaporation losses account for 60% of mean annual precipitation in eastern Scotland. This equates to an effective mean annual rainfall input to the land surface that ranges from less than 200 mm in Lincolnshire and East Anglia to greater than 2500 mm in southwest England, northwest England, coastal Wales, and western Scotland, albeit with substantial seasonal variability (Environment Agency, 2008; Marsh and Hannaford, 2008).

The recent review of UK-centric methods and data pertaining to evapotranspiration by Kay *et al.* (2013b) reproduces output from MORECS (Field, 1983; Hough and Jones, 1997) that broadly corroborate these indicative values, modelled using a modified implementation of the Penman-Monteith method (Monteith and Unsworth, 1990), and concludes that the few studies of potential and actual evapotranspiration in the UK lack consensus of method and indication of long-term historical trend.

The degree to which water resource is exploited is uncertain, for example: Hoekstra and Chapagain (2008) and Yu *et al.* (2010) estimate that 30%-50% of freshwater resources are abstracted; annual withdrawal from freshwater resources is around 12×10^3 Ml in England and Wales (Environment Agency, 2012a) and 35×10^3 Ml in Scotland (Moran *et al.*, 2007), suggesting that the exploitation of freshwater resources exceeds 17%, 44%, and 31% of the total resource available in England and Wales, Scotland, and Great Britain, respectively. Ecological status is another indicator of water resource exploitation. In the first round of assessment under the EU Water Framework Directive (European Commission, 2000), over 80% of the 390 surface water bodies and 58% of the 304 groundwater bodies that contribute to water supply in England and Wales failed to achieve ‘good’ ecological status, possibly reflecting over-abstraction. Similarly, water abstraction threatens the ecological state of as many 27% of catchments in Scotland (Ioris, 2008).

In accordance with recharge rate and storage capacity, the most productive aquifers in England and Wales are found in the south and east of England, as illustrated by Downing (1993) the Environment Agency (2006b) and Grey *et al.* (1995), while MacDonald *et al.* (2005) cite formations in southwest Scotland, Fife, Strathmore and Morayshire as the most productive geological formations in Scotland. In addition, inspection of water supply service providers' published disclosures of deployable output by source type indicates that that many groundwater sources are of regional importance throughout the UK (e.g. Severn Trent Water Ltd, 2011). Downing (1993) reports an upward trend in groundwater use between 1948 and 1989 prior to the implementation of legislation designed to curtail exploitative over-mining of aquifer storage in excess of recharge capacity, while the Environment Agency (2012c) estimate that, in the period 2000-2011, abstraction from groundwater sources consistently contributed approximately 11% of all water abstracted in England and Wales, and around 30% of all water put into the public water supply of England and Wales. In Scotland, Scottish Water (2009a) estimate that water from groundwater sources constitutes only around 4% of the total water supply.

Quantities licensed for abstraction are further indicative of water resource. Between 1995 and 2005, the Environment Agency licensed an average of 46 553 abstractions per year, falling to an average of 21 964 licenses per year following partial deregulation of abstractions in 1995 (Environment Agency and Scottish Environment Protection Agency, 2010). Around 25% of licenses are in the EA Anglian region, and a further 20% are in the EA Midlands region; while other regions each contain between 7% and 11% of licenses (Environment Agency and Scottish Environment Protection Agency, 2010). Between 1992 and 2011, the Environment Agency licensed an average of 127 642 Ml/d for abstraction (Environment Agency, 2010a; Environment Agency, 2012e), equivalent to approximately 67% of the available water resource. Comparable data for Scotland are not available.

A few authors investigate trends in river flows, groundwater and associated 'hydrological' drought. In their analysis of precipitation, river flows, temperature and groundwater levels for the period 1800-2006, Marsh *et al.* (2007) described drought as a "recurring feature of the UK climate." They identified nine 'major' large-scale droughts post-1850, often associated with sequences of winters having below-average rainfall. For example, the drought of 1890-1910 commenced with four successive winters each having exceptionally below-average rainfall, followed by below-average rainfall in 11 of the subsequent 16 years – particularly in 1898, 1902, 1905 and 1909. Although they found no overall trend in the patterns of rainfall associated with extended periods of drought, or the frequency of drought episodes, the authors did report a trend towards increasing severity of drought, driven primarily by increasing temperatures. Hannaford and Buys (2012) studied 89 catchments using data collected between 1969 and 2008, and suggested a trend toward increasingly elevated river flows in autumn and winter, decreasing flows in spring, and no overall trend in summer, but noted that such trends could be strongly dependent on location and study period. This is reinforced by Hannaford (2015).

2.3.2 Future

Kay *et al.* (2013a) reviewed future projections of potential evapotranspiration for Britain, summarising some thirteen studies. The majority of such studies show increases in potential evapotranspiration, of variable magnitude, influenced by climate model, emissions scenario, time horizon, location and formulation of potential evapotranspiration employed. Furthermore, comparison of the ratio of potential evapotranspiration to precipitation indicated that east England could be particularly sensitive to the choice of formulation.

Evidence suggests that global climate change will exacerbate the natural variability of hydrological processes across the UK to an uncertain degree, with a general consensus on a pattern of elevated winter flows and depressed summer flows relative to the 1961-1990 baseline period (Environment Agency, 2011a).

In the context of global or continental-scale studies, Milly *et al.* (2005), Alcamo *et al.* (2007) and Dankers and Feyen (2009) are among those authors whose results suggest increases in annual average discharge relative to the baseline period across the UK (e.g. European Environment Agency, 2012). Rojas *et al.* (2012) present results supporting this interpretation, which, in addition, suggest relative increases in average winter (and, to a lesser extent, spring and autumn) river discharge across the UK by the 2080s, widespread decreases of a lesser magnitude of the same quantity in summer for the same period most acute in southern and central England, and progressive diminution of minimum river flows over the 21st Century, most notably in Scotland, Wales and northern England.

Relevant contemporary studies scoped specifically to the UK paint a similar picture. For example, Prudhomme *et al.* (2012) show broad increases in mean winter flow and decreases in mean summer flow across the UK, relative to the 1961-1990 baseline; however, changes in spring and summer flows are mixed, showing no clear trend or apparent clustering of changes in mean flow. This is consistent with the implications of earlier studies such as those by Sefton and Boorman (1997), Pilling and Jones (1999), Arnell and Reyard (1996), Limbrick *et al.* (2000) and Arnell (2003b).

Projection of climate-change impacts on groundwater systems alone are less numerous. Herrera-Pantoja and Hiscock (2008) and Jackson *et al.* (2011) are among those few studies that focus on groundwater recharge, baseflow, or groundwater levels. Using dissimilar methods and source data but similar emissions scenarios, both studies suggest a shortening of the winter recharge season and reduced annual-average groundwater recharge. Herrera-Pantoja and Hiscock (2008) reported changes in annual potential groundwater recharge of -40%, -20%, and -7% by the 2080s for locations in southeast England, East Anglia and western Scotland, respectively. For a similar forecast horizon, the multi-model ensemble method of Jackson *et al.* (2011) found changes in annual average groundwater recharge ranging from -26% to +31% and changes in river baseflow of between -16% and +33% in March and -68% to -56% in October across multiple catchments in central-southern England sharing the same aquifer. Citing Jackson *et al.* (2015), Watts *et al.* (2015) report that no link has been found between anthropogenic climate change and UK groundwater levels, i.e. that there is insufficient evidence to attribute observed changes in groundwater levels to climate change.

The design of each of these studies, while appropriate for the research questions addressed, exhibits one or more limitations or design choices that limit the applicability of their output data and/or methods to a national-scale study of the UK's water resource and the research questions addressed by this thesis.

Firstly, although large-scale studies such as Milly et al. (2005), Alcamo et al. (2007) and Dankers and Feyen (2009) encompass the spatial extent of the UK, they do so at a resolution too coarse to resolve differences in hydrological quantities affecting sources of water at an appropriate scale. Secondly, and conversely, comparatively high-resolution studies like Limbrick et al. (2000), Herrera-Pantoja and Hiscock (2008) and Jackson et al. (2011) project impacts only for relatively small areas of the UK. Thirdly, the data and methods used by some studies (Prudhomme *et al.*, 2012) are either inconsistent or unable to represent nonlinearities in hydrological processes. Finally, all studies use an 'ensemble of opportunity', and therefore present an incomplete or downright incoherent representation of the uncertainty arising from climate change projection.

2.3.3 Modelling approaches

Assessment of the impacts of projected climate change on the availability of water resource for human use requires quantification of, and comparison between, the likely spatiotemporal distributions of total water resource in the natural environment both presently and in the future. The primary determinant of these distributions is the complex interaction between the atmosphere and the land surface (e.g. Houghton, 2002). Complete representation of this interaction with total certainty is presently impossible; however, there is an expansive and diverse literature detailing myriad alternative approximations, or models, that transform observations of climate variables into observable components of water resource, such as river flow.

In essence, there are two modelling approaches: simulation and stochastic. The first characterises the response of a land surface to precipitation input in terms of the physical processes observed to occur, while the second does so in terms of the relationships exhibited between, say, precipitation input to a land surface and the discharge of liquid water observed in response, directly and without explicit physical basis. The former is perhaps more suitable, therefore, to the projection of climate change impacts due to the explicit physical basis of its constituents, on the assumption that the physical processes that determine hydrological response in a given model are unlikely to change over the study period.

Simulations models lie on a spectrum defined by the level of detail engendered by their structure, which correlates broadly with data requirements and computational requirements, i.e. the more physically representative models required highly detailed observations of a wide range of input data, and take a long time to execute, while the least physically representative, more ‘conceptual’ models require fewer, less detailed, observations of input data, and execute in a relatively short time. The primary strength of probabilistic climate change impact projection is the capacity to execute many models; thus, there is clearly the need to err on the side of the latter in this context. As a result, studies integrating hydrological simulation with the generation or application of probabilistic climate change projections do so via 'conceptual' models executed at coarse spatiotemporal scales. Examples include PDM (Moore, 2007; Prudhomme and Davies, 2009), Catchmod (Wilby and Harris, 2006; von Christierson *et al.*, 2012), and ARNO (Todini, 1996; Fowler *et al.*, 2008). The detailed review by Franchini and Pacciani (1991) serves to illustrate some of the similarities and differences that exist between many of the popular conceptual hydrological models, and the variability that exists in the physical basis of models' representation of, for example, groundwater storage.

There is no 'optimal' choice of model: this decision must follow the performance of a model in the specific circumstances of its intended application (Loucks *et al.*, 2005), although it is important to account for specific processes, such as aquifer storage and discharge and snow accumulation and ablation, where they occur. Within the context of climate change impacts projection, the skill of a model in reproducing statistics of the observed hydrological regime is a typical metric of its suitability. A further concern is of the capacity of the model to project anticipated changes to those statistics, as represented by climate model outputs, robustly, without failure or violation of the concepts and assumptions that underpin the model, and without requiring unreasonable confidence in the specification of a model formulation that is clearly approximate.

As this study focuses on the development of a nationally consistent methodology for the simulation of the hydrological processes that determine the quantity of water available to meet demand via the public water supply of Great Britain, it is reasonable to implement a hydrological model that represents the physical processes, such as evaporation, known to influence the behaviour of hydrological regimes occurring in the country and to test model skill against quantities thought authoritative in the management of water resource, such as mean flow, the flow exceeded in 95% of observations (Q95), and the total volume of water discharged from a land surface in a specified period.

Given that evaporation drives the surface hydrology of the UK, it is reasonable to choose a model structure that represents the balance of moisture in the soil that constitutes much of the land surface in terms of precipitation input to a soil moisture store and water lost from the soil moisture store via evapotranspiration, lateral flow, and percolation (e.g. Wood *et al.*, 1992; Liang *et al.*, 1994; Zhao and Liu, 1995; Todini, 1996; Todini, 2002); however, regional variation of low river flows and groundwater yield indicate considerable sensitivity to subsurface processes, while river flows in some regions are sensitive to seasonal disruption due to snow accumulation and ablation. Additional model components are necessary to account for these processes.

2.3.4 Modelling aquifer storage and discharge

Water from boreholes and springs constitutes approximately one-third of abstraction for public water supply, equivalent to around 15% of all water abstracted in the UK (e.g. Grey *et al.*, 1995; Burgess, 2002). Groundwater occurrence is dependent on the existence of certain geological formations that are not present uniformly across the UK, limiting the potential for its exploitation in a national water resource strategy (e.g. Grey *et al.*, 1995; Downing, 2004; MacDonald *et al.*, 2005); however, groundwater is of regional importance across central, south and east England (e.g. Thames Water Utilities Ltd, 2009; Anglian Water Services Ltd, 2010; Severn Trent Water Ltd, 2010). Although these resources have thus far been resistant to drought, the resilience of their role in stabilising low river flows and their ability to sustain direct abstraction under future climate conditions remains uncertain (Holman, 2005; Herrera-Pantoja and Hiscock, 2008).

Comprehensive evaluation of the deployable output of groundwater resources and their interaction with surface-water resources is infeasible on a national scale: it is computationally expensive and requires accurate observations of sub-surface processes and their influence on the land surface. Studies that consider the regional or national role of groundwater resources of the UK therefore focus on conceptual representations of aquifer storage and recharge, particularly when the impact of climate change is being considered (e.g. Cooper *et al.*, 1995; Henriques, 2007).

The discharge from groundwater sources is often conceptualised as a continuous but constrained 'base flow' emanating from an aquifer of arbitrary dimensions storing a volume of water recharged by percolation from adjacent water-bearing land surface.

Models such as ARNO (Todini, 1996) and HBV (Bergström, 1976; Bergström, 1992; Lindström *et al.*, 1997) assume a linear relationship between storage and discharge; however, a non-linear relationship is demonstrably superior in most circumstances, and has a physical basis in at least one case (Wittenberg, 1999). Moore and Bell (2002) describe mutually exclusive implementations of the non-linear model under assumptions that facilitate analytical solution.

2.3.5 Modelling snow accumulation and ablation

The processes that dominate the hydrological characteristics of the UK are subject to seasonal disruptions by snow accumulation and ablation (e.g. Ferguson, 1984; Ferguson, 1999; Moore *et al.*, 1999; Marsh and Anderson, 2002). Although only a second-order influence on flow regimes in the UK, snowmelt is particularly influential in the upland areas from which the country derives a large proportion of its surface water resource; thus, it demands consideration in this study. There is little precedent, however, as the paucity of studies appraising the role of snowmelt as a constituent of water resource in the UK focus on flood risk assessment rather than simulation of the broad hydrological response (e.g. Archer, 1981; Soulsby *et al.*, 1997; Helliwell *et al.*, 1998; Bell and Moore, 1999).

The spatiotemporal distribution of snow, the formation of compressed snowpack via cyclic melting and re-freezing of lying snow and the transformative impacts of freezing and thawing on infiltration and other hydrological processes exhibit extreme variability across several dimensions attributable to heterogeneities in the environment (DeWalle and Rango, 2008). Numerous models exist that are capable of resolving observed snowmelt processes at the scale of observation (e.g. Leavesley, 1989; Kirnbauer *et al.*, 1994; Tarboton *et al.*, 1995; Cline *et al.*, 1998; Luce *et al.*, 1998; Liston, 1999; Melloh, 1999); however, few areas of the UK demonstrate the causative properties that would justify the implementation of a comprehensive model of melt-water hydrology at a national scale. These are essentially characterised by elevation, and, correspondingly, air temperature (Bell and Moore, 1999).

HBV (Bergström, 1976; Bergström, 1992; Lindström *et al.*, 1997) and SRM (Martinec *et al.*, 2008) are among the long list of hydrological models that use a deterministic empirical linear relationship relating air temperature to snowmelt discharge when temperature exceeds a critical threshold. The underlying assumption that air temperature and model parameters together form an integrated index of the energy balance that drives snowmelt processes appears to perform at least as well as more detailed model structures at large spatiotemporal scales (Zeinivand and De Smedt, 2009; Karpouzos *et al.*, 2010). When thought of as a threshold temperature of phase change, there is some physical basis in the assumption of values for the critical threshold (e.g. Shaw, 1994); however, the values of other parameters derive from observational data (e.g. Martinec and Rango, 1986).

2.3.6 Model calibration and validation

The physical processes that determine hydrological behaviour are highly variable in both space and time. Their assumed and empirically informed dependence on the physical properties of flow media yield complex mathematical descriptions that require a great breadth of observational data to solve in their completeness. If sufficiently detailed observations are unavailable, or observations are altogether inappropriate, it is common practice to simplify these relationships using representative parametric models. A particular example arises when the spatiotemporal scale of simulation is sufficiently large to warrant the assumption of isotropy and homogeneity in the values of the physical properties of flow media. In this case, the parameters are metaphysical, prohibiting observation.

Where observation is impossible, it is conventional to assume that a 'correct' value of a metaphysical parameter exists, and that its value is obtainable through the optimisation of an objective function of both observational data and model data computed using candidate parameter values. Historically, hydrologists created an analogy between this process and the calibration of a scientific instrument. A scheme to 'calibrate' the parameter values of a model requires a strategy for selecting candidate solutions, observations of input variables to drive the model and an objective function that evaluates the performance of candidate solutions. Where the model represents one or more physical processes, and the objective function evaluates the model's ability to simulate these processes, the objective function requires observations of output variables as a baseline for comparison. These must be congruent with any observations driving the model. The design process is somewhat convoluted, in that decisions made regarding one aspect inevitably influence the others, although a well-designed calibration scheme should use objective functions and selection methods that exploit the constraints of a model's structure within the context of the intended application of the model, maximising the information mined from available observational data.

Practitioners of hydrological science also emphasise the importance of efficiency through parameter parsimony, accountability through repeatability, and robustness through the quantification of uncertainties.

A typical conceptual hydrological model features parametric representations of infiltration, actual evapotranspiration, interflow, percolation, aquifer storage and recharge and snow accumulation and ablation assumed representative of the dominant hydrological processes when aggregated over large spatiotemporal scales. Such models assume non-linear dependence between the output variable, e.g. mean daily discharge of water output from a unit area of foliated land surface, and input variables of climate observed simultaneously for the same day and unit area, and assumed therefore to correlate with one another and the output variable. Model states persist between observations, encouraging serial correlation of the output variable.

In this study, the intended purpose of hydrological modelling is to provide synthetic time-series of daily inflows to nationally strategic water resources for baseline and projected future climates. Model structure should be sufficiently generic to be equally applicable to any region of the UK whilst being detailed enough to capture the major differences in hydrological behaviour between regions as expressed in the values of the parameters. It follows that each region or watershed should have its own set of parameter values. These values should be robust in the sense that the model is not so finely tuned that anticipated perturbations in the input variables due to climate change cause the model to become unrepresentative of the physical processes it parameterises. This context demands that each regional instance of the model, as defined by its parameter values, should capture the daily fluctuations in mean flow relevant to the feasibility of river abstraction and the occurrence of spilling from reservoirs in the region the instance represents, whilst preserving longer-term variability in the total volume of water available for use within the region. An appropriate objective function should therefore promote the selection of candidate solutions meeting these criteria by penalising those that do not.

There is an extensive volume of technical literature regarding the design of an 'ideal' calibration scheme for use in hydrological modelling applications. Many studies compare and contrast the performance of various objective functions (e.g. ASCE, 1993; Boyle *et al.*, 2000; Krause *et al.*, 2005; Kavetski *et al.*, 2006; Moriasi *et al.*, 2007). Each possesses strengths and weaknesses that are often context-specific, and there are no definitive recommendations or conclusions applicable to a general calibration problem.

There are a profound number of publications relevant to the use of optimisation by heuristic algorithms in the calibration of hydrological model parameter values. Established meta-heuristics adapted for this purpose include the downhill simplex algorithm (Nelder and Mead, 1965; Press *et al.*, 2007), genetic algorithms (Goldberg, 1989; Holland, 1992), particle swarm optimisation (Bonabeau *et al.*, 1999; Kennedy *et al.*, 2001), simulated annealing (Press *et al.*, 2007) and shuffled complex evolution (Duan *et al.*, 1992; Duan *et al.*, 1993). As is the case with objective functions, heuristic performance varies between studies and is context-specific, and only a few direct comparisons exist (e.g. Demarée, 1982; Gan and Biftu, 1996; Thyer *et al.*, 1999; Blasone *et al.*, 2007); however, the conclusions of Madsen (2000) and Perrin *et al.* (2001) are of particular interest. The former asserts that the solution surfaces of objective functions used in the calibration of hydrological model parameters are often multimodal, and that probabilistic methods are superior to local search methods in such circumstances. The latter suggests that probabilistic methods are incapable of identifying the exact value of the global maximum efficiently in search spaces of high dimensionality. To this study, identification of the exact value of the global maximum is not as important as finding robust solutions efficiently; however, the calibration algorithm should be capable of approximating the global maximum, subject to constraints.

Genetic algorithms (GAs) are a popular and versatile global search method capable of meeting these requirements. Described summarily by Goldberg (1989) and in the updated seminal work by Holland (1992), GAs have been applied to a broad range of optimisation problems where high dimensionality and solution surface complexity prohibit more traditional hill-climbing techniques from identifying the global maximum with consistency and efficiency. Several studies apply GAs to hydrological parameter estimation problems (e.g. Wang, 1991; Franchini, 1996; Wang, 1997; Cheng *et al.*, 2006); Jain and Srinivasulu present a review (2008).

GAs consist of several sub-processes, including initialisation, selection, reproduction, mutation, evaluation, and termination. There is an almost limitless range of alternative functions supporting each of these processes from which to choose. The choice of a particular combination of functions, or their implementation, depends on the specific optimisation problem. Given the same genome and objective function, and sufficient time and numerical precision, all combinations and permutations should converge on the same result from optimisation; however, in practice, each variation affects the solution obtained. Sometimes, superior variations are obvious from inspection; more often, relative performance differences between variations are very subtle, and are difficult to classify as positive or negative without experimentation. Hybridisation of GAs with more conventional search techniques and constraint of candidate solution values can provide improved convergence rates.

The specification of an objective function strongly influences the convergence rate and applicability of any given optimisation method: the objective function must complement the optimisation method, and *vice versa*. A wide variety of objective functions suit the optimisation of the parameter values of hydrological models, many of which have been subject to numerous analyses and comparisons in the literature, without consensus on comparative performance. In consideration of these observations, it is logical to choose an objective function that is not only well suited to the optimisation problem at hand, but also sufficiently well-recognised and well-understood to enable broad acknowledgement of model performance against the wider research background; however, if calibration proceeds using a more esoteric objective function, an orthodox metric should still be output as diagnostic information for the same comparative purpose. In general, the most desirable outcome is to develop a calibration scheme that uses multiple diagnostic and objective performance metrics to avoid over-reliance on a single metric that may be unreasonably sensitive to uncertainty (Jakeman *et al.*, 2006; Bennett *et al.*, 2010).

A formal combinative solution to this integration of information across multiple performance metrics, multiple criteria decision analysis (MCDA) is itself a large field of study focused on the determination of Pareto-optimal solutions to complex multi-objective optimisation problems. Figueira *et al.* (2005) and Ehrgott (2010) provide overviews of contemporary thinking in MCDA, while Efstratiadis and Koutsoyiannis (2010) review applications of the principles of MCDA to problems in hydrology. When considering the aims of this project, the most pragmatic method of incorporating multiple criteria into the calibration process is to optimise on a scalar objective function computed as an aggregation of several relevant metrics, while additional information about the desirable minimum performance of the system is implementable as a constraint on the objective function.

For example, the Mean Squared Error (MSE) and the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) are related scalar objective functions ubiquitous in hydrological simulation. They are integrated measures of correlation, conditional bias and unconditional bias between model output and observations (Murphy, 1988). Gupta *et al.* (2009) reformulated the decomposition of Murphy (1988) to describe how models calibrated by maximisation of NSE must inevitably underestimate the observed variance of the output variable, and that exclusive use of NSE in this capacity may cultivate errors in the magnitude of model output if the observed variance is large. These outcomes support and formalise many of the empirically-based criticisms of NSE (e.g. McCuen *et al.*, 2006; Jain and Sudheer, 2008) and form the basis for the argument of Gupta *et al.* (2009) for the alternative Kling-Gupta efficiency (KGE) (Equation 1).

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \qquad \mathbf{1}$$

In Equation 1, r is the linear correlation coefficient between the observations and the model output, α is the ratio between the standard deviation of the model outputs ($\hat{\sigma}$) and the standard deviation of the observations (σ) (Equation 2), and β is the ratio between the mean of the model outputs ($\hat{\mu}$) and the mean of the observations (μ) (Equation 3).

$$\alpha = \hat{\sigma}/\sigma \qquad \mathbf{2}$$
$$\beta = \hat{\mu}/\mu \qquad \mathbf{3}$$

KGE resolves the structural weaknesses of NSE cited by Gupta *et al.* (2009), and is an aggregated objective function of the Euclidean-distance type in the context of MCDA (e.g. Madsen, 2000).

Finally, it is customary to perform validation of a calibrated model. This typically involves driving the model with a set of input variable time-series different to those used to calibrate the parameter values, and re-evaluating the model's predictive performance under these changed conditions on the assumption that a model with 'good' predictive performance in validation indicates a more generally applicable and/or transferable model. Such 'split-sample' validations are not without limitations, most notably in the comparison of performance between models (Clarke, 2008), but it provides a minimum level of confidence in the robustness of the calibrated parameter values.

2.4 Public water supply infrastructure

2.4.1 Existing

2.4.1.1 Ownership, operation and planning

A number of private companies own, operate and maintain the assets of the public water supply infrastructure network in England and Wales; Scottish Water operates a publically owned water supply infrastructure network in Scotland (OFT, 2010). Table 2.1 and Figure 2.1 summarise undertakers appointed to provide both water and sewerage services; Table 2.2 and Figure 2.2 summarise the largest undertakers appointed to provide water services only. Various appointments to provide water services using the asset networks also exist (Ofwat, 2014); of these, only Veolia Water Projects is large enough to visualise at the same scale as the larger water service providers. A small number of these companies are inter-related; for example, Essex & Suffolk Water is part of Northumbrian Water, and Anglian Water owns Hartlepool Water. These undertakers are the principal sources of data and supporting information pertaining to the present state of the public water infrastructure system of Great Britain.

Under the Water Industry Act (1991a), water undertakers in England and Wales have a statutory duty to prepare, maintain and publish a plan of "how the water undertaker will manage and develop water resources" so as to meet its obligations as described by the Act, and, in addition, a further statutory duty to similarly prepare, maintain and publish a plan as to "how the water undertaker will, during a period of drought, continue to meet its obligations to supply adequate quantities of wholesome water, with as little recourse as reasonably possible to drought orders or drought permits." Likewise, the Water Industry (Scotland) Act (2002b) obliges Scottish Water to "provide the Scottish Ministers with such information relating to the exercise of its functions as they may require," including the publication of an annual report on its activities, subject to duties to "secure the collection, preparation, publication and dissemination of information and statistics relevant to such resources and supplies," as established by the Water (Scotland) Act (1980).

As a result, each provider of public water supply services in England and Wales has a statutory duty to periodically prepare and continuously maintain a water resource management plan that demonstrates how the provider will meet the demand for water services within their zones of operation over a planning horizon of at least 25 years (Environment Agency *et al.*, 2012). Appointees in England and Wales produce a water resource plan every 5 years from 1989; Scottish Water produce plans at less regular intervals. Planning typically occurs on the spatial scale of water resource zones: the largest possible area over which all resources, including external transfers, are allocable, i.e. the area in which all consumers experience equal risk of supply failure due to resource shortfall. There are some 105 water resource zones in England and Wales (Environment Agency, personal communication), and over 200 in Scotland (Scottish Water, 2009b).

All such plans contain data and supporting tables that, to a greater or lesser extent, encode the gross attributes and operating characteristics of the assets of each undertaker at a resource-zone (and sometimes source) level, such as population, demand, leakage, and deployable output; however, both the Water Industry Act (1991a) and the Water Industry (Scotland) Act (2002b) reserve the right of the Secretary of State and/or Scottish Ministers to withhold publication of information should such information be deemed commercially confidential and/or where publication would be contrary to the interests of national security. In practice, this results in a variable level of disclosure between water undertakers, and, in most cases, incomplete information. Attributes valuable to modelling, such as the location and operating characteristics of abstractions from sources of water, are often encrypted or wholly redacted in published reports, aggregated to be un-attributable to individual sources, or omitted altogether. Requests for redacted or omitted information made under the Freedom of Information Act (2000) and/or the Freedom of Information (Scotland) Act (2002a) are subject to similar exceptions (e.g. Scottish Water, Personal Communication).

The regulators and governmental actors described in §2.4.1.2 are among those actors furnished with privileged information regarding the water supply infrastructure system under the Water Industry Act (1991a) and the Water Industry (Scotland) Act (2002b), and often publish raw data from water undertakers in addition to their own data and analyses. For example, prior to 2011, Ofwat collected information from the water undertakers of England and Wales each year on a number of key themes, many of which include data relevant to the water supply infrastructure, such as population, demand, leakage, and water available for use by source type (e.g. Ofwat, 2011). Aggregated to strategic levels, most of the metrics presented in these 'June Returns' are descriptive of the water undertaker's overall activities, but less informative of water resource at the resource-zone level. The Scottish Government publish a limited subset of similar metrics for Scottish Water on an annual basis (e.g. Scottish Government); perhaps the most comprehensive studies of these data in Scotland were published by the Scottish Development Department (1973; 1980).

Planning requires quantitative evaluation of the behaviour and performance of each component of the provider's water infrastructure, the interactions between those components, and the impacts of operational decisions, subject to a framework of assumptions concerning the desirable reliability, resilience and cost of the system. All water service providers plan for at least the 'dry year annual average' scenario, which models the performance of the water supply system subject to low flow from a dry year in combination with unconstrained demand; some may choose to create a 'critical period' scenario, e.g. all resource from groundwater, run-of-river abstractions or limited storage, where security of supply is acutely vulnerable to peak demand, or where resource management more crucial than operation. Constraints of system performance during planning, such as the frequency of failure at a given level of service, vary between service providers.

Although resource planning is a statutory process, the plan itself is not statutory: schemes and actions arising from the plan require permission from environmental regulators, who facilitate planning through the prescription of *de facto* standard methodologies for estimating, with accounting of specified uncertainties, the balance between demand and capacity, subject to the impacts of climate change (e.g. Environment Agency, 2011c).

	Service provider
1	Anglian Water
2	Dŵr Cymru (Welsh Water)
3	Northumbrian Water
4	Scottish Water
5	Severn Trent Water
6	South West Water
7	Southern Water
8	Thames Water
9	United Utilities
10	Wessex Water
11	Yorkshire Water

Table 2.1: Water and sewerage service providers.

	Service provider
12	Affinity Water
13	Bournemouth & West Hampshire Water
14	Bristol Water
15	Cambridge Water
16	Cholderton & District Water Company
17	Dee Valley Water
18	Essex & Suffolk Water
19	Hartlepool Water
20	Portsmouth Water
21	South East Water
22	South Staffordshire Water
23	Sutton & East Surrey Water
24	Veolia Water Projects

Table 2.2: Water-only service providers.

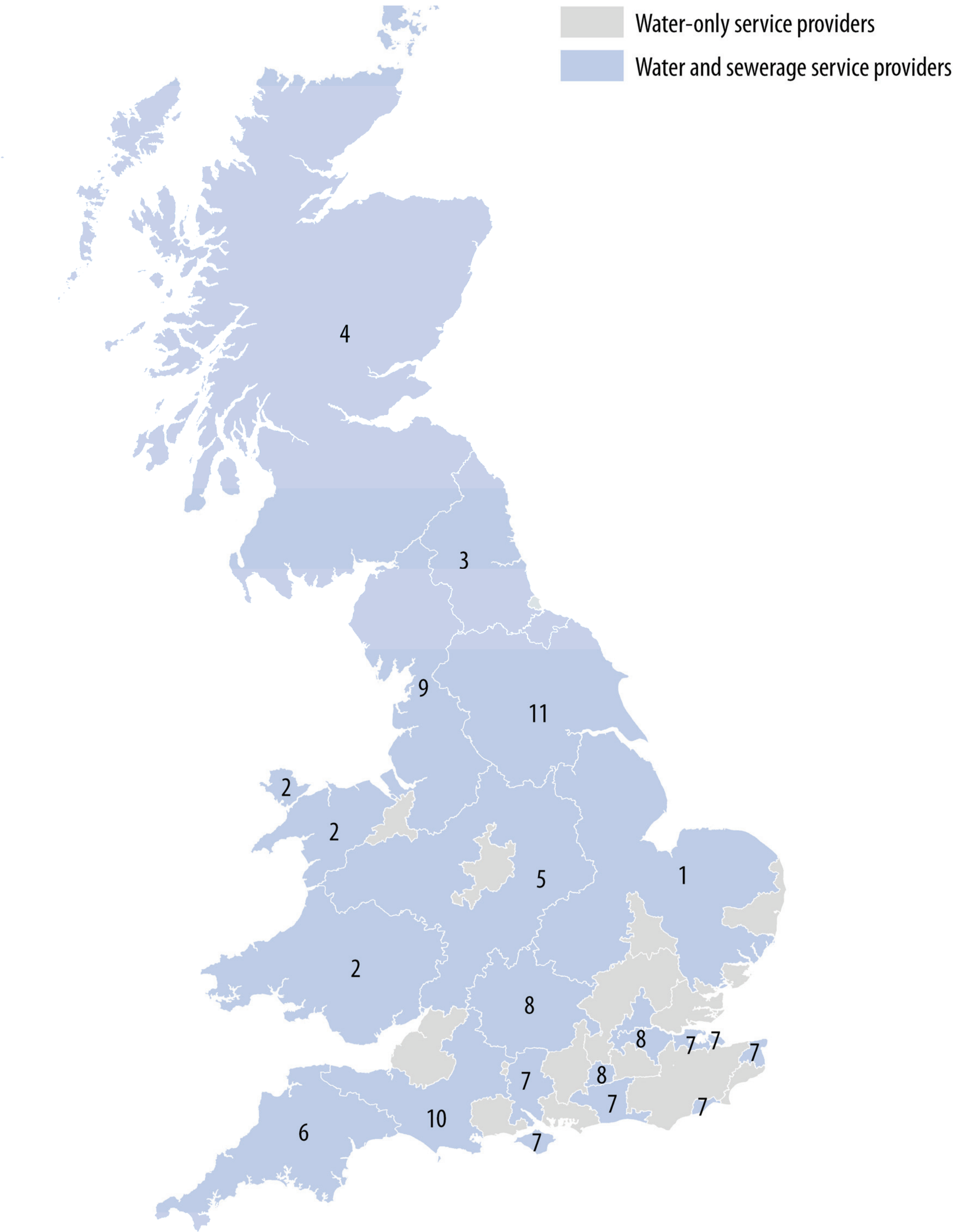


Figure 2.1: Water and sewerage service providers.

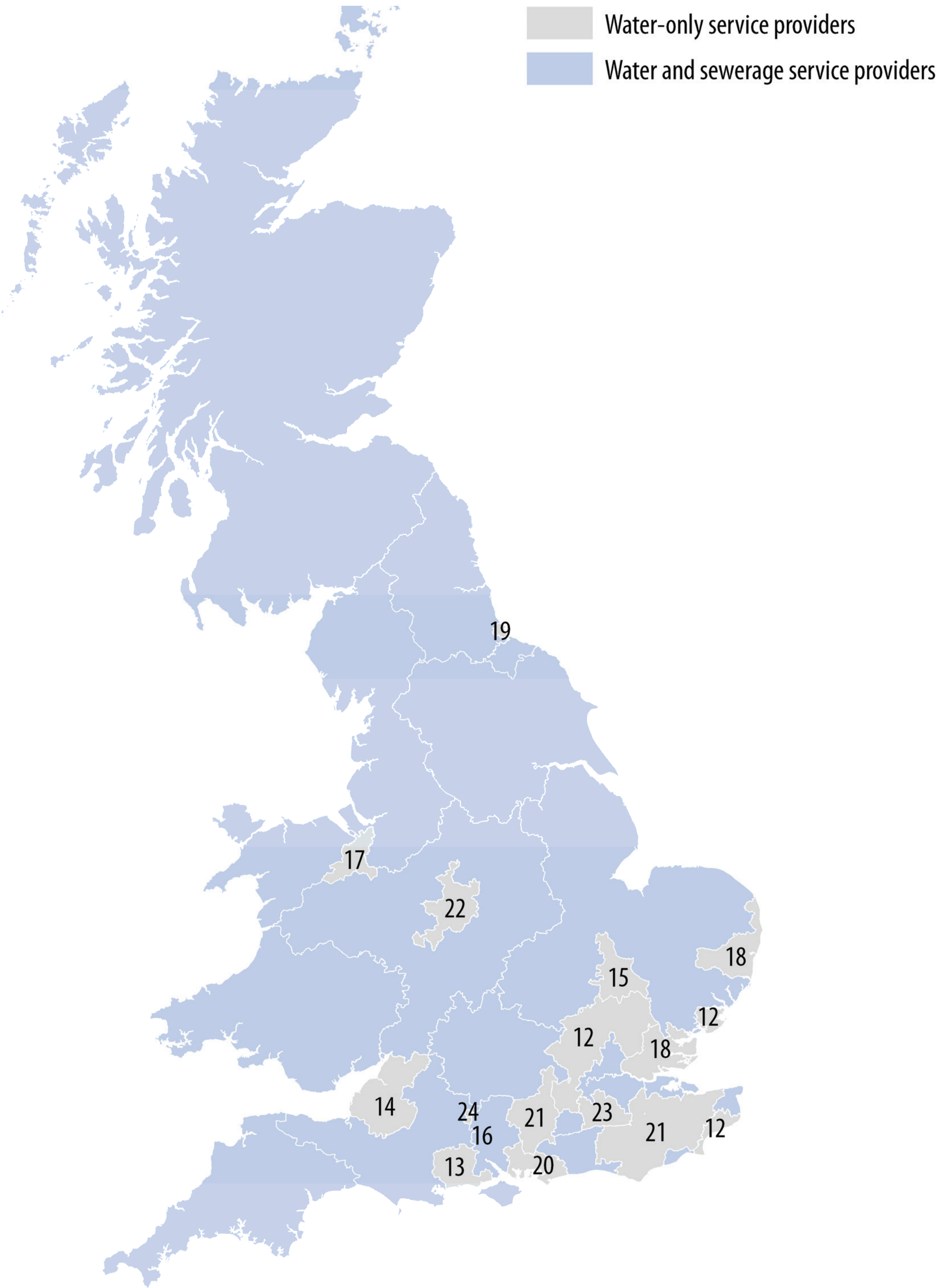


Figure 2.2: Water-only service providers.

2.4.1.2 Regulation

Regulation of the water supply industry is necessary to encourage competition in an otherwise monopolistic industry and thereby maintain an equitable balance of the benefits of water use between stakeholders (e.g. Cave, 2009). The principal regulatory actors that influence the configuration and operation of the public water supply system differ between England, Wales and Scotland (Figure 2.3).

The economic regulators Ofwat and WICS are executive non-departmental public bodies responsible for setting prices, encouraging competition and monitoring performance in England and Wales and Scotland, respectively. The primary instrument of economic regulation is a periodic review of the prices charged to consumers of water services in the context of proposed capital investment needed to meet anticipated future demand and anticipated gains in operational efficiency. Economic regulators are also responsible for establishing sustainable and economic levels of leakage and monitoring levels of actual leakage, having powers to sanction those service providers that are unsuccessful in meeting these targets.

The environmental regulators EA, Natural Resources Wales and SEPA exist to "protect or enhance the environment, taken as a whole" (Environment Act 1995), and are responsible for the management and conservation of water resources via the licensing of the abstraction and impoundment of water and the discharge of effluent into water in England, Wales and Scotland, respectively. They are responsible for the approval of measures required to maintain or improve the security of water supply, as described in water resource management plans, prior to their enactment.

The water quality regulators DWI and DWQR monitor the quality of drinking water in England and Wales and Scotland, respectively. The environmental and water quality regulators are empowered by the European Union, particularly the Water

Framework Directive (European Commission, 2000) and the European Drinking Water Directive (European Commission, 1998), which provides a common statutory regulatory framework. Both groups of regulators have powers of enforcement, including economic sanction and prosecution.

The Consumer Council for Water and Consumer Futures participate in the regulatory processes by advocating the rights of consumers of water services in England and Wales and Scotland, respectively, providing crucial mechanisms for feedback between water supply service providers and economic regulators (Gray, 2011). Complaints from customers are a key reporting metric to economic regulators, for which water service providers receive economic sanctions. For example, in 2008, Ofwat fined Thames Water £9.7 million and Severn Trent Water £35.8 million for, among other misdemeanours, "delivering poor service to customers" (Ofwat, 2008a; Ofwat, 2008b).

The prevailing regulatory system has a profound influence on the performance of the water supply infrastructure system. While the enforcement of mandatory water quality regulations and consumer service targets establish clear constraints on some aspects of planning, in price setting through inspection of proposed capital expenditure, economic regulators have substantial power to determine which interventions to the public water supply infrastructure are cost-effective, and therefore feasible. Similarly, environmental regulators can veto any intervention they determine does not protect or enhance the environment and/or water resource within the scope of the available evidence. The rejection of, and subsequent public inquiry into, Thames Water's proposal for a new reservoir in southern England is a particularly high profile instance of the interaction between these regulators (Burden, 2010).

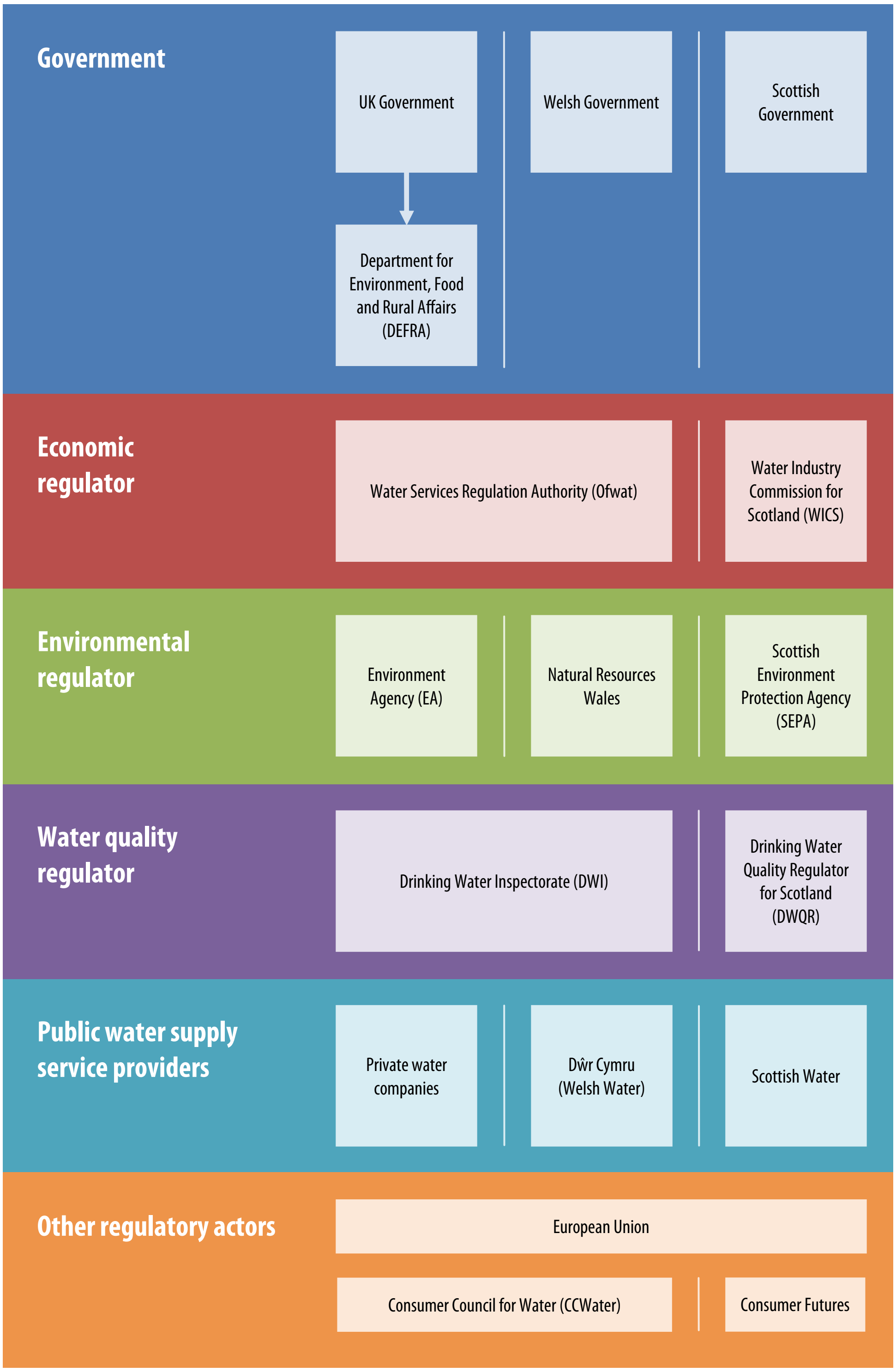


Figure 2.3: Principal regulatory actors in England, Wales and Scotland.

2.4.1.3 Abstractions

The Water Resources Act (1991b), the Water Resources (Abstraction & Impounding) Regulations (2006) and the Water Environment (Controlled Activities) (Scotland) Regulations (2011b) oblige the environmental regulators to maintain registers of licenses for water abstraction from freshwater, groundwater and tidal sources. Records in these registers include the location at which abstraction is licensed, the identity of the licensee, and rates of abstraction agreed with the regulator, but do not disclose the capacity of the infrastructure, and are often sparsely populated (Environment Agency, Personal Communication). Furthermore, while the register of abstractions and impoundments maintained by the Environment Agency is public, centralised, and digitised, the equivalent register maintained by SEPA is neither centralised nor digitised (SEPA, Personal Communication).

Abstraction licences evidence the presence of water abstraction infrastructure and indicate the ecologically sustainable yield of a source as assessed by the Environment Agency and/or SEPA. There are 1 617 licences for the abstraction of water for the purpose of public water supply to England and Wales (Table 2.3), corresponding to 3 807 sources, and 387 sources of water for the same purpose in Scotland (Table 2.4). Of these 4 184 sources, 3 075 (73%) are groundwater sources, 1 116 (27%) are surface water sources, and 3 (less than 1%) are tidal water sources.

Region	Groundwater	Surface water	Tidal water	TOTAL
EA Anglian	221	28		**249**
EA Midlands	168	47	1	**216**
EA North East	88	73		**161**
EA North West	100	95		**195**
EA South West	122	89		**211**
EA Southern	165	16	1	**182**
EA Thames	222	16	1	**239**
EA Wales	29	135		**164**
TOTAL	**1 115**	**499**	**3**	**1 617**

Table 2.3: Number of abstraction licences by Environment Agency region (Environment Agency, Personal Communication).

Region	Groundwater	Surface water	Tidal water	TOTAL
EA Anglian	736	46		782
EA Midlands	401	86	1	488
EA North East	145	142		287
EA North West	149	161		310
EA South West	211	123		334
EA Southern	489	24	1	514
EA Thames	771	40	1	812
EA Wales	51	229		280
England & Wales	*2953*	*851*	*3*	*3807*
Scotland (North)	60	150		210
Scotland (East)	29	61		90
Scotland (West)	33	54		87
Scotland	*122*	*265*	*0*	*387*
TOTAL	**3 075**	**1 116**	**3**	**4 194**

Table 2.4: Number of sources by source type and region (Environment Agency, Personal Communication; Scottish Government, 2010).

Derived from the public register of water abstraction, Figure 2.4 and Figure 2.5 show the location and quantity licensed for abstraction daily from non-tidal surface water sources in England and Wales and groundwater in England and Wales, respectively. Note that London and its environs depend on a few abstractions of high licensed capacity, whereas the majority of the remainder of the country relies on more numerous abstractions with lower licensed rates of abstraction. Furthermore, many licences prescribe low (or zero) daily rates of withdrawal under typical circumstances, in addition to a typically (much) higher 'maximum' daily rate for use in unusual circumstances.

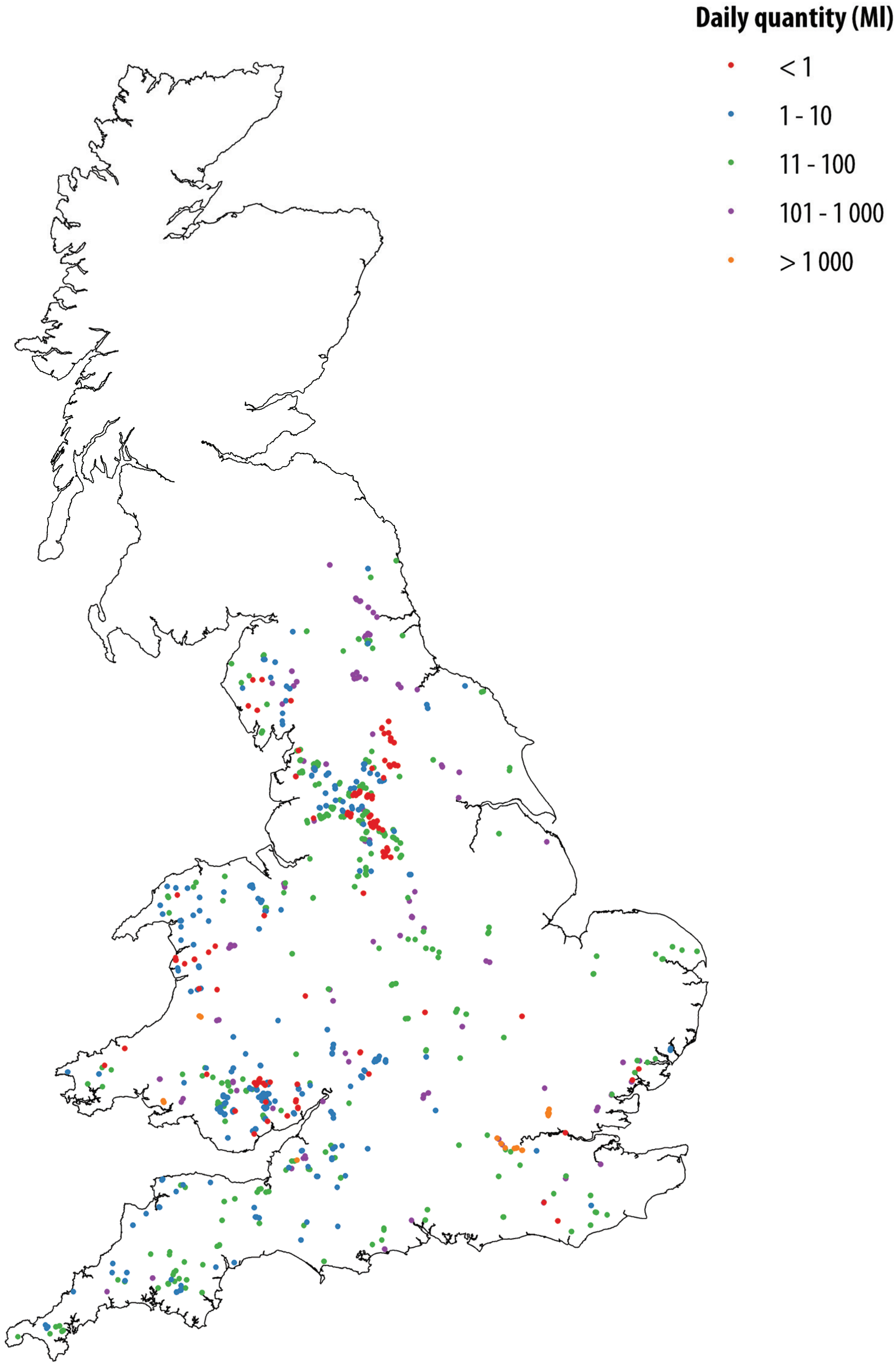


Figure 2.4: Licences for the abstraction of water from non-tidal surface water sources for the purpose of public water supply (Environment Agency, Personal Communication).

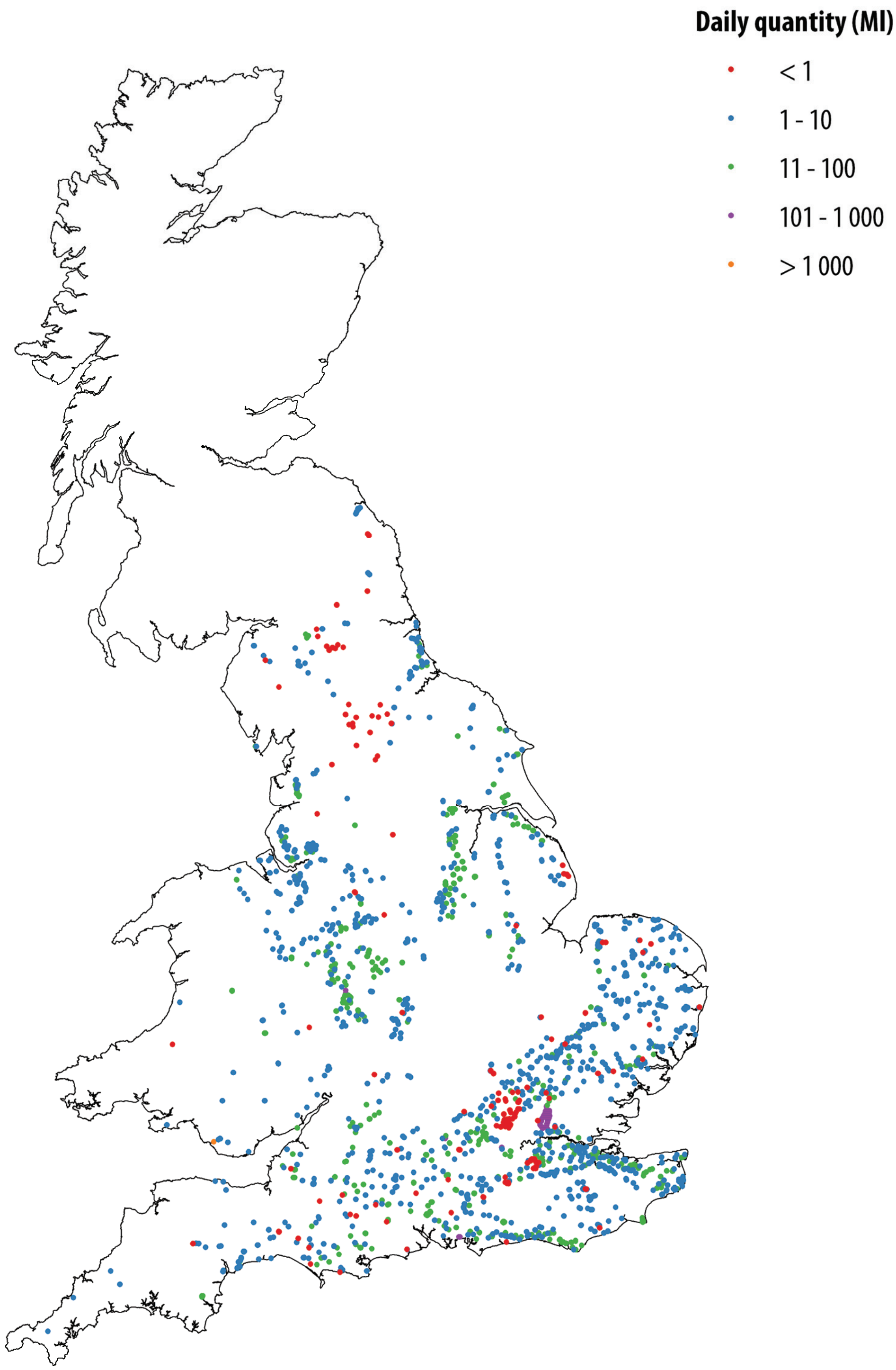


Figure 2.5: Licences for the abstraction of water from groundwater sources for the purpose of public water supply (Environment Agency, Personal Communication).

The majority of licenses are for abstraction from groundwater sources, and 70% of licences to abstract from groundwater sources in England and Wales are located in the Thames basins, East Anglia, the Midlands and the south and southeast of England (Table 2.3). The apparent spatial trend is somewhat reversed in consideration of the proportion of licences to abstract from non-tidal surface water sources: 79% of abstractions are located in Wales, northwest England, northeast England and southwest England. One licence to abstract from a tidal surface water source exists in each of the Midlands, south England and the Thames basin.

Aggregation of the number of licenses by water undertaker and source type shows that most undertakers have more licenses for abstraction from groundwater sources than from any other source type, up to an order of magnitude in the cases of Thames Water and Affinity Water (Table 2.7).

Undertaker	GW	SW	TW	TOTAL
Anglian Water	175	20	1	**196**
Dŵr Cymru	24	121		**145**
Northumbrian Water	35	14		**49**
Severn Trent Water	149	52		**201**
South West Water	28	46		**74**
Southern Water Services	42	5	1	**48**
Thames Water	127	12		**139**
United Utilities Water	103	90		**193**
Wessex Water	71	24		**95**
Yorkshire Water	49	62		**111**
Water and sewerage companies	*803*	*446*	*2*	***1 251***
Affinity Water	104	5		**109**
Sembcorp Bournemouth Water	7	5		**12**
Bristol Water	17	11		**28**
Cambridge Water	25			**25**
Cholderton & District Water	1			**1**
Dee Valley Water	3	9		**12**
Essex & Suffolk Water	22	5		**27**
Portsmouth Water	15			**15**
South East Water	86	9		**95**
South Staffordshire Water	12	3		**15**
Sutton & East Surrey Water	18	3		**21**
Water-only companies	*310*	*50*	*0*	***360***
TOTAL	**1 113**	**496**	**2**	**1 611**

Table 2.5: Number of abstraction licenses by water company and source type.

A similar pattern is evident with respect to the number of sources (i.e. licensed locations for abstraction) with the exception that northern Scotland has more surface water sources than northeast England, but fewer than northwest England (Table 2.4).

With reference to Table 2.6, around 9.9×10^6 Ml are licensed for abstraction per annum in England and Wales: 2.7×10^6 Ml (27%) from groundwater sources, 7.1×10^6 Ml (72%) from non-tidal surface water sources, and 0.1×10^6 Ml (1%) from tidal sources. 47% of the total volume licensed for abstraction from groundwater sources is located in the south and southeast of England; East Anglia (14%) and the Midlands (17%) constitute a further 31%. The quantity licensed to abstract annually from non-tidal surface water sources is greatest in northeast England, followed by the Thames region, Wales and the Midlands. Only the Thames region contains licences for the abstraction of a significant quantity of tidal water.

A number of water undertakers are licensed to withdraw the majority of their licensed volume from groundwater sources, including Wessex Water (64%), Southern Water (55%), Anglian Water (43%) and Thames Water (36%) (Table 2.7).

Region	Groundwater	Surface water	Tidal water	TOTAL
EA Anglian	391	844		**1 235**
EA Midlands	456	1 028	8	**1 492**
EA North East	162	1 282		**1 444**
EA North West	188	873		**1061**
EA South West	202	573		**775**
EA Southern	505	204	4	**713**
EA Thames	757	1 155	73	**1 986**
EA Wales	41	1 122		**1 163**
TOTAL	**2 704**	**7 082**	**84**	**9 870**

Table 2.6: Annual quantity licensed for abstraction by EA region and source type in units of mega-litres per year (Environment Agency, Personal Communication).

Undertaker	**GW**	**SW**	**TW**	**TOTAL**
Anglian Water	371	475	8	**854**
Dŵr Cymru	37	793		**830**
Northumbrian Water	48	630		**678**
Severn Trent Water	359	1066		**1425**
South West Water	30	352		**382**
Southern Water Services	128	102	4	**234**
Thames Water	409	713		**1122**
United Utilities Water	186	841		**1027**
Wessex Water	114	64		**178**
Yorkshire Water	119	747		**866**
Water and sewerage companies	*1 801*	*5 784*	*11*	***7 596***
Affinity Water	249	593		**742**
Sembcorp Bournemouth Water	17	72		**88**
Bristol Water	41	81		**122**
Cambridge Water	27			**27**
Cholderton & District Water	< 1			**< 1**
Dee Valley Water	1	298		**299**
Essex & Suffolk Water	33	242		**275**
Portsmouth Water	98			**98**
South East Water	217	75		**292**
South Staffordshire Water	66	124		**190**
Sutton & East Surrey Water	62	30		**92**
Water-only companies	*809*	*1 416*	*0*	***2 225***
TOTAL	**2 611**	**7 200**	**11**	**9 821**

Table 2.7: Annual quantity licensed for abstraction by water company and source type in units of megalitres per year.

2.4.1.4 Storage

There are over 1 100 reservoirs in Great Britain operated by a water service provider or operated for the purpose of public water supply. Some 745 are located in England and Wales, with a further 377 in Scotland. (Environment Agency, personal communication; Building Research Establishment, 1994; Scottish Executive, 2001; Scottish Executive, 2002).

With few exceptions (e.g. Thames Water, Personal Communication), these sources rarely, if ever, disseminate the attributes of reservoirs in any form. For example, these databases do not include the catchment areas of reservoirs, which, if required, must be estimated from other sources. Under the Reservoirs Act (1975), the Environment Agency and Natural Resources Wales maintain public registers of reservoirs of storage capacity equal to or greater than 25 Ml in England and Wales, which include records of name, location, volume, associated undertaker, and classification as either impounding or non-impounding (Environment Agency, Personal Communication). The various Scottish Councils performed this function in Scotland prior to the Reservoirs (Scotland) Act (2011a), whereupon SEPA inherited this responsibility, and the threshold volume for registered reservoirs became 10 Ml. The register of Scottish reservoirs is somewhat sparser than that of England and Wales, excluding volume and classification and generalising location. Gustard *et al.* (1987) and the Building Research Establishment (1994) publish much more complete sets of attributes of a number of dams and reservoirs across Great Britain, which, from comparison with the public register, evidently underpin the public register of reservoirs and impoundments maintained by the Environment Agency (Environment Agency, Personal Communication). In addition, descriptions of specific pieces of infrastructure in the literature (e.g. Henzell, 1890; Kennard and Kennard, 1962) clearly inform these later works and provide valuable insight into the functionality of these physical assets of the water supply system; however, only a few such assets possess such detailed publically-available documentation. The major limitations of these sources of information regarding reservoirs and impoundments are a dearth of reliable data on catchment areas, compensation flows and yield. Measurements of these attributes are available for only a small subset of reservoirs, and the methods used to derive them vary hugely between studies and even between individual reservoirs in the same study. For example, as detailed by Gustard *et al.* (1987), compensation releases are variously defined as ‘constant’, ‘varying’ and ‘maintained flows’, depending on the location. Their magnitudes are calculated based on flows and other environmental concerns prevalent at the time of impoundment, and potentially reviewed during operation, but the exact method used for each and reservoir may not be known. Catchment areas quoted in this study were originally estimated from Ordnance Survey maps, with additional local knowledge of the drainage areas of catchwaters added on a per-dam basis.

Of 1 056 reservoirs of known individual capacity on the Great Britain mainland, those in England and Wales provide around 2.4×10^6 Ml of storage, while those in Scotland provide around 0.7×10^6 Ml of storage. 56% of reservoirs in England and Wales are impounding reservoirs, having a dam blocking the natural flow of a river, and comprise some 2.1×10^6Ml of storage, while the remaining 0.3×10^6 Ml is attributable to non-impounding reservoirs filled by pumping water from rivers. Impounding reservoirs tend to be of greater capacity than non-impounding reservoirs. The majority of reservoirs provide storage less than or equal to 1 000 Ml; only around 1% have storage capacity exceeding 10 000 Ml (Table 2.8). Kielder Water and Rutland Water are the two most capacious reservoirs in the country, with capacities of 200 000 Ml and 124 000 Ml, respectively (Environment Agency, personal correspondence). Both are lynchpins in strategic regional water supply systems, the former in northeast England and the latter in the East Midlands and east of England (Coats *et al.*, 1982; Coats and Ruffle, 1982; Knights, 1982; Coats *et al.*, 1983; Winder *et al.*, 1985).

Storage capacity (Ml)	Number of reservoirs Impounding	Non-impounding	Total
≤ 100	147	159	306
101 - 1 000	362	77	439
1 001 - 10 000	227	22	249
10 001 - 100 000	51	9	60
> 100 000	2	0	2
TOTAL	**789**	**267**	**1 056**

Table 2.8: Size distribution of reservoirs in Great Britain.

From the register of large raised reservoirs (Environment Agency, personal communication), 53% of total reservoir storage by volume on mainland Great Britain is located in the midlands, northwest and northeast of England, and Wales, equivalent to 50% of the total number of reservoirs. The spatial distribution and capacity of reservoirs suggests that the location of impounding reservoirs reflects topography, land use, and historical actual and forecast demands for water, while impounding reservoirs are concentrated around large population centres such as London, Birmingham, Liverpool and Manchester.

Reservoir storage in Scotland is concentrated in the centre of the country, ostensibly to support the principal population centres of Glasgow and Edinburgh (e.g. General Register Office for Scotland, 2009): over 32% of reservoirs in Scotland are located in Ayr, Dunbartonshire and Renfrew & Inverclyde, and 54% of reservoir storage by volume is concentrated in the Borders, Dunbartonshire, and Stirling (Building Research Establishment, 1994). Furthermore, the yield of reservoir sources in the east and west of Scotland is over eight times that of those in the north (e.g. Scottish Executive, 2003). The remaining storage volume associated with the public water supply mostly lies in proximity to minor population centres distributed along the coastal regions of Scotland.

Figure 2.6 and Figure 2.7 show the locations and capacities of reservoirs considered impounding and non-impounding, respectively.

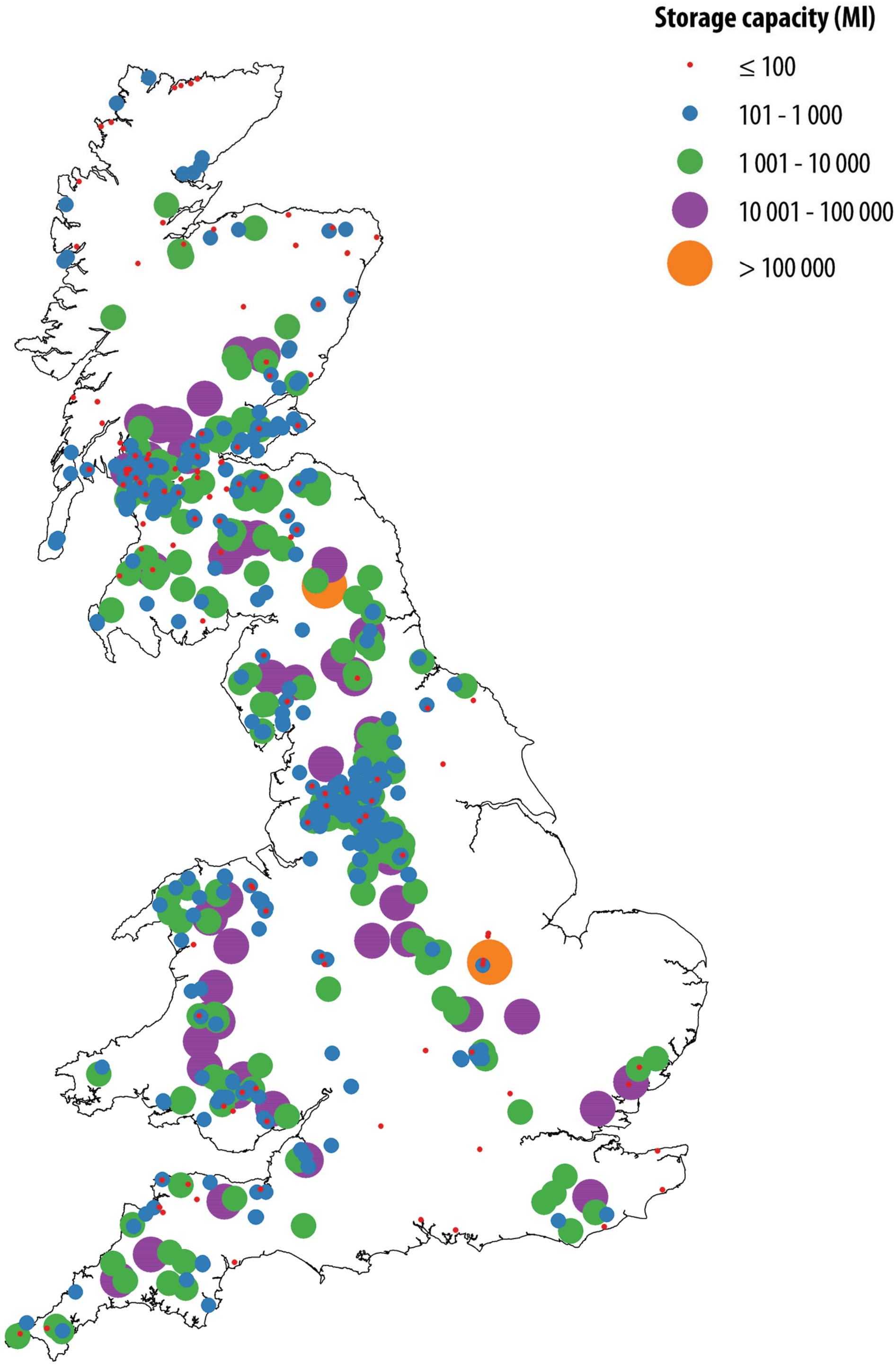


Figure 2.6: The location and capacities of impounding reservoirs.

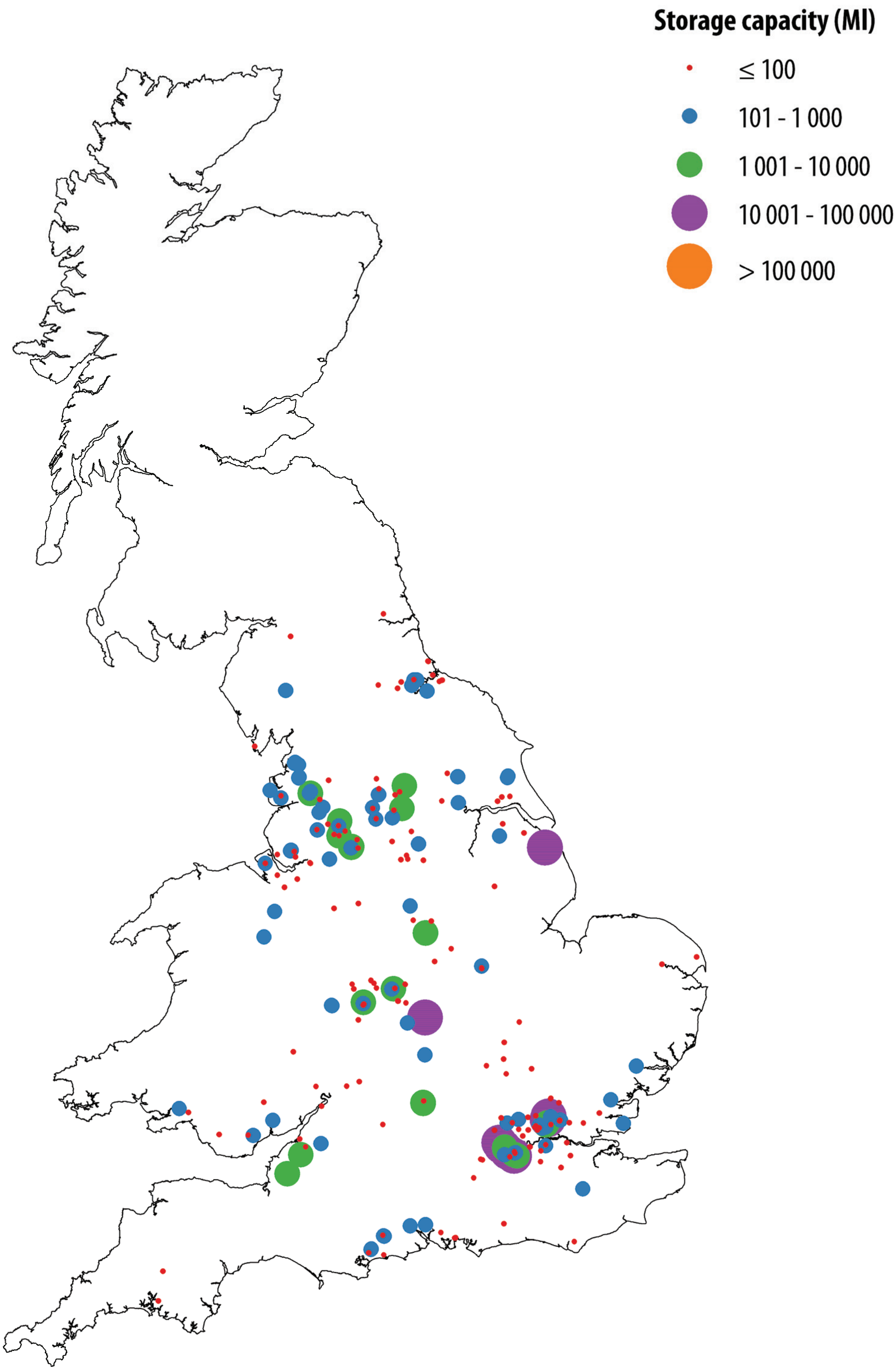


Figure 2.7: The locations and capacities of non-impounding reservoirs.

2.4.1.5 Esoteric sources

Sources of water regarded as 'esoteric' typically include desalination, recycling/reuse of effluent/blackwater, and water transfers.

Desalination plays a minor role in meeting the demand for water in the UK: there are several desalination plants of low capacity distributed throughout Scotland to meet the needs of remote communities (Grose *et al.*, 1998) and a large-scale desalination plant, located on the River Thames at Beckton, that supplies up to 150 Ml/d to London (Moore *et al.*, 2009).

Reuse of treated wastewater occurs throughout the UK. After Keremane (2007) and Chanan *et al.* (2013), for example, this may be categorised as planned or unplanned, direct or indirect, and potable or non-potable. Not all combinations of these categories exist in the UK. For example, direct reuse of wastewater, wherein treated wastewater is returned directly to the water supply, is commonplace in non-potable uses of water, but is not employed in potable uses such as public water supply. Indirect reuse, wherein treated wastewater is discharged into an environmental buffer (such as a river) for abstraction downstream, is more common. In most cases, this reuse is unplanned: the wastewater discharge policy does not explicitly intend reuse of wastewater through the definition of quality and quantity constraints linked to reuse. This is particularly so in the case of the River Thames (Eden *et al.*, 1977). Estimates of the quantity of water reused in this fashion are not forthcoming in the UK, but are likely to vary seasonally and by cost optimality (e.g. Sala-Garrido *et al.*, 2011). There is but one instance of planned reuse of wastewater for potable supply in the UK, where the discharge policy contains explicit constraints on quality and quantity linked to reuse. This is located on the River Chelmer at Langford (Diaper *et al.*, 2001; Lazarova *et al.*, 2001), and augments flow in the River Chelmer and inflows to Hanningfield Reservoir by some 40 Ml/d (Angelakis *et al.*, 2002).

There are some 759 unique licences for abstraction in England and Wales for either the transfer of water between sources or groundwater augmentation (Environment Agency, personal communication; Environment Agency, 2012f). 113 of these are designated 'water supply related'. Of the 111 licences for abstraction from sources of water located on the mainland of Great Britain, 46 are from groundwater sources, 64 are from surface water sources, and one is from a tidal source. A total rate of 796.8 Ml/d is licensed for abstraction from groundwater sources, mostly in the Midlands and East Anglia, while some 17 716.0 Ml/d is licensed for abstraction from surface water sources, mostly in Wales, East Anglia and the northeast of England. The sole tidal abstraction is in the northeast of England, licensed for 66.4 Ml/d. The licensed daily rate of abstraction is typically much less for abstractions from groundwater sources than abstractions from surface water sources: the mean rates are 9.1 Ml/d and 233.1 Ml/d, respectively. By licensed rate of abstraction, the most significant schemes are the River Dee regulation scheme (e.g. Lambert, 1988) and Teifi Pools in Wales, the Kielder Water transfer scheme in the northeast of England (e.g. Coats and Ruffle, 1982), and the Empingham Reservoir / Rutland Water scheme (e.g. Winder *et al.*, 1985), the Trent-Witham-Ancholme scheme and the Ely-Ouse transfer scheme in East Anglia (e.g. Smith, 1997). Figure 2.8 and Figure 2.9 summarise these data for surface water and groundwater sources, respectively.

Information on water transfers and other esoteric and/or heavily modified sources of water and water bodies is mostly accumulated by word-of-mouth, as public records of such assets are presently incomplete (Environment Agency, Personal Communication) or but illustrative (e.g. Environment Agency, 2012f). Although detailed descriptions of a few individual assets do exist (e.g. Coats *et al.*, 1982), they are by no means comprehensive of all transfers in a national context.

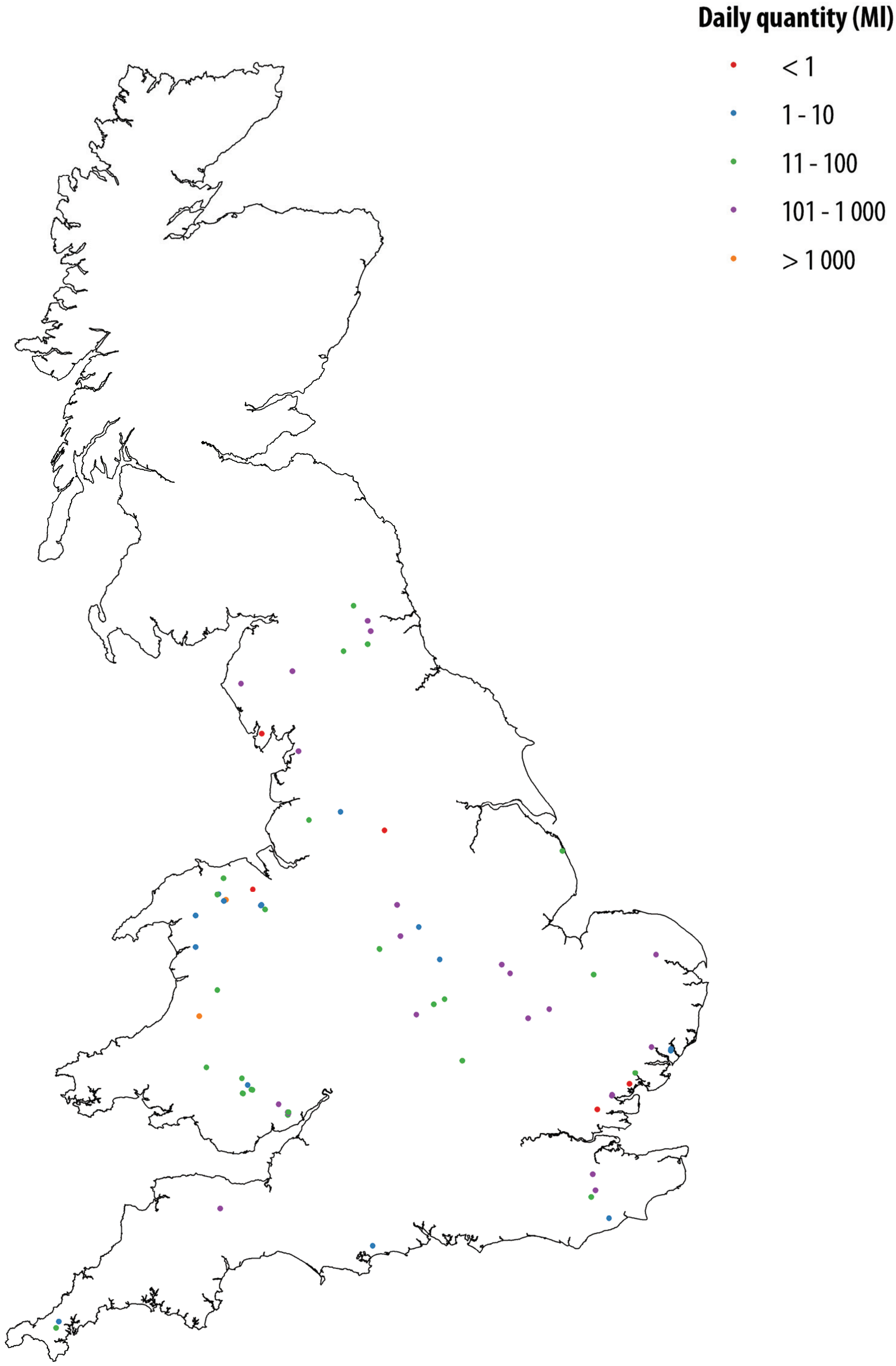


Figure 2.8: Abstraction licenses granted for the transfer of water from surface water sources (a subset of the data shown in Figure 2.4).

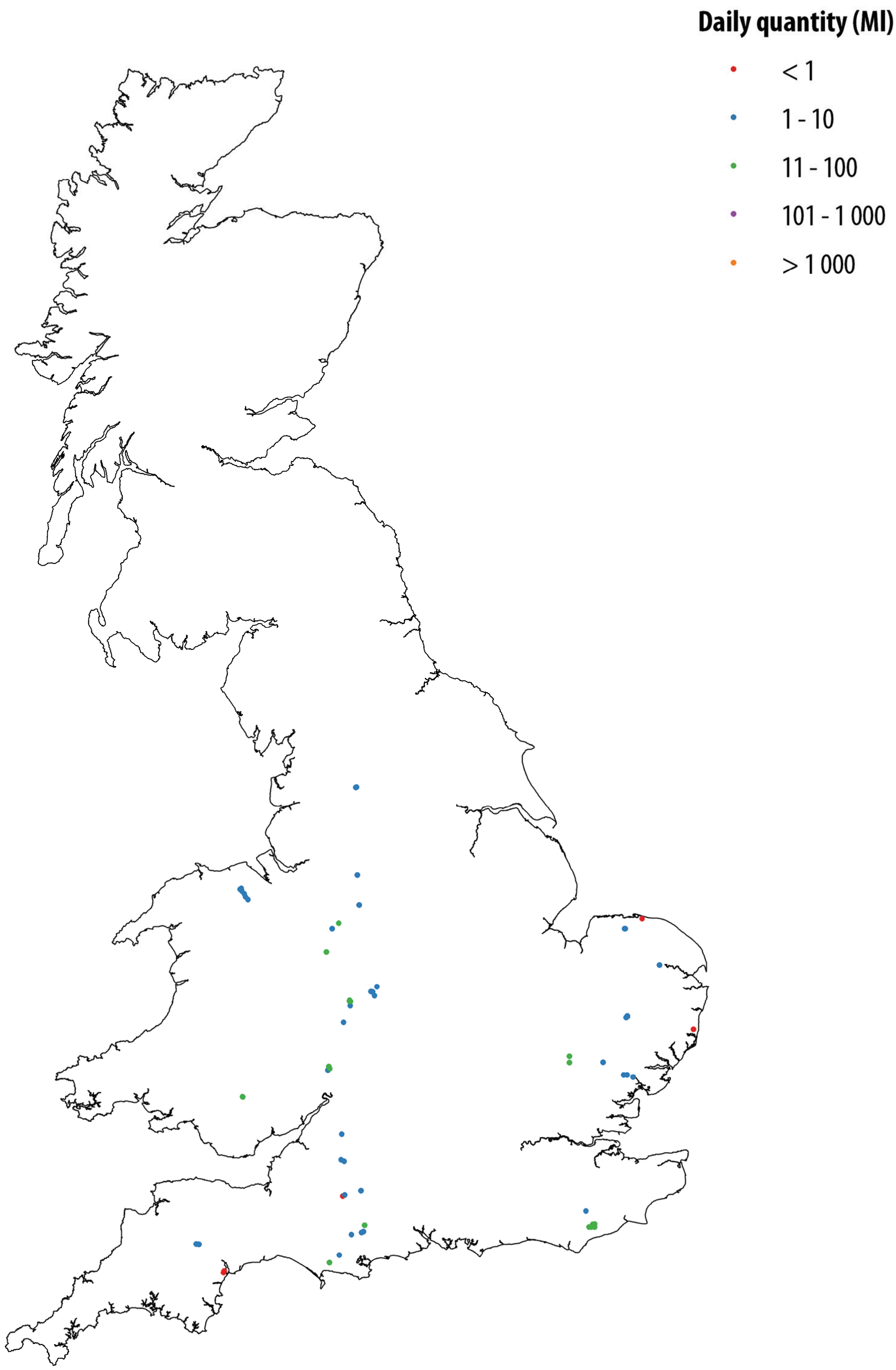


Figure 2.9: Abstraction licenses granted for the transfer of water from groundwater sources (a subset of the data shown in Figure 2.5).

2.4.1.6 Demand

The public water supply infrastructure system of England and Wales serves approximately 99% of the population in England and Wales (Water UK, 2008), while the public water supply infrastructure system of Scotland serves 97% of the population of Scotland (DWQR, 2013). The total population served approached 56 million people in 2010, of which the water and sewerage service providers served 78% of the population; together with Affinity Water, Essex & Suffolk Water and South East Water, they served over 90% of the population (Table 2.9).

Rank	Service provider	2010 population Population (000s)	% of total	Cumulative %
1	Thames Water	8 796.9	16%	16%
2	United Utilities	6 865.9	12%	28%
3	Scottish Water	5 222.0	9%	37%
4	Yorkshire Water	4 851.2	9%	46%
5	Anglian Water Services	4 298.6	8%	54%
6	Affinity Water	3 472.4	6%	60%
7	Dŵr Cymru (Welsh Water)	2 925.6	5%	65%
8	Severn Trent Water	2 925.6	5%	70%
9	Northumbrian Water	2 521.2	5%	75%
10	Southern Water	2 359.0	4%	79%
11	South East Water	2 004.2	4%	83%
12	Essex & Suffolk Water	1 817.2	3%	86%
12	South West Water	1 671.4	3%	89%
13	South Staffordshire Water	1 275.8	2%	91%
14	Wessex Water	1 257.4	2%	94%
15	Bristol Water	1 162.9	2%	96%
16	Portsmouth Water	659.6	1%	97%
17	Sutton & East Surrey Water	654.3	1%	98%
18	Bournemouth Water	429.7	1%	99%
19	Cambridge Water	313.3	1%	99%
20	Dee Valley Water	265.7	0%	100%
21	Hartlepool Water	89.7	0%	100%
22	Veolia Water Projects	5.1	0%	100%
23	Cholderton & District Water	2.1	0%	100%
	TOTAL	**55 846.8**	**100%**	

Table 2.9: Population served by the public water supply in 2010.

To meet the demand for water at the point of use, the quantity of water abstracted for the purpose of public water supply must equal or exceed not only the demand from both domestic and non-domestic consumers, but also, in addition, losses occurring during treatment, leakage from raw water mains, treated water distribution networks and customers' supply pipes, and operational losses such as standpipes, fire service use, hydrant misuse, use by water companies, wastewater treatment works, and sewer jetting.

The Environment Agency (2012b) report the abstraction of 16 373 Ml/d of water for the purposes of public water supply in England and Wales in 2010-11, concomitant with some 14 770 Ml/d input for distribution to meet demand and 3 361 Ml/d lost as leakage from distribution mains and customers' supply pipes (Environment Agency, 2011b). During this period, water companies delivered 6 872 Ml/d to household customers and 3 099 Ml/d to non-household customers (Ofwat, 2011). Note that the sum of water delivered does not equal the water put into supply, as such a sum does not account for such quantities as water taken unbilled, imports and exports. For the same period, Scottish Water report the abstraction of 2 095 Ml/d for the purposes of public water supply in Scotland, of which household customers consumed 445 Ml/d, non-household customers consumed 751 Ml/d, 95 Ml/d were lost during treatment and raw water distribution, and 757 Ml/d were lost as leakage (Scottish Water, 2011).

Disaggregated, these quantities demonstrate spatiotemporal variability broadly attributable to sensitivity to the determinants of the demand for water such as population, price and income, as well as the condition and operational circumstances of regional public water supply networks, without displaying particular trend other than to say that population and population density are general indicators of the components of water demand in the UK (e.g. Ofwat, 2011).

Decreases in treatment process losses, leakage from raw water mains, treated water distribution networks and customers' supply pipes, non-domestic consumption and demand *per capita* have offset the impacts of population growth on the demand for water in recent years, leading to attenuation of the total abstraction from all sources of water for the purpose of public water supply (Ofwat, 2009; ONS, 2011b; Scottish Water, 2011; Environment Agency, 2012e). As most water companies now operate their infrastructure at levels of leakage that approach targets defined by the economic regulators, further efficiencies are unlikely in this component of demand without further incentives to do so or a substantial change in the methodology used to establish economic levels of leakage (NAO, 2007). This implies that other principal determinants of demand, such as population, may become increasingly significant (UK Government, 2011); however, forthcoming revisions to the methodology to incorporate social and environmental costs of leakage may mitigate this to an uncertain degree (e.g. Strategic Management Consultants, 2012).

Environmental regulators' guidelines for the planning of water resources stipulate a hierarchy of methods for the forecasting of demand (Environment Agency *et al.*, 2012). The most ubiquitous of these is estimation from micro-component data, which, although having the capacity to explain water consumption at the finest scale possible, is costly, data-intensive, and relatively sparsely evidenced in the UK, particularly with respect to climate variables (Parker and Wilby, 2012). Furthermore, as part of the water resource planning process, these forecasts are relatively short-range, having a typical planning horizon of 25 years.

Longer-range forecasts of demand are few. Those constructed by the Environment Agency describe scenarios of water consumption for the 2050s and 2100s that differ radically from the contemporary picture (Environment Agency, personal communication, The Futures Company, 2012). The difference in detail between the scenarios for the 2050s and those for the 2100s reflects extreme uncertainty in the determinants of demand over the latter half of the 21st Century, and limits their use in quantitative modelling.

2.4.2 Future

The water resource planning documents produced by water undertakers for the purposes of meeting the statutory obligations defined by the Water Industry Act (1991a) and the Water Industry (Scotland) Act (2002b) include a component of future strategic planning with a time horizon of 25 years.

As water undertakers often evaluate very many options prior to recommending a final subset of preferred options in their water resource and business plans, both the plans and their supporting documentation are indicators of which interventions to the public water supply are most likely to be necessary and/or feasible over that timescale. All plans are subject to commercially orientated financial constraints and negotiation with economic and environmental regulators, from whom it is necessary for water undertakers to obtain approval that their plans maintain an adequate balance of demand and supply whilst protecting the environment and presenting best value to customers. The selection of preferred options often proceeds on the basis of methodologies that are not fully transparent or reproducible, and inconsistent between undertakers, but may be generalised as cost minimisation over the forecast horizon, subject to a prescribed level of service. These conditions have resulted in successive cycles of planning and investment focused on factors that return benefits in the short-term, such as reductions in leakage and demand per capita, but which have left few remaining opportunities for further reductions without substantial additional investment (e.g. Bridgeman, 2011; Byatt, 2013). In addition, the methodology for incorporating climate change information into the water resource plans, as described by Charlton and Arnell (2011) and Arnell (2011), is pragmatic in accommodating legacy methods and limitations arising from the commercial practices of water undertakers, but very conservative in its treatment of uncertainty and risk. In combination with the short planning horizon, which concludes in advance of the more significant impacts of climate change projected to occur in the 2050s (e.g. Jenkins *et al.*, 2009; Rance *et al.*, 2012), these restrictions discourage the preferment of capital-intensive major resource development schemes. As a result, preferred options are often demand-side or small in scale.

The development of one or more abstractions is an occasional inclusion in water resource plans (e.g. Thames Water, 2011); however, the increase in yield is often relatively small, so as to be of only local consequence, if the negative environmental impacts of abstraction are to be acceptable (e.g. Cascade Consulting, 2011). Opportunities for new abstractions of strategically significant yield are few: analysis of the reliability of new licenses to abstract water suggests that such sources are unlikely to be suitable options for substantial future development in England and Wales: at present, 25% of surface- and ground-water bodies in England, and 7% of those in Wales, would be able to support abstraction only 30% of the time (Environment Agency, 2011a), with some 35% of groundwater bodies being of poor quantitative status (Environment Agency, 2010b). Rance *et al.* (2012) project decreases in the low flows that determine the viability of such abstractions for all regions of the UK under all but the wettest scenarios.

Where major resource development schemes have been proposed, limitations in the methodologies used to evaluate these more substantial investments, particularly those relating to climate change and drought risk, have led to the repudiation of water resource plans both unfit for purpose and inadequately evidenced via public enquiry (e.g. Burden, 2010), public opposition (e.g. GARD, 2013), and revision (e.g. Thames Water, 2014). However, following the Cave Review of competition in the water industry (Cave, 2009) and a metamorphosis of governmental policy (e.g. UK Government, 2011), the language of the economic and environmental regulators implies a greater openness to water transfers as a means of strategically deploying existing resource with greater efficiency than has been prevalent in the period since the subsuming of the National Rivers Authority by the Environment Agency. In particular, transfer from the River Severn to the River Thames (e.g. National Rivers Authority, 1994) is one of three options for a major resource development supporting London (Thames Water, 2014). The set of mooted transfer schemes providing strategically significant yield is reducible to transfers exploiting just four resources: Kielder Water; the River Severn; the River Trent, and; Craig Goch reservoir.

Owned and operated by Northumbrian Water, and located in Northumberland, Kielder Water has a volume of some 200 000 Ml and a catchment area of around 240 km^2, plays a pivotal role in the regulation of the rivers Tyne, Wear, and Tees, and contributes to the support of a population of some 2.5 million people (Gustard *et al.*, 1987; Ofwat, 2011). Northumbrian Water's water resource plan projects the water available for use in this water resource zone to exceed the demand by at least three times the target amount over the forecast horizon; thus, many view Kielder Water as an under-exploited resource (e.g. McCulloch, 2006; Northumbrian Water, 2011). Thames Water, United Utilities and Yorkshire Water all present options for increasing the water available for use by their customers that in some way integrate dependence on Kielder Water (United Utilities Water plc, 2009; Yorkshire Water, 2009; Thames Water Utilities Limited, 2011).

The River Severn has a watershed of some 11 420 km^2, excluding the River Wye and the River Avon, and plays a key role in the strategic water grid of Severn Trent Water, supporting both direct abstraction and acting as a conveyance medium for raw water transfer (e.g. Severn Trent Water, 2010). Llyn Vyrnwy, in the upper reaches of the River Severn, supports the demand for water in Liverpool and Merseyside. The Severn forms an integral part of several alternative schemes proposed by Thames Water, including the licensing of a new abstraction in Worcestershire and, optionally, the construction of a new storage reservoir in Gloucestershire to augment the yield of the abstraction, as well as transfer of raw water by pipeline or canal from the River Severn to existing storage reservoirs and water treatment works in the South Oxfordshire and London resource zones (e.g. Cascade Consulting, 2011; Thames Water, 2014).

The River Trent, having a watershed of 10 435 km^2, performs strategic functions similar to those of the River Severn. The only reservoir along its course supports the Caldon Canal, and is not used for water supply (Environment Agency, Personal Communication); however, abstraction from the River Trent supplies water to the East Midlands and the East of England, most notably via the Trent-Witham-Ancholme River Transfer Scheme (e.g. Anglian Water Services Ltd, 2010) and the Ely-Ouse (or Ely-Ouse-Essex) Transfer System (e.g. Essex and Suffolk Water, 2010). Anglian Water and Essex & Suffolk Water suggest increased abstraction from the River Trent coupled with enhancement and/or increased use of the Trent-Witham-Ancholme River Transfer Scheme and the Ely-Ouse Transfer System, while Yorkshire Water suggest a new abstraction and storage reservoir to supply the Yorkshire Water 'Grid' resource zone (Yorkshire Water, 2009; Anglian Water Services Ltd, 2010; Essex and Suffolk Water, 2010).

Finally, Craig Goch reservoir, in the Elan Valley, has a capacity of around 9 219 Ml (Gustard *et al.*, 1987), and supports Birmingham and the West Midlands as part of a chain of reservoirs. As Craig Goch's location enables support of both the River Severn and the River Trent, and a raising of the dam to increase storage would result in only minor land take, enhancement of the reservoir through raising of the dam is a component of several alternative schemes for strategic water transfer (e.g. National Rivers Authority, 1994; Thames Water, 2014).

2.4.2.1 Water security

Trends in the demand for water services and the availability of water to meet demand imply progressive erosion of water security across the UK (e.g. UK Government, 2011). Despite using a range of metrics and approaches, various studies agree on the direction of change in water security implied by these trends.

Of the several definitions of water security, the metric used by water service undertakers in the UK is the margin between the demand for water services from a water supply infrastructure system and the quantity of water deployable to meet demand from that system, or 'headroom' (Lawson *et al.*, 1998; Carnell *et al.*, 1999; Chadwick and Thomas, 2002). It is the recommended expression of water security for the planning and management of the public water supply (Environment Agency *et al.*, 2012), and integrates information about demand and water available for use in the context of a range of uncertainties, including loss of bulk imports and the impact of climate change on deployable output. Implementation of the headroom methodology is at the discretion of each water undertaker, leading to little consistency in its application; however, projections of headroom produced for the purposes of water resource planning show that, without intervention and under supposition of conservative impacts from climate change, water resource zones in the south and east of England may experience significantly degraded headroom and thus exacerbated water stress prior to 2035 (Southern Water Services Limited, 2009; Anglian Water Services Ltd, 2010; South East Water plc, 2010; Charlton and Arnell, 2011; Thames Water Utilities Limited, 2011).

The Environment Agency and Natural Resources Wales have recently published an alternative methodology for the assessment of water security as the modal ratio of demand from water companies, businesses and farmers to the water available from rivers, groundwater, storage, discharges and transfers (Environment Agency, 2012d).

Application of this methodology classified a number of water company areas in the south and east of England as 'areas of serious water stress' both currently and under a number of future scenarios of demand and climate change: Affinity Water, Anglian Water, Essex & Suffolk Water; South East Water; Southern Water; Sutton & East Surrey Water, and; Thames Water (Environment Agency and National Resources Wales, 2013).

Some authors, such as Wilby *et al.* (2006) and Manning *et al.* (2009) look directly at the frequency of flows at or below a given threshold as a measurement of the time available to abstract, and, thus, a pragmatic proxy for water available for use from a resource, providing insight into when abstraction is likely to be 'switched on' or 'switched off' in practice.

In a study summarised by the European Environment Agency (2012), Flörke *et al.* (2011) computed water stress as the ratio of water withdrawals to availability. They projected increases in water stress from 'low' to 'mild' or 'severe' across much of England under a range of scenarios of demand and climate change.

Finally, in the most comprehensive study since Arnell (2003a), Rance *et al.* (2012) derived response functions between an 'aridity index', dependent upon temperature and precipitation, and variables key to water resources management in the UK, such as Q95, deployable output, and per capita demand. They found dramatic decreases in the quantity of water available for use across England in all but the most extremely wet futures. For example, under a 'medium' emissions scenario, changes in deployable output ranged from -9% to +10% in the 2020s and -39% to 0% in the 2050s, with the decreases of greatest magnitude occurring in northwest England. Under scenarios of similar emissions, population growth derived from Downing *et al.* (2003) and the assumption of no connectivity between regional water supply networks, the authors reported changes of up to -70% in the low flows that determine the viability of sources of water. Their results showed deficits in the supply-demand balance of water of between 0 Ml/day and 400 Ml/day in the south and east of England by the 2020s, and more widespread deficits of between 0 Ml/day and 1800 Ml/day by the 2050s, with correspondingly diminished and exacerbated impacts under 'low' and 'high' emissions scenarios, respectively, suggesting that tens of thousands of people could be affected by water shortages under even the most conservative of estimates.

This suggests that intervention is required to maintain or improve the security of the UK's public water supply infrastructure system.

Methods used more commonly internationally, such as RRV (Hashimoto *et al.*, 1982) have been used occasionally (e.g. Fowler *et al.*, 2003), but are not commonplace. This is perhaps because very few studies consider the performance of water supply infrastructure systems directly, and many more look at climate and hydrological factors.

2.4.2.2 Intervention measures

There are two categories of interventions available to maintain or improve the security of water supply: 'demand-side' measures, which reduce the demand for water services or mitigate the growth in demand, and 'supply-side' measures, which enhance the capacity of the water supply infrastructure system to meet demand for water services. Demand-side measures include behavioural change, leakage reduction, pressure management and price controls, while supply-side measures include the construction or enhancement of new or existing water infrastructure such as abstractions, storage reservoirs, desalination plants and water transfers. Operational practices, such as varying reservoir releases and river regulation, typically span both categories of intervention measure, and can have substantial impacts on the performance of water supply systems. Adeloye *et al.* (2016), for example, revise the operating rules of a single reservoir to demonstrate reductions in vulnerability of around 40% under historical and projected future scenarios. See Loucks *et al.* (2005) and Ratnayaka *et al.* (2009) for a more detailed description of water supply infrastructure and intervention measures.

UK guidelines for water resources planning recommend a 'twin-track' approach comprising portfolios of both such measures (Environment Agency *et al.*, 2012). This is reflected in companies' water resource management plans (e.g. Thames Water Utilities Limited, 2011). Recent plans feature demand-side measures predominantly in response to pressure to maximize the efficiency of existing sources of water (e.g. Cave, 2009) and in recognition that there are few opportunities for additional supply-side measures (e.g. Environment Agency, 2011a). Among preferred options, the primary themes are undoubtedly leakage management, enhanced water efficiency and increased metering of water use, which are present in all available water resource management plans. Secondary themes conspicuous by their inclusion as 'preferred options' or listed as 'feasible' options include aquifer storage and recovery (Severn Trent Water Ltd, 2010;

Thames Water Utilities Limited, 2011) and enhanced efficiency of water use through greater integration of regional networks (Yorkshire Water, 2009) and conjunctive use of sources (Dŵr Cymru Welsh Water, 2011), while other mooted major supply-side schemes, such as a proposed reservoir in Abingdon, Oxfordshire, have been found to be based on incomplete evidence (Burden, 2010).

2.4.2.3 Proposed inter-basin transfers

A supply-side intervention measure, inter-basin transfer is the movement of water from a donor river basin, where water is relatively abundant, to a recipient river basin, where water is relatively scarce or more valuable (e.g. Ghassemi and White, 2007).

Until recently, regulators routinely dismissed the notion of new large-scale inter-basin transfers as an adaptation to diminished water security on environmental grounds (Environment Agency, 2006a); however, concerns over security of supply and the level of competition in the water sector have yielded policy receptive to their implementation, where need is evidenced (UK Government, 2011). Strategies unimplemented but still viewed as feasible, such as those developed by the National Rivers Authority (1994), have resurfaced, and transfers are being discussed as alternatives to the 'preferred' options of water companies and evaluated as part of the wider planning exercise (e.g. United Utilities Water plc, 2009; Burden, 2010; Thames Water Utilities Limited, 2011). Unfortunately, the scope and methods predominant in the UK's water resources planning exercises preclude the rigorous assessment of large-scale, strategic water transfers under climate change (Cave, 2009).

In addition, recent national-scale studies such as Rance *et al.* (2012) use not only a simplified representation of the relationship between climate variables and the water available for use by the water supply infrastructure system, but also a treatment of the uncertainty inherent in climate change projection that precludes the possibility of assessing concurrent supply-demand deficits across hydrological boundaries.

2.4.3 Modelling the UK public water supply infrastructure system

While models of the water supply infrastructure of the UK exist, they are not suitable for the simulation of probabilistic climate change impacts at national scale.

As detailed in §2.4.1.1, all undertakers of public water supply services in Great Britain have a statutory obligation to manage and develop water resources. Practically, this often takes the form of estimating the optimal quantity of resource to allocate across a regional water supply infrastructure system in the context of physical, legislative and business constraints. Modelling is an intrinsic part of this process, explicitly so in the case of undertakers regulated by the Environment Agency (e.g. Environment Agency *et al.*, 2012). As a result, all but the minor undertakers develop and maintain computational models of their infrastructure systems for the purposes of water resources planning and management. Such models are typically very granular, complex and highly detailed representations of the physical infrastructure systems, informed with empirical evidence and local knowledge; however, they are also proprietary and often exist only in esoteric and computationally demanding modelling environments. As a result, it is often impossible or impractical to connect these models for meaningful simulation of resources across regional boundaries. Furthermore, much of the detailed technical information and material local knowledge informing the models is commercially sensitive, and often goes unpublished and unacknowledged, making it difficult to duplicate the detailed behaviour of undertakers' models or re-implement them in open environments.

Models of water supply infrastructure systems conventionally represent each individual component of the system, its behaviour and interactions, as collections of vertices and edges within a graph network. Canonically, each network element has a number of properties, such as parameterisations of the cost, productivity and quality of individual sources of water and individual infrastructure elements as functions of system operating parameters. Further models of external constraints, such as aquifer yield and seasonal demand, in turn inform these relationships. This is convenient not only from the perspective of being analogous to physical reality, but also from the perspective of resource flow optimisation: the problem of computing resource flows through such a network subject to constraints is approachable using a range of readily available and well-understood algorithms. For example, undertakers perform minimum-cost, maximum-flow optimisation of water resource allocations within their resource networks over a time horizon of 25 years, subject to regulatory constraints i.e. they search for the lowest cost of operation at a given level of performance over the statutory planning window. Such models represent time dependence by varying the values of attributes such as river discharge, groundwater source yield and demand for water services, and re-computing optimised flows under the new conditions. State variables manage persistent side effects, such as the quantity of water stored in a reservoir. These time-varying attribute values are therefore the entry point for the representation of physical constraints on the quantity of water available for use due to climate change. Most undertakers choose a representation of uncertainty due to climate change that follows advice after Arnell *et al.* (1990b), extensions to that apply UKCIP02 (UKWIR, 2007), and, contemporarily, Rance *et al.* (2012), which uses an ensemble of RCM outputs and therefore does not capture the full range of uncertainties evidenced by Jenkins *et al.* (2009). Furthermore, the methods by which these time-series are constructed are not consistent between undertakers.

Finally, as undertakers typically have the resources, information and freedom within the prevailing commercial environment to build detailed models only of the resources they operate, quantities of water imported and/or exported across regional boundaries are applied as constant external constraints rather than being intrinsically dynamic network elements. This precludes the meaningful simulation of water transfers.

A more appropriate treatment of uncertainty due to climate change and inter-regional water transfers must therefore scale appropriately across multiple regions and be driven by projections of future water availability that are fit for purpose.

2.5 Research gap and proposed alternative methodology

2.5.1 Research gap

The review summarised in §2.2-§2.4 identified two key research gaps to be addressed in this thesis.

Firstly, very few studies have applied the output of UKCP09 to studies of water resource availability, despite UKCP09 being the most complete projection of climate change available for the UK. Furthermore, those that do so apply RCM outputs associated with UKCP09 rather than fully-fledged probabilistic outputs and/or apply UKCP09 to a small number of river basins. There is a clear opportunity to apply the output of UKCP09, without restriction to a small subset of RCM outputs, to the problem of quantifying the impact of climate change on the performance of the water supply infrastructure system of the UK, as well as to look in detail at the output in the context of meteorological, hydrological and water resources drought on a national scale.

Secondly, water service undertakers perform planning of the UK's water supply infrastructure system on a regionally segregated basis, with short forecast horizons, and a limited application of climate projection information. As a result, water resource plans cannot simulate the efficacy of water transfers over long forecast horizons. There is opportunity here to develop a national-scale model of water infrastructure capable of performing such simulation, particularly in the context of UKCP09. Additional research will be needed to add spatial coherence to the outputs of the UKCP09 weather generator and to generate sufficient data to build a consistent model of the national water supply infrastructure system.

2.5.2 Proposed alternative methodology

This section describes a proposed alternative methodology comprising a nationally consistent modelling framework suitable for answering research questions relating to the impact of inter-basin water transfers on the performance of the UK water supply infrastructure system under projected future climate. The framework represents the salient details of the water resource infrastructure system of the UK (described in §2.4), and addresses the limitations of existing data and methods and the research gap identified (described in §2.2-§2.4).

The modelling framework comprises three models: a model of climate variables, a model of hydrological processes, and a model of the public water supply infrastructure system of the UK. The framework arranges the three models as a cascade in which the model of climate variables feeds into the model of hydrological processes and the model of hydrological processes feeds into the model of water supply infrastructure.

The model of climate variables takes as input a spatial definition of the public water supply infrastructure system of the UK in terms of a set of locations representative of the hydrological processes that determine the freshwater available to meet demand, and outputs spatially coherent time-series of precipitation, air temperature, and evapotranspiration. The model provides a nationally consistent methodology for the projection of climate variables across the UK that is also consistent with the methods used for climate projection, and encapsulates the uncertainty inherent in climate projection by synthesising time-series of climate variables using probabilistic projections for each of four time-slices: 1961-1990 (the 'baseline'), 2010-2039 (the '2020s'), 2040-2069 (the '2050s') and 2070-2099 (the '2080s'). This produces ensembles of time-series climate variables for each location and for each time-slice. The model of climate variables is described in §3.

The model of hydrological processes takes as input the time-series of climate variables output from the model of climate variables and outputs time-series of daily mean discharge. The model represents surface and subsurface physical processes conceptually, using well-known methods, consistently across Great Britain. The model propagates the encapsulation of uncertainties due to climate projection by driving instances of the model with the ensembles of time-series of precipitation, temperature and potential evapotranspiration output from the model of climate variables. This results in ensembles of hydrological variables for each location and for each time-slice. The model of hydrological processes is described in §4.

The model of the water supply infrastructure system of the UK takes as input the time-series of discharge and base-flow output from the model of hydrological processes and outputs time-series of the water allocated to meet demand. The model provides a nationally consistent and highly scalable representation of water supply infrastructure. The model propagates the encapsulation of uncertainties due to climate projection by driving instances of the model with ensembles of discharge and baseflow output from the model of hydrological processes. This results in ensembles of allocation for each time-slice. The model of water supply infrastructure is described in §5.

The cascaded modelling framework introduces national-scale consistency and encapsulation of uncertainties due to climate projection via the model of climate variables. It maintains national-scale consistency and facilitates treatment of uncertainties by passing ensembles of variables across the partitions between the three models. As such, in the context of the UK, this modelling framework is a significant, original step forward in the assessment of the impact of climate change on the performance of the water resources infrastructure system, and a solution necessary for the simulation of large-scale inter-basin water transfers.

Figure 2.10 illustrates the methodology of this study, showing the cascade of models comprising the modelling framework and the flow of information between them.

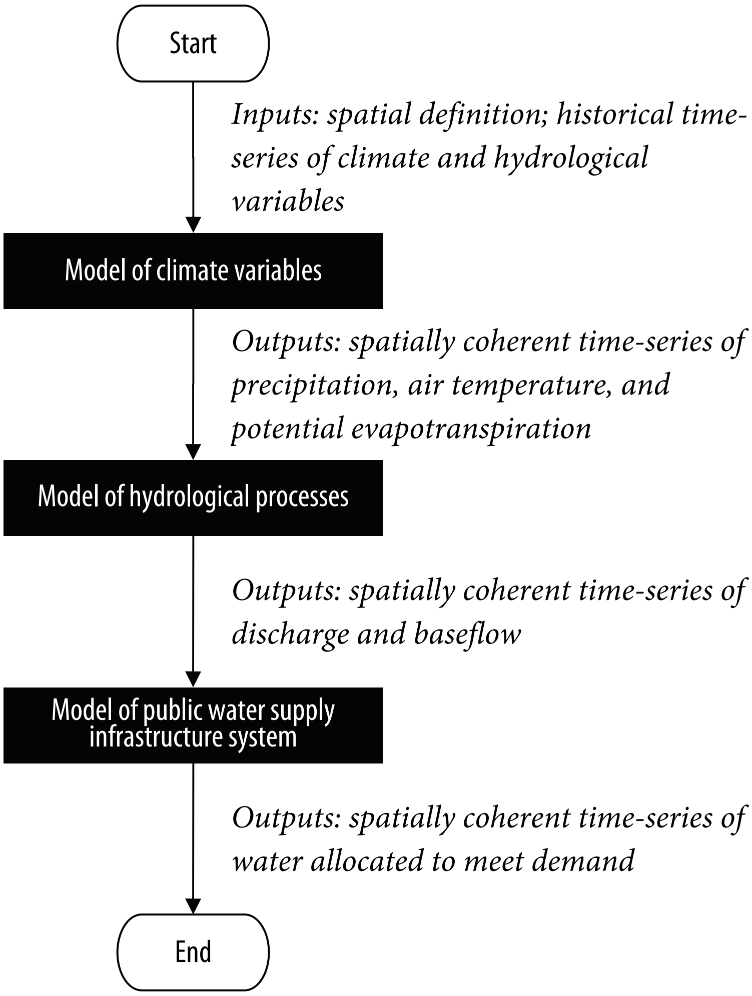


Figure 2.10: Schematic representation of the overall methodology of this study, including principal models and their outputs.

3 Model of climate variables

3.1 Chapter outline

This chapter describes the development of a methodology for the synthesis of time-series of climate variables suitable for the calibration of a simulation model of the hydrological processes that determine the quantity of water available to meet demand via the public water supply of Great Britain and the use of the model to project the impacts of climate change on the availability of water resource in Great Britain throughout the 21st Century. The methodology combines well-established paradigms with a unique and innovative implementation of the UKCP weather generator (Jones *et al.*, 2009a) to produce historical daily time-series of total precipitation, total potential evapotranspiration, mean air temperature, and mean daily discharge for 59 locations for the control period 1961-1990 and statistically plausible and internally consistent daily time-series of total precipitation, total potential evapotranspiration, and mean air temperature for 72 locations for three scenarios of climate change corresponding to the impacts of the SRES A1B greenhouse gas emissions scenario (Nakicenovic *et al.*, 2000) in the 2020s, 2050s and 2080s, each consisting of 1 000 samples of length 30 years.

3.2 Introduction

The framework for national-scale assessment of the impacts of climate change on water resource described in §2.4.2.1 requires time-series of precipitation, temperature and potential evapotranspiration for the calibration, verification, and execution of multiple hydrological simulation models over a variety of spatiotemporal scales, including both series consistent with projections of future climate and series consistent with historical observations of a baseline climate, for comparison.

As described in §2.2.1, there are a variety of sources from which to obtain observations of climate variables suitable for the construction of a baseline climate; however, while suitably high-resolution data products derived from observations of precipitation and temperature are readily available (e.g. Perry and Hollis, 2005b; Perry *et al.*, 2009), comparable data products derived from observations of potential evapotranspiration do not exist for the UK. In addition, the spatiotemporal scales of the available climate variable observations do not agree with the spatiotemporal scales of the available hydrological observations, necessitating transformation of the data.

In lieu of a suitable data product derived from observations of potential evapotranspiration, this study synthesises an appropriate dataset through application of Allen *et al.* (1998), who describe an implementation of the Penman-Monteith combination equation (Monteith, 1965) that is suitable for estimating potential evapotranspiration ET_0 in terms of net radiation at a crop surface (R_n), soil heat flux density (G), mean daily air temperature (T), wind speed at 2 m height (u_2), saturation vapour pressure (e_s), actual vapour pressure (e_a), slope vapour pressure (Δ) and the psychrometric constant (γ) (Equation 4).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T + 273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad \mathbf{4}$$

It assumes that an actively growing and adequately watered 'reference crop' of uniform height, surface resistance and albedo covers the evaporating surface, and requires observations of radiation, air temperature, humidity and wind speed, which are available, either directly or indirectly, from UKCP09 and the UK Met Office (Perry and Hollis, 2005b), and includes alternative parameterisations to compensate for variable data availability and spatiotemporal scales.

The most suitable hydrological data available from the NRFA are observations of daily mean discharge. For calibration and verification of hydrological models of these gauged areas, the time-series of climate variables must be appropriately aggregated so as to represent the gauged area. To a first approximation, this can be achieved by computing the mean value of each variable over the gauged areas.

The UKCP09 weather generator (Jones *et al.*, 2009a) synthesises statistically plausible, internally consistent daily time-series, of length up to 100 years, of a range of climate variables that includes precipitation, air temperature and potential evapotranspiration, estimated using the FAO guidelines (Allen *et al.*, 1998). Based on an established methodology (e.g.Kilsby *et al.*, 2007), the weather generator's use of UKCP09 (Murphy *et al.*, 2009) renders it the UK's *de facto* standard for the generation of high-resolution projections of climate variables that encapsulate uncertainty. The version of the UKCP09 weather generator available to this study produces time-series for a point location assumed representative of a single 5 km cell, meaning that many runs of the weather generator are necessary to obtain sufficient data to represent the whole of the UK; however, the UKCP09 methodology on which the weather generator is based does not explicitly preserve the spatial relationships between climate variables, and, in any case, the weather generator does not provide a mechanism to intentionally reproduce samples of climate variants to facilitate this.

As the spatial relationships between climate variables are necessary for the characterisation of water resource system behaviour over large spatial domains, use of the UKCP09 weather generator in a simulation of national water resource requires surmounting these limitations. As the weather generator uses rainfall as its primary variable, and accepts an external time-series of precipitation as input rather than one generated using its own internal rainfall model, it follows that spatial coherence can be preserved implicitly by driving independent runs of the UKCP09 weather generator with appropriately aggregated spatially coherent daily rainfall data. This demands further modification of the weather generator to attribute and store vectors of sampled climate variants for re-use.

This chapter describes the procedures undertaken to construct 'baseline' datasets suitable for the calibration and verification of a conceptual hydrological simulation model intended for application in climate-change impact-assessment, and the projection of those datasets into the future, detailing the steps taken to maintain a high degree of consistency between the 'baseline' and 'future' scenarios. By the end, the reader should understand which climate variables are required as time-series for the hydrological simulation, the sources, aggregation processes and computational models contributing to the assembly of these series for both 'baseline' and 'future' climates, and how the explicit and implicit assumptions necessary for this assembly limit the strength of results achieved based on these data.

3.3 Methods

3.3.1 Historical time-series

This study obtained gridded observations of daily total precipitation, daily maximum air temperature, daily minimum air temperature, monthly mean vapour pressure, monthly mean wind speed at 10 m, and monthly mean sunshine duration from UKCP09 and the UK Met Office (Perry and Hollis, 2005b). Table 3.1 summarises the data acquired.

Variable	Units	Daily	Monthly
Days of snow lying	days		1971-2000
Maximum temperature	°C	1961-2002	1914-2006
Minimum temperature	°C	1961-2002	1914-2006
Mean vapour pressure	hPa		1961-2005
Mean wind speed at 10 m	knots		1969-2002
Precipitation total	mm	1961-2002	1914-2006
Sunshine duration	hours per day		1929-2006

Table 3.1: Data used to construct historical time-series of climate variables.

The observations of daily maximum temperature, daily minimum temperature, mean monthly vapour pressure mean monthly wind speed at 10 m, and monthly sunshine duration were used to estimate daily total potential evapotranspiration as reference crop evapotranspiration for each 5 km grid cell using the FAO Revised Penman-Monteith method (Allen *et al.*, 1998). This necessitated imputation of observations of mean wind speed where values were otherwise missing, e.g. for the period 1960-1968, using the mean value of mean wind speed at 10 m by month.

The observations of daily maximum temperature and daily minimum temperature were averaged for each 5 km cell to yield daily mean temperature.

The gridded observations of daily precipitation, daily potential evapotranspiration and daily mean temperature over the range 1961-2002, and number of days of snow lying per month over the range 1971-2000, were spatially aggregated over the extents of 59 gauged areas for which daily observations of mean flow are available from the NRFA by computing the mean value, by the appropriate time variable, of each climate variable for each set of 5 km cells whose centroids are encompassed by the geometry of each gauged area. The geometries of the gauged areas derives from watershed analysis of NRFA gauge locations (Marsh and Hannaford, 2008) and a DTM of the UK (Ordnance Survey, 2009) and is shown in Figure 3.1.

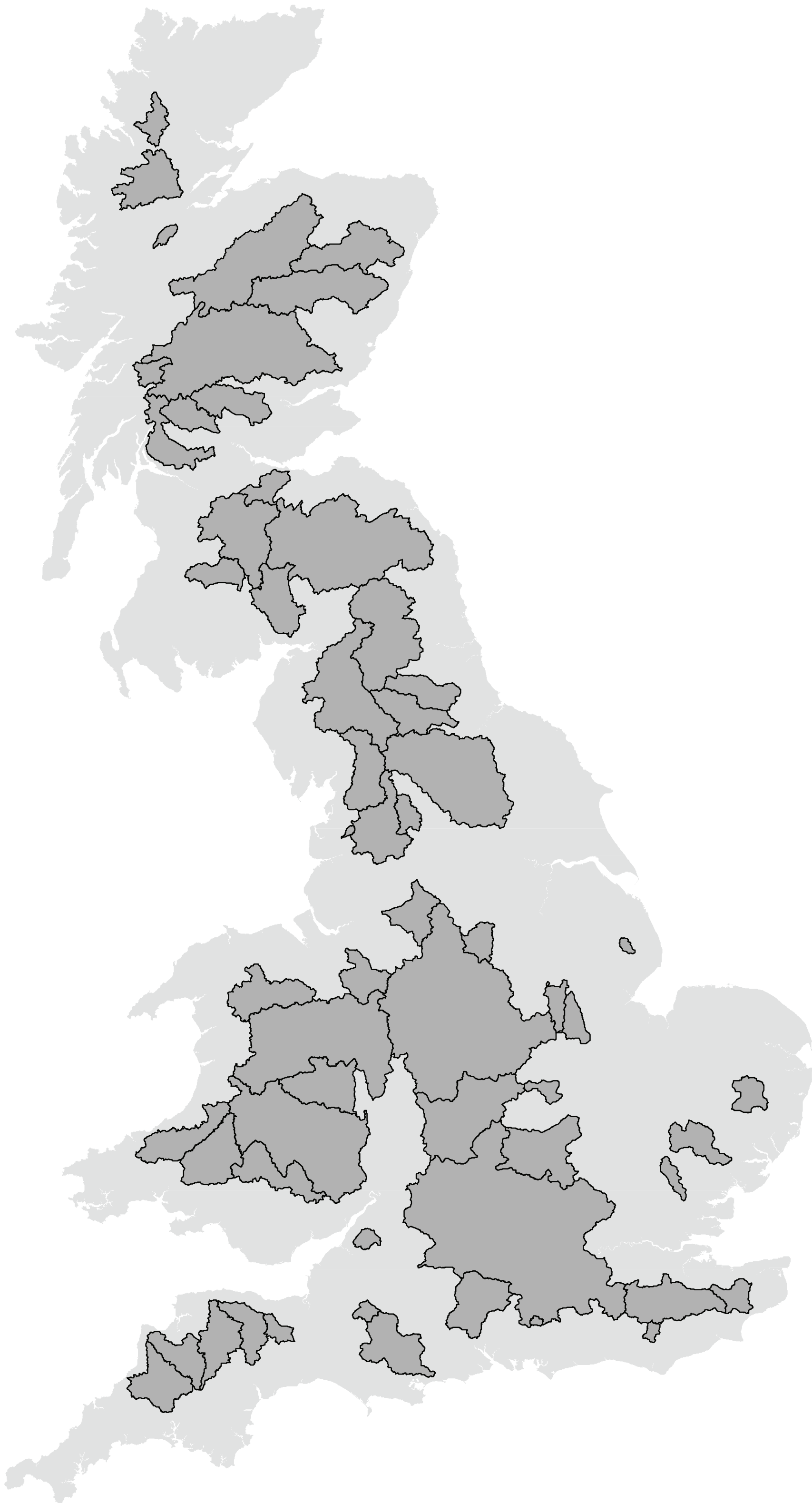


Figure 3.1: The 59 NRFA gauged areas modelled in this study.

3.3.2 Climate baseline and future time-series

42 years' observations of daily total precipitation 1961-2002 and 93 years' observations of monthly total precipitation 1914-2006 were obtained from UKCP09 and the UK Met Office (Perry and Hollis, 2005b) and spatially aggregated over the extents of 72 non-coastal Water Information System for Europe (WISE) River Basin Districts (RBDs) (European Environment Agency, 2008) (Figure 3.2) on the mainland of Great Britain by computing the mean value of precipitation per month for each set of 5 km cells whose centroids are encompassed by the geometry of each river basin. Each RBD was assigned a unique ordinal identifier, $r \in \{1, \ldots, 72\}$. Although these basins provide much better coverage of the UK than the NRFA gauged areas shown in Figure 3.1, they are un-gauged and therefore unusable in the calibration/validation of hydrological models.

Figure 3.2: The 72 WISE river basins modelled in this study.

For each river basin, r, month ordinate, $m \in \{1, \dots, 12\}$, and year, $y \in \{1914, \dots, 2006\}$, the spatially aggregated observations of monthly total precipitation, $x_{r,m,y}$, were transformed using a square-root transformation (Equation 5).

$$x'_{r,m,y} = \sqrt{x_{r,m,y}} \tag{5}$$

The transformed values were then deseasonalised using the mean and standard deviation of the transformed values by river basin and month ($\mu(x'_{r,m})$ and $\sigma(x'_{r,m})$, respectively) (Equation 6).

$$x''_{r,m,y} = \frac{x'_{r,m,y} - \mu(x'_{r,m})}{\sigma(x'_{r,m})} \tag{6}$$

12 multivariate-Normal distributions (MVNs) of 72 dimensions were constructed from the means, $\boldsymbol{\mu}$, and covariance matrices, $\boldsymbol{\Sigma}$, of the transformed data, each distribution representing a given month, and each dimension of each distribution corresponding to a river basin (Equation 7).

$$X''_m \sim \mathcal{N}\left(\boldsymbol{\mu}(x''_{r,m}), \boldsymbol{\Sigma}(x''_{r,m})\right) \tag{7}$$

Sampling once from a given MVN yields a vector of 72 covariant random deviates of transformed monthly total precipitation for a given month. Samples from a given distribution are therefore covariant between river basins, and it is this property that provides spatial consistency to the overall model of climate variables.

To embed future climate information, relative changes in the mean and standard deviation of monthly precipitation were computed using the UKCP09 weather generator (Jones *et al.*, 2009b) for each of three climate scenarios, each month, and each river basin (as the UKCP09 grid cells intersecting the centroids of each of the 72 WISE RBDs). The weather generator was run using its inbuilt model of precipitation for 100 independent executions for the 1961-1990 climate control period, and 1 000 independent executions for each of three scenarios of climate change corresponding to the impacts of the SRES A1B greenhouse gas emissions scenario (Nakicenovic *et al.*, 2000) in the 2020s, 2050s and 2080s. From experience operating the UKCP09 weather generator, these numbers of repetitions are sufficient and appropriate for sampling the variability in each time-slice. Each execution yielded a vector of climate model output variants and daily time-series of precipitation, potential evapotranspiration, and mean air temperature, of length 30 years. Each execution was associated with an integer 'model run' index, i, and a climate scenario index, $s \in \{0, \ldots, 3\}$, where $s = 0$ implies the control period, $s = 1$ implies the 2020s, $s = 2$ implies the 2050s, and $s = 3$ implies the 2080s, $i \in \{1, \ldots, 100\}\ \forall\ s = 0$, and $i \in \{1, \ldots, 1\,000\}\ \forall\ s \in \{1, \ldots, 3\}$. The time-series of precipitation were summated by climate scenario index s, river basin r, month m, and run index i, and the relative changes in the mean and standard deviation of monthly precipitation relative to the control period ($\Delta\mu_{s,r,m}$ and $\Delta\sigma_{s,r,m}$, respectively) computed by s, r and m using Equation 8 and Equation 9.

$$\Delta\mu_{s,r,m} = \begin{cases} 1, & s = 0 \\ \dfrac{\mu_{s,r,m} - \mu_{0,r,m}}{\mu_{0,r,m}}, & s \in \{1, \ldots, 3\} \end{cases} \qquad \mathbf{8}$$

$$\Delta\sigma_{s,r,m} = \begin{cases} 1, & s = 0 \\ \dfrac{\sigma_{s,r,m} - \sigma_{0,r,m}}{\sigma_{0,r,m}}, & s \in \{1, \ldots, 3\} \end{cases} \qquad \mathbf{9}$$

33 000 samples were drawn from each MVN and arranged sequentially, such that a sample from the MVN representing month m was preceded by a sample from the MVN representing month $m - 1$ and succeeded by a sample from the MVN representing month $m + 1$, and cyclically such that samples from December (month

m = 12) preceded samples from January (month m = 1). 100 of the resulting sequences were associated with the control period, and 1 000 were associated with each of the 2020s, 2050s and 2080s. Each sequence was divided into 30-year slices, each slice having 360 elements. As the samples were independent, further ordering was unnecessary.

Having been associated with a climate scenario (by arbitrary attribution), a river basin (by design of the MVNs), and a month (by virtue of the MVN from which the sample was drawn), the deviates, $\hat{x}''_{s,r,m}$, were re-standardised, re-seasonalised and inversely transformed to the scale of the source data according to Equation 10.

$$\hat{x}_{s,r,m} = \left(\hat{x}''_{s,r,m} \times \left(1 + \Delta\sigma_{s,r,m}\right) + \mu_{r,m} \times \left(\Delta\mu_{s,r,m} - \Delta\sigma_{s,r,m}\right)\right)^2 \qquad \textbf{10}$$

The resulting monthly precipitation totals were downscaled to daily resolution using first-order Markov processes (i.e. Markov chains) to model daily rainfall occurrence and exponential models of daily rainfall amount. Each model was parameterised independently for each river basin, r, and month, m, using the spatially aggregated observations of daily precipitation 1961-2002.

Each Markov chain was used to generate a sequence of 'dry' days (having < 1 mm of precipitation observed) and 'wet' days (having ≥ 1 mm of precipitation observed) for each river basin and month. The transition matrix of each Markov chain was constructed by computing the probability of transition between these two states. Such analysis yields a 2×2 transition matrix containing the probability of transition from a 'dry' day to a 'dry' day ($P_{dry,dry}$), the probability of transition from a 'dry' day to a 'wet' day ($P_{dry,wet}$), the probability of transition from a 'wet' day to a 'dry' day ($P_{wet,dry}$), and the probability of transition from a 'wet' day to a 'wet' day ($P_{wet,wet}$). This is shown in

Equation 11 for the states at the current timestep, $s_{r,m,t}$, and the state at the next timestep, $s_{r,m,t+1}$.

$$s_{r,m,t+1} = \begin{pmatrix} (P_{dry,dry})_{r,m} & (P_{dry,wet})_{r,m} \\ (P_{wet,dry})_{r,m} & (P_{wet,wet})_{r,m} \end{pmatrix}^T s_{r,m,t} \qquad \mathbf{11}$$

Each exponential model was used to generate precipitation amounts, $X_{r,m}$, for each 'dry' day generated for each river basin, r, and month, m, where decay rate $\lambda_{r,m}$ is conditioned on rainfall amounts ≥ 1 mm observed in the 1961-2002 aggregated daily precipitation datasets constructed for each river basin (Equation 12).

$$X_{r,m} \sim \mathrm{Exp}(\lambda_{r,m}) \qquad \mathbf{12}$$

To synthesise correlated time-series of mean daily air temperature and potential evapotranspiration, each 30-year precipitation sequence was associated with a model run index from the set of such values appropriate to the hitherto associated climate scenario, and used in combination with the associated vector of climate model output variants to drive the UKCP09 weather generator, substituting the weather generator's model of precipitation for these data. This yielded 100 daily series of total precipitation, total potential evapotranspiration and mean air temperature of length 30 years representative of the baseline climate, and 1 000 series consisting of the same variable, again each of length 30 years, representative of each of the 2020s, 2050s, and 2080s, spatially coherent between 72 locations at the monthly level.

3.4 Results

3.4.1 Drought severity

This subsection summarizes changes in drought severity projected in 72 basins nationwide between the 1961-1990 control period and the 2020s, 2050s and 2080s. Simulation of the control period 1961-1990 produced 100 model runs of length 30 years under conditions of historical atmospheric composition, while simulation of the 2020s, 2050s and 2080s each consisted of 1000 model runs of length 30 years under conditions of the SRES A1B emissions scenario. Results are presented using the three-monthly and six-monthly Drought Severity Index (DSI3 and DSI6, respectively) (e.g.Phillips and McGregor, 1998), details of which are provided in Appendix A.

Figure 3.3 summarises relative change in the mean, 10th percentile and 90th percentile of maximum DSI3 event peak severity projected between the 'control' period 1961-1990 and 2010-2039 ('2020s'), 2040-2069 ('2050s') and 2070-2099 ('2080s'). By the 2020s, changes range from ≤ 0% of SAAR to ≤ +5% of SAAR at the 10% probability level, and from ≤ -2% of SAAR to ≤ +10% of SAAR at the 90% probability level. Only 3% of modelled basins show a decrease in severity at the 10% probability level, all in Scotland. Over 15% of modelled basins show a decrease in severity at the 90% probability level, split between Scotland and Wales. By the 2050s, changes range from ≤ +1% of SAAR to ≤ +7% of SAAR at the 10% probability level, and from ≤ 0% of SAAR to ≤ +12% of SAAR at the 90% probability level. Basins exhibiting a decrease in maximum DSI3 event peak severity are sparsely distributed; the largest increases occur in western Scotland, northwest, southwest and southeast England. This pattern changes somewhat by the 2080s, when basins in northeast and southwest England experience the largest changes in maximum DSI3 event peak severity. In this period, changes range from ≤ +2% of SAAR to ≤ +9% of SAAR at the 10% probability level, and from ≤ 0% of SAAR to ≤ +16% of SAAR at the 90% probability level.

Figure 3.4 shows similar analyses of the peak severity of DSI6 events. By the 2020s, changes range from ≤ -1% of SAAR to ≤ +6% of SAAR at the 10% probability level, and from ≤ -7% of SAAR to ≤ +12% of SAAR at the 90% probability level. Relatively few basins exhibit a decrease in severity, being located in Scotland, northwest England and central England, while the greatest increases in severity occur in the southwest, southeast, and northwest of England. By the 2050s, changes range from ≤ -1% of SAAR to ≤ +7% of SAAR at the 10% probability level, and from ≤ -6% of SAAR to ≤ +16% of SAAR at the 90% probability level. The spatial pattern of change is broadly similar to that of the 2020s; however, pronounced increases in severity are visible in northwest England and East Anglia. By the 2080s, changes range from ≤ 0% of SAAR to ≤ +9% of SAAR at the 10% probability level, and from ≤ -4% of SAAR to ≤ +18% of SAAR at the 90% probability level. Acute increases in severity occur in northwest England, southwest England and East Anglia, while Scotland and Lincolnshire appear less affected.

In this analysis, the Coefficient of Variation (CV) of the 1961-1990 'control' period is a metric of the natural variability present in the simulations, while the CV of future time-slices is a metric of the variability present in the projections. The severity of both DSI3 and DSI6 events show similar trends in CV relative to the control period: by the 2020s, there is a mixed spatial distribution of increases and decreases in the variability of drought event severity relative to the mean of each time-slice; however, by the 2050s, this gives way to widespread decreases in CV, particularly in the northwest of Scotland, Wales, and the south of England. This suggests progressively decreasing variability in drought severity throughout the 21st Century.

Note that DSI is normalised by the mean annual precipitation over the 1961-1990 climate control period (also known as Standard Average Annual Rainfall, or SAAR) according to the location and period of analysis. Thus, severity is expressed as a percentage of SAAR.

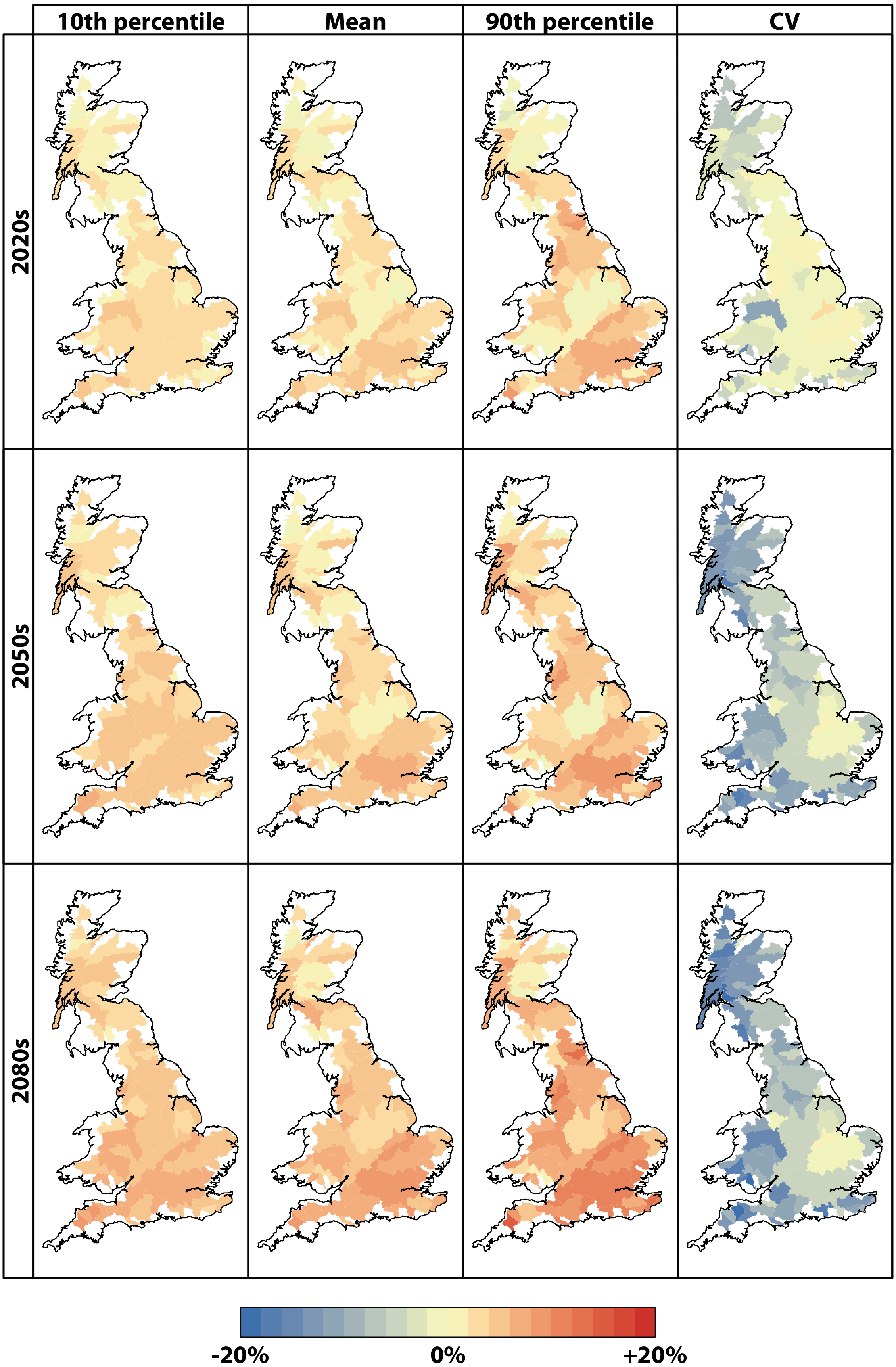


Figure 3.3: Projected changes in DSI3 severity.

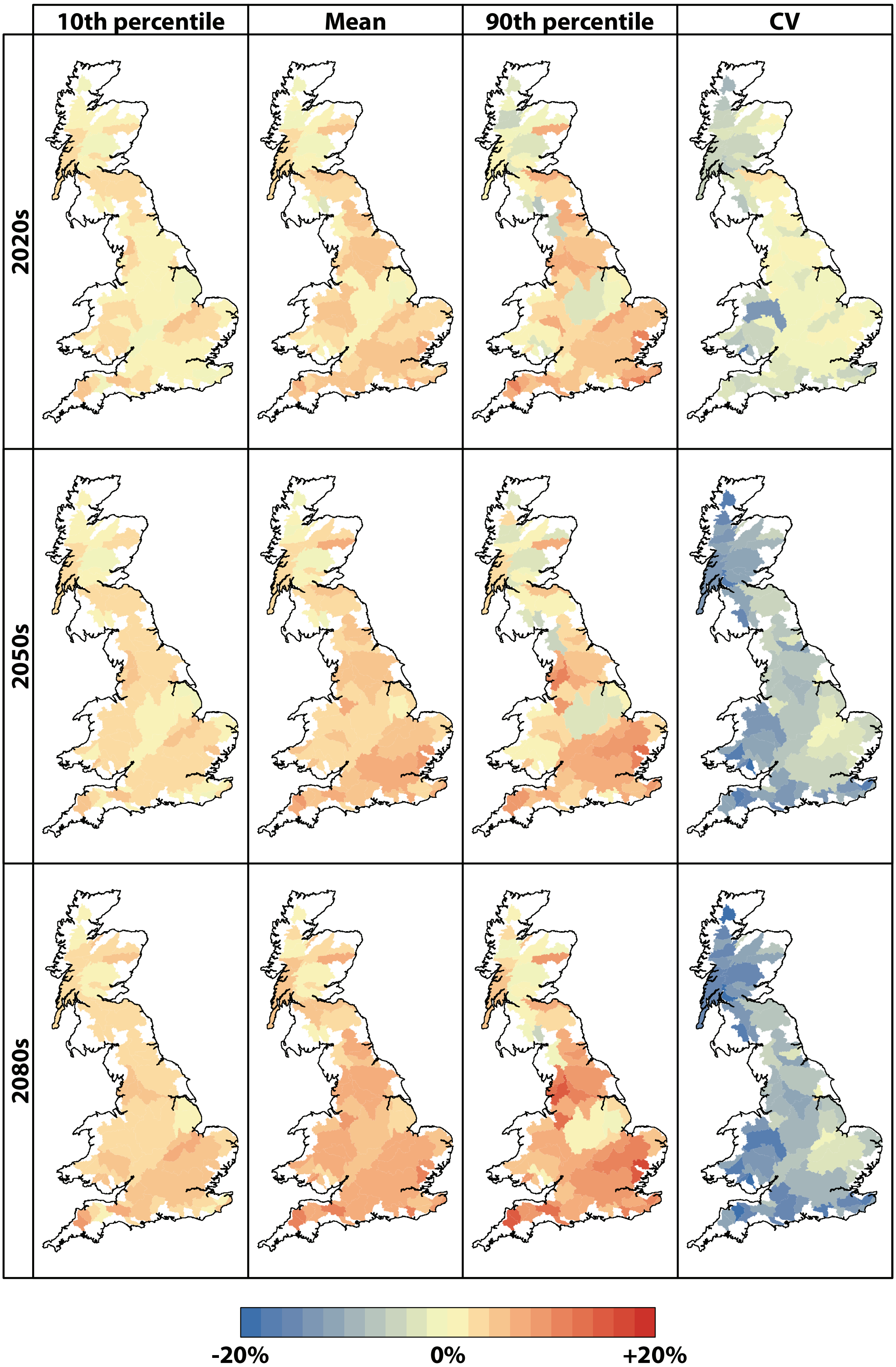


Figure 3.4: Projected changes in DSI6 severity.

3.4.2 Drought duration

Figure 3.5 summarises absolute change in the mean, 10th percentile and 90th percentile of the maximum duration of DSI3 events projected between the 'control' scenario 1961-1990 and 2010-2039 ('2020s'), 2040-2069 ('2050s') and 2070-2099 ('2080s'). These data suggest that the maximum duration of DSI3 events remains static over the 21st Century in over half of modelled basins at the 10% probability level, and in over one quarter of modelled basins at the 90% probability level. The range of changes in maximum DSI3 duration are also static throughout the 2020s, 2050s, and 2080s; from ≤ -1 months to ≤ +1 months at the 10% probability level, and from ≤ -3 months to ≤ +2 months at the 90% probability level. The spatial distribution of changes in maximum DSI3 duration is highly variable; however, it is evident that most basins exhibit minor decreases in maximum DSI3 event duration, with the exception of a strip of basins running coast-to-coast from Wales to coastal Lincolnshire that show relatively shorter droughts than neighbouring basins, and clustering of basins showing increased maximum DSI3 event duration in the north of England.

Changes in the maximum duration of DSI6 events (Figure 3.6) are, in general, greater in magnitude than those changes observed for DSI3 events, and show more sensitivity to changes in monthly total precipitation in the 2020s, 2050s, and 2080s. A majority of basins exhibit decreases in DSI6 event duration both on average and at the 10% probability level in the 2020s, 2050s, and 2080s, and at the 90% probability level in the 2050s and 2080s. In the 2020s, changes range from ≤ -4 months to ≤ +2 months at the 10% probability level and from ≤ -3 month to ≤ +5 months at the 90% probability level. Decreases in DSI6 duration are widespread across Wales, Scotland, and southern England, at the 10% probability level; however, at the 90% probability level, decreases are visibly greater in magnitude across Wales, Lincolnshire, East Anglia, and western Scotland, while more severe increases in DSI6 event duration occur in south west and south east England, north England and southern Scotland. Further changes in precipitation exacerbate this pattern in the 2050s and 2080s: in the case of the former, changes in DSI6 event duration range from ≤ -5 months to ≤ +1 month at the 10% probability level, and from ≤-9 months to ≤ +3 months at the 90% probability level; in the case of the latter, changes in DSI6 event duration range from ≤ -5 months to ≤ +2 months at the 10% probability level, and from ≤-9 months to ≤ +3 months at the 90% probability level.

Trends in the CV of drought event duration relative to the 1961-1990 ‘control’ period are similar to those observed for severity: mixed spatial distribution of increases and decreases by the 2020s, followed by widespread decreases in CV, particularly in the northwest of Scotland, Wales, and the south of England. This suggests that the durations of drought events may become progressively less variable throughout the 21st Century.

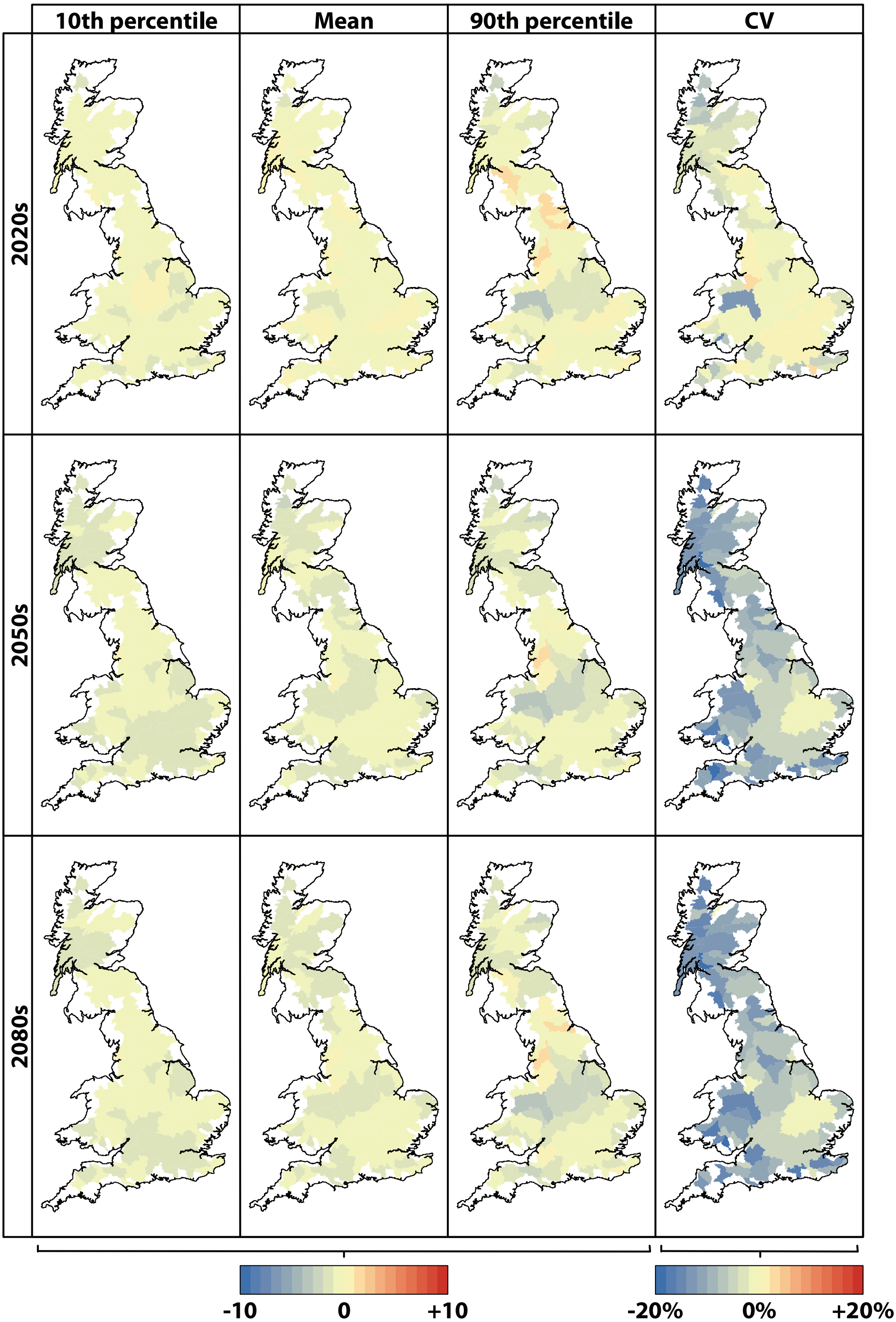


Figure 3.5: Projected changes in maximum DSI3 duration (months).

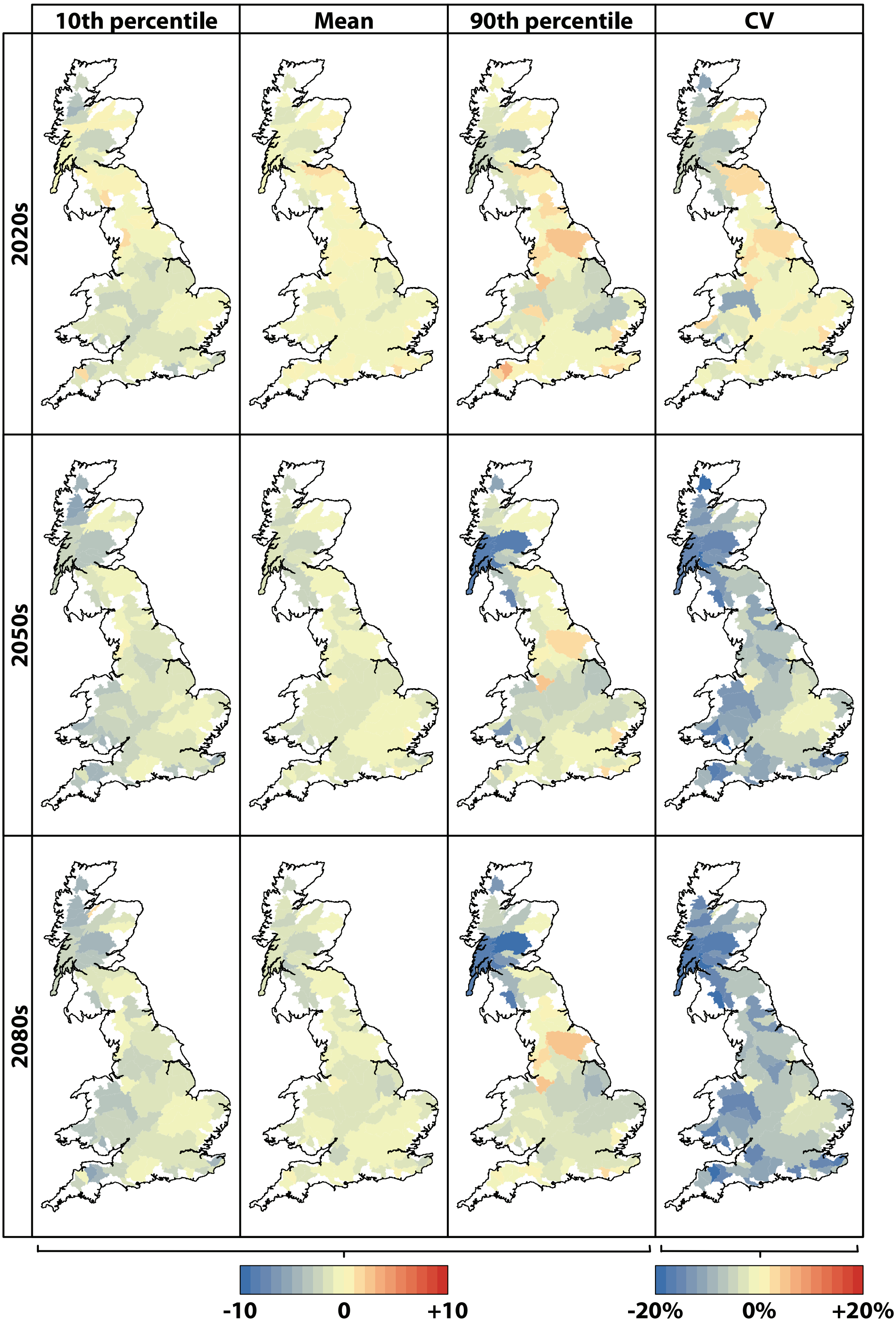


Figure 3.6: Projected changes in maximum DSI6 duration (months).

3.4.3 Drought frequency

Visualised in Figure 3.7, these data suggest that, in as many as 90% of simulations, the majority of modelled basins experience between one and two fewer DSI3 events in the 2020s, 2050s, and 2080s in comparison with the 1961-1990 baseline climate; however, there appears to be no substantial difference in DSI3 frequency in two-thirds of basins, and no change at all in one-third of basins, until the 2050s. Despite outlying decreases of up to ≤ -2 events at the 10% probability level and ≤ -3 events at the 90% probability level in central Scotland and Wales, much of Great Britain exhibits increases in DSI3 frequency of up to ≤ +2 events at both the 10% and 90% probability levels by the 2020s, although the average increase is ≤ +1 event. By the 2050s, DSI3 events become less frequent across most of Great Britain: on average, most basins experience one fewer DSI3 event in the 2050s than in 1961-1990; some basins basins exhibit ≤ 3 and ≤ 4 fewer DSI3 events at the 10% and 90% probability levels, respectively. Increases in DSI3 event frequency are far less likely by the 2050s than by the 2020s, by which time the average increase is ≤ +1 events at both the 10% and 90% probability levels, with basins in East Anglia and the Midlands exhibiting up to ≤ +2 DSI3 events at both the 10% and 90% probability levels. This pattern remains in the 2080s, when decreases in DSI3 event frequency range reach up to ≤ -4 events at the 90% probability level, and increases reach only up to ≤ +1 event.

Projected changes in DSI6 event frequency (Figure 3.8) suggest that, across the 2020s, 2050s and 2080s, a greater proportion of basins exhibit no change in the frequency of DSI6 events than in the frequency of DSI3 events. Furthermore, although DSI6 event frequency may increase in around half of all simulated basins both on average, and at the 10% probability level, the magnitude of all changes in DSI6 event frequency are smaller than those in DSI3 event frequency both on average and in the majority of basins. The greatest decreases occur in south west and east England, ranging from ≤ -1 events at the 10% probability level to ≤ -2 events at the 90% probability level, while increases reach only as much as ≤ +2 events at both the 10% probability level and the 90% probability level.

Changes in the CV of the frequency of DSI3 and DSI6 drought events are mixed. In the case of the former, no clear spatial pattern emerges; however, in the case of the latter, central England exhibits a broad increase in the variability of drought event frequency. Through the 2050s and 2080s, the majority of basins tend towards a decrease in the variability of the frequency of both DSI3 and DSI6 drought events.

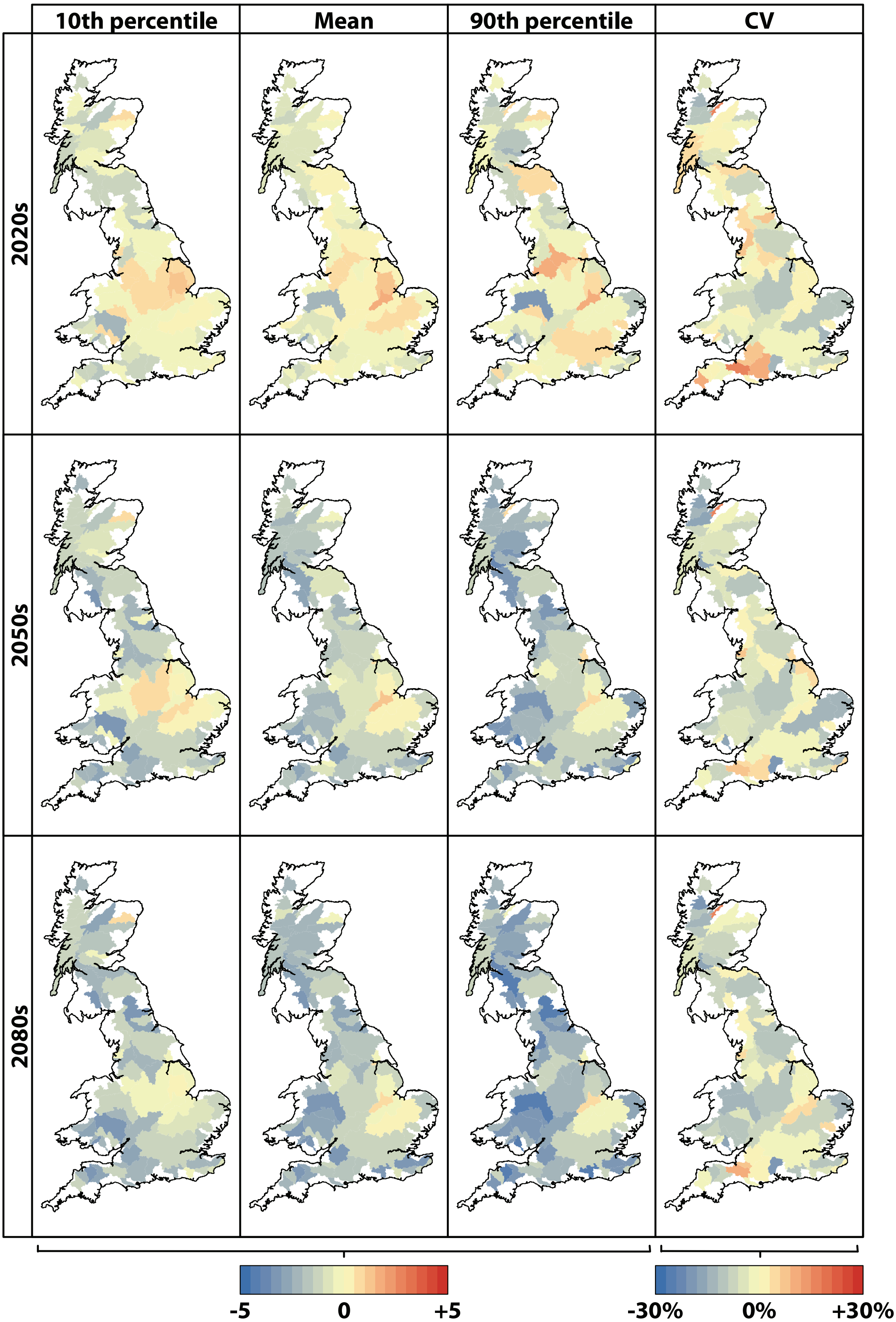


Figure 3.7: Projected changes in DSI3 frequency (count of drought events).

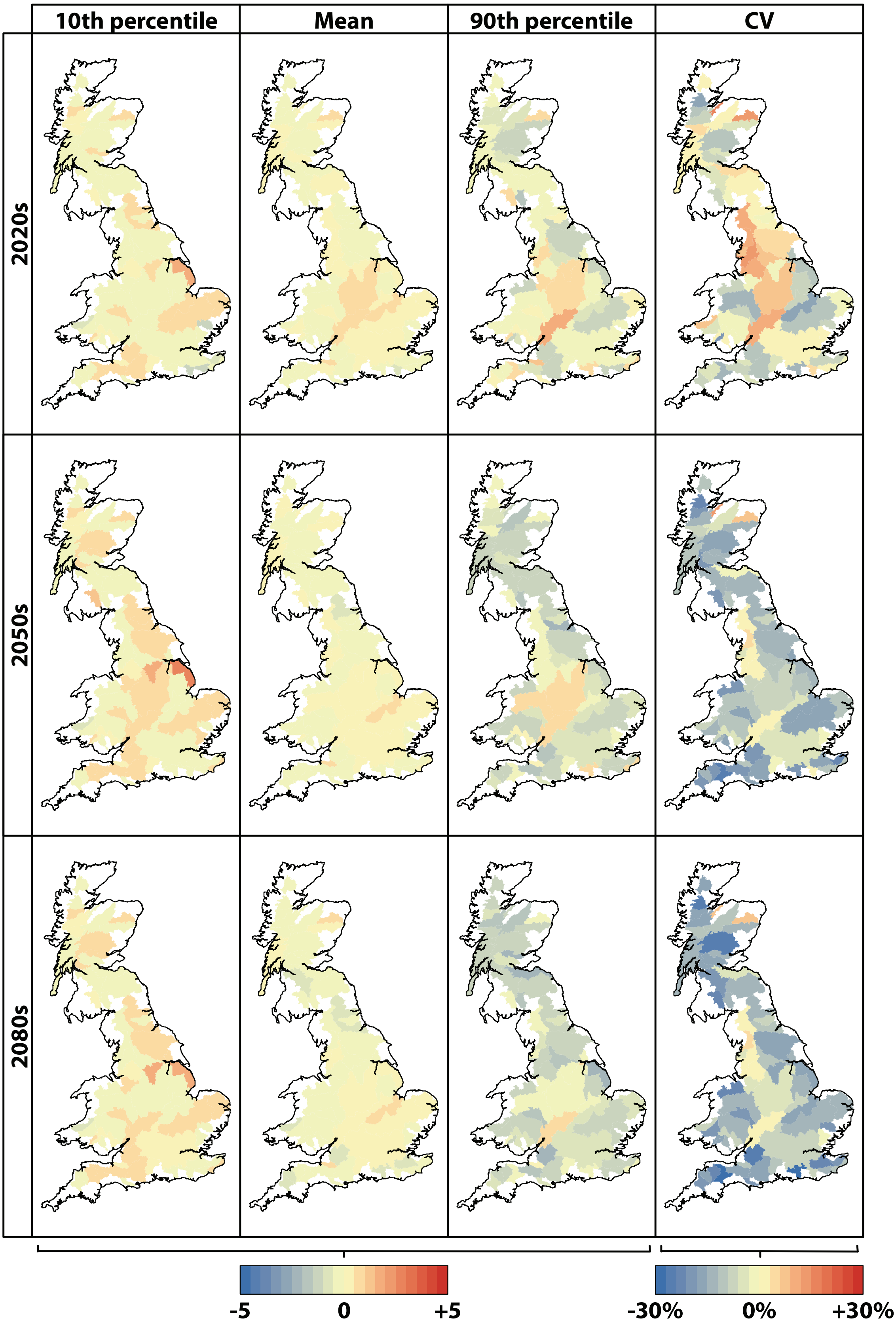


Figure 3.8: Projected changes in DSI6 frequency (count of drought events).

3.5 Discussion

This study is the first assessment of the impact of climate change on the climate variables that determine the quantity of water available to meet demand via the public water supply of Great Britain undertaken using a nationally consistent and application-specific modelling approach and probabilistic projections of climate variables that fully exploit the capacity of the UKCP09 weather generator to sample the uncertainties inherent in climate projection. Ninety percent of simulations exhibited increases in DSI3 and DSI6 severity in the majority of modelled basins by the 2020s that persisted and became more acute in the 2050s and 2080s. Projected changes in DSI3 and DSI6 duration and frequency were smaller in magnitude than projected changes in drought severity, but present a more complex picture. DSI3 duration exhibited small to moderate decreases in most modelled basins, with greater changes in duration projected for DSI6 events with a broadly similar spatial pattern. Projected changes in drought frequency suggest a mixture of small to moderate increases in DSI3 frequency in the midlands of England and small to moderate decreases in DSI3 frequency elsewhere, with some exceptions, by the 2020s. This pattern intensifies in the 2050s and 2080s, with 90% of simulations exhibiting decreases in DSI3 frequency by the 2080s. Projected changes in DSI6 frequency are more coherent, with 90% of simulations suggesting decreases in DSI6 frequency in the majority of basins by the 2080s.

With very few exceptions of small magnitude in northwest and northeast Scotland, the results of this study suggest increases in DSI3 severity across the majority of Great Britain relative to catchments' AAR as early as the 2020s, and intensifying through the 2050s and 2080s. The spatial pattern of changes in DSI3 severity is noisy, but indicates a broadly recognisable trend for greater DSI3 severity in England and Wales than in Scotland, with particular emphasis on the south and east of England. Particularly severe DSI3 events emerge in the southwest of England by the 2080s under the 90th percentile. Changes in DSI6 severity are more variable and less spatially coherent than changes in DSI3 severity: more catchments in Scotland show projected decreases in DSI6 severity from the 2020s onward, while catchments in the northwest and central England show projected decreases in 90% of simulations. The most substantial intensifications of severity again occur in the southwest of England, but DSI6 severity shows exacerbated magnitude in the northwest and east of England from the 2020s, but particularly by the 2080s.

Projected changes in drought duration show decreases in this metric for both DSI3 and DSI6 events across Great Britain, with some notable exceptions. Decreased duration of DSI3 events seems clustered in north Wales and the midlands of England, with some increases indicated in the northwest and northeast of England. Projected changes in DSI6 are greater, with a more distinctive spatial pattern. In this case, drought duration appears broadly lessened along the west coast of Great Britain in 10% of simulation, but these changes appear more distributed, and less certain in direction, both on average and at the 90th percentile. In the latter case, substantial reductions in DSI6 emerge in the west of Scotland and east England, with increases in DSI6 duration suggested along the east coast of Scotland and northern England. Several 'transient' changes emerge, such as increases in DSI6 duration in south Wales that occur in the 2020s and 2050s, but which wane by the 2080s.

Projected changes in drought frequency show apparent differences in DSI3 and DSI6 severity. In the case of the former, these data suggest that DSI3 events could become more widespread across much of Great Britain in the 2020s, but successively and progressively less frequent in the 2050s and 2080s. In the case of the latter, the frequency of DSI6 events shows an initially contrasting and somewhat mixed picture, particularly at the 10th percentile and on average, as the direction of change in DSI6 frequency appears inconsistent across Great Britain: frequency appears slightly intensified in the 2050s and the 2080s, in comparison with the 2020s, but, at the 10th

percentile, the overall direction of change is not clear, while, at the 90th percentile, the direction of change tends towards decreases in the frequency of DSI6 events, of greater magnitude.

It is perhaps notable that the changes in DSI presented in Figure 3.3 are Figure 3.4 somewhat more noisy than the projected changes in annual precipitation presented in Jenkins *et al.* (2009), despite being founded on essentially the same climate change information. This is ostensibly due to Jenkins *et al.* (2009) presenting gross changes in precipitation, smoothed by aggregation and independent in space, while this study presents a metric of rainfall deficit computed from time-series of precipitation based on deviations in long-term monthly precipitation, incorporating spatial covariance and both month-to-month and inter-annual variability. In addition, results in Jenkins *et al.* (2009) are presented at 5 km scale, while results in this study are presented at the scale of river basins.

Other studies concerned with projecting drought characteristics across the UK have typically used ensembles of opportunity, as opposed to probabilistic projections. Consequently, these studies often exhibit little coherency between ensemble members, making direct comparison difficult. Most report large uncertainties in the direction of change of drought characteristics (e.g. Burke *et al.*, 2010). Of the many studies using the 11-member ensemble output from HadRM3, Burke and Brown (2010) compared drought severity, frequency and duration between 1951-2001 and 2049-2099 using an index derived from 12-month rainfall deficits calculated at the spatial scale of Alexander and Jones (2001). Much like this study, their results showed a mixed picture of change, with some ensemble members showing increases in frequency of up to 20%, while others showed decreases of up to 20%, with no apparent spatial patterns; however, changes in severity bore little similarity between ensemble members. Rahiz and New (2013) computed DSI6 for 23 regions and four 30-year periods: 1970-1999 (the '1980s'), the 2020s, the 2050s, and the 2080s. Summarised for the ensemble mean, their results showed increases in drought severity, duration and frequency, particularly over England and Wales, exacerbated in the 2050s and 2080s. This is broadly similar to the findings of this study; however, direct comparison is difficult due to choices in presentation.

Alternatively, Blenkinsop and Fowler (2007) used an ensemble of six RCMs to compare drought characteristics derived from DSI3 and DSI6 between 1961-1990 and 2071-2100. Their results showed an increase in DSI3 events over the majority of the UK, with uncertainty in the direction of change in Scotland and northern England, a decrease in the frequency of DSI6 events, and a mixed picture for changes in severity. This is somewhat at odds with the findings of this study; however, there is some similarity in projected changes in DSI6 duration.

3.6 Conclusions

This study progresses the overall aims of this thesis by synthesising daily time-series of precipitation, potential evapotranspiration and mean daily air temperature for the calibration and verification of hydrological models and the use of those models in projecting the impacts of climate change on hydrological quantities, probabilistically. It is novel in its use of the multivariate-Normal distribution to inject spatial covariance into the otherwise spatially independent outputs of the UKCP09 weather generator (Jones *et al.*, 2009a), and constructs a number of data products not available previously, such as a model of potential evapotranspiration at 5 km scale.

As a secondary objective, this study performs analysis of changes in the severity, duration and frequency of drought events defined by the Drought Severity Index (Phillips and McGregor, 1998) for three-month and six-month retrospectives. The outputs of this analysis suggest a tendency towards progressively fewer drought events of shorter duration and elevated severity relative to the 1961-1990 baseline climatology. The spatial pattern is noisy, but suggests progressively more severe drought events in England than Scotland, with some clustering in the southeast, and a greater decrease in the frequency of three-month than six-month events.

This is consistent with expectations arising from the use of the UKCP09 weather generator, which exhibits enhanced seasonal variability and an enhanced rainfall gradient from west to east across Great Britain that are increasingly exacerbated over the course of the century (e.g. Jones *et al.*, 2009b), in that rainfall deficits are more severe, but are increasingly relieved by elevated winter rainfall (and progressively so).

4 Hydrological modelling

4.1 Chapter outline

This study sought to develop a robust and computationally efficient nationally consistent methodology for the simulation of the hydrological processes that determine the quantity of water available to meet demand via the public water supply of Great Britain within a framework of probabilistic climate change impact projection, and to apply the methodology for three probabilistic scenarios of future climate derived from UKCP09 (Jones *et al.*, 2009b) under the SRES A1B greenhouse gas emissions scenario (Nakicenovic *et al.*, 2000). It combined established paradigms to produce a lightweight and versatile conceptual lumped hydrological model of 11 parameters driven by daily observations of total precipitation, total potential evapotranspiration and mean air temperature, and calibrated for 59 catchments using coupled global and local search methods operating over multiple objective functions relevant to the operation of water infrastructure systems. The calibrated model performed satisfactorily in terms of an unbiased metric of its power to predict observed mean daily and total monthly river discharge for all calibration records and a smaller subset of verification records. Results from the application of the model to the 59 gauged calibration catchments and a further 13 un-gauged catchments broadly suggest negative changes in mean daily river discharges and the 5th percentiles of river discharges across Great Britain.

4.2 Introduction

Withdrawals from sources of liquid freshwater, such as rivers, lakes, reservoirs and groundwater provide nearly all of the water input to the public water supply of Great Britain. A large and growing body of evidence suggests that global climate change will exacerbate the natural variability of the quantity of freshwater available for withdrawal in the UK, perhaps increasing the vulnerability of the water supply infrastructure system to low river and groundwater flows to an uncertain degree (e.g. Arnell *et al.*, 1990a; Arnell and Reynard, 1996; Arnell, 1998; Limbrick *et al.*, 2000; Arnell, 2004; Lehner *et al.*, 2006; Parry *et al.*, 2007; Herrera-Pantoja and Hiscock, 2008; Prudhomme and Davies, 2009; Lavers *et al.*, 2010; Environment Agency, 2011a; Jackson *et al.*, 2011; Ledbetter *et al.*, 2011; Kay *et al.*, 2011 ; Jackson *et al.*, 2012; Prudhomme *et al.*, 2012; Sanderson *et al.*, 2012). The majority of studies implement a chain of modelling tools that translate the output of GCMs into river flows via hydrological simulation (e.g. Fowler *et al.*, 2007).

Improved understanding and quantification of the uncertainties inherent in the projection of future climate motivates recent research in this area, with focus not only on climate simulation as the predominant source of uncertainty (e.g. Murphy *et al.*, 2007; Prudhomme and Davies, 2009), but also the cascade of uncertainty that results from the methodologies necessary to apply the output of general circulation models (e.g. Fowler *et al.*, 2007; Kay and Jones, 2012). Attempts to describe uncertainty in probabilistic terms have become significantly more popular in recent years, partially in response to a paradigm shift in the UK water industry towards a risk-based model of water infrastructure management (e.g. Harris *et al.* (2014). New *et al.* (2007), Fowler *et al.* (2008), Manning *et al.* (2009), Jackson *et al.* (2012) and von Christierson *et al.* (2012) all demonstrate alternative methodologies for the synthesis of probabilistic estimates of the impact of climate change on the water resources of the UK; however, none does so on the national scale with experimental design focused explicitly on hydrological simulation for the purposes of driving models of water infrastructure).

One of the principal limitations of these studies is the synthesis of time-series of the climate variables necessary to drive models of hydrology and water resource in sufficient quantity to compile a probabilistic estimate that is satisfactorily representative of both the uncertainties inherent of climate projection and the spatiotemporal variations in climate exhibited in the UK. Weather generators are one method by which it is possible to produce very large numbers of statistically plausible time-series of climate variables at high spatiotemporal resolution (e.g. Wilks, 2012).

In their recent review, Harris *et al.* (2014) summarise progress-to-date on the application of probabilistic climate projection output from weather generators to the management of water supply in the UK, making a number of critical observations. Firstly, that the series of climate variables produced by weather generators lack spatial coherency over the spatial scales relevant to water supply infrastructure planning and management. Secondly, that the number of calculations necessary to sample fully the uncertainty space of probabilistic climate projections is computationally expensive and time-consuming, often prohibitively so. Thirdly, that the hydrological modelling activities integral to such studies are undertaken opportunistically, using pre-existing models designed for alternative applications that are not tailored for the reproduction of values of significance in the context of water supply infrastructure planning and management.

This study directly addresses the observations of Harris *et al.* (2014) by developing, calibrating, validating and demonstrating a nationally consistent framework for the probabilistic projection of climate change impacts on hydrological processes relevant to water resource planning and management across Great Britain using time-series of spatially coherent climate variables synthesised using a weather generator. See §3 for details of climate variable synthesis.

4.3 Data

The development of a nationally consistent model of hydrology for the UK requires spatiotemporally correlated series of climate variables constituting input to the model, and hydrological data for the determination of model performance and for the calibration of model parameter values and the validation of the model.

This study uses the daily time-series of climate variables produced by the study described in §3 of this thesis as input data, and un-naturalised records of mean daily discharge for 59 gauges across Great Britain from the National River Flow Archive (NRFA, Personal Communication) as hydrological data for parameter value calibration and verification.

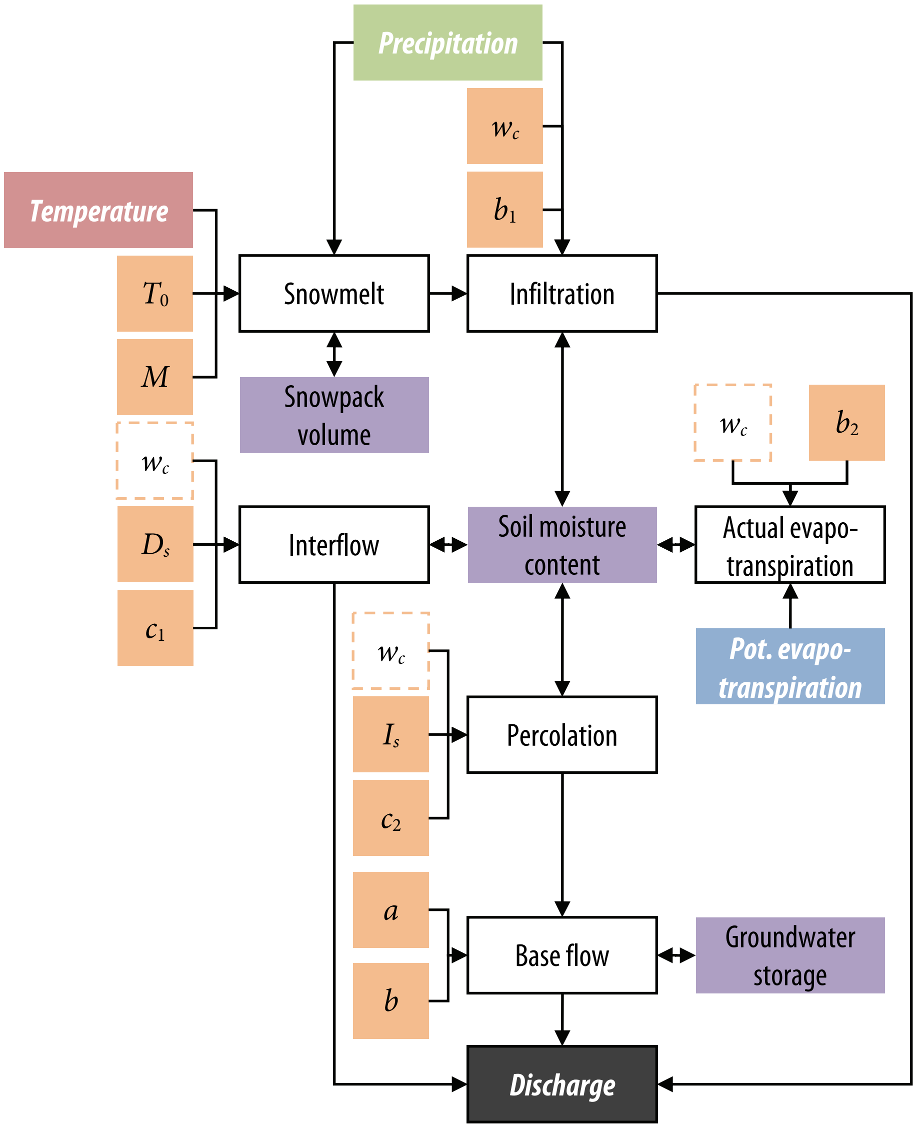
4.4 Methods

In this study, a system of coupled differential equations models the rate at which liquid water discharges from a land surface in response to incident precipitation. Each equation conceptualises the characteristic behaviour of one or more determinant hydrological processes over a unit area as a relationship between input variables, state variables, output variables and parameters. The model aggregates the observed hydrological response into six processes: snow accumulation and ablation, evapotranspiration, infiltration, interflow, percolation, and base flow. Snow accumulation and ablation, and evapotranspiration, require additional input data, correlated with precipitation, that describe mean air temperature and potential evapotranspiration, respectively; calibration against historical records determines the values of parameters. This study sources expressions for these processes from a number of tried-and-tested models, combining them to create a new, novel model.

Figure 4.1 shows the flow of information between model components. Soil moisture content is the primary state variable, coupling the processes of infiltration, interflow, percolation, and evapotranspiration. Together with snowpack volume and groundwater storage, soil moisture content provides persistence between iterations of the algorithm used to solve the system of equations in discrete time for each observation of precipitation.

Figure 4.2 illustrates the order of computation over a single iteration of the algorithm used to solve the system of equations for each observation of precipitation.

This subsection details the solution method employed for each process, in the order of computation, as well as the methods used to calibrate parameter values and to construct time-series of climate variables for use in calibration.



Parameters

W_c	Soil moisture capacity	c_1	Saturation exponent	b	Recession exponent
b_1	Soil moisture exponent	I_s	Percolation at saturation	T_0	Threshold temperature of phase change
b_2	Evapotranspiration	c_2	Saturation exponent		
D_s	Interflow at saturation	a	Recession constant	M	Melting rate

Input variables	**Model components**	**Output variables**
Potential evapotranspiration	Process	Discharge
Mean air temperature	State variable	
Precipitation	Parameter	

Figure 4.1: The exchange of information within the hydrological model.

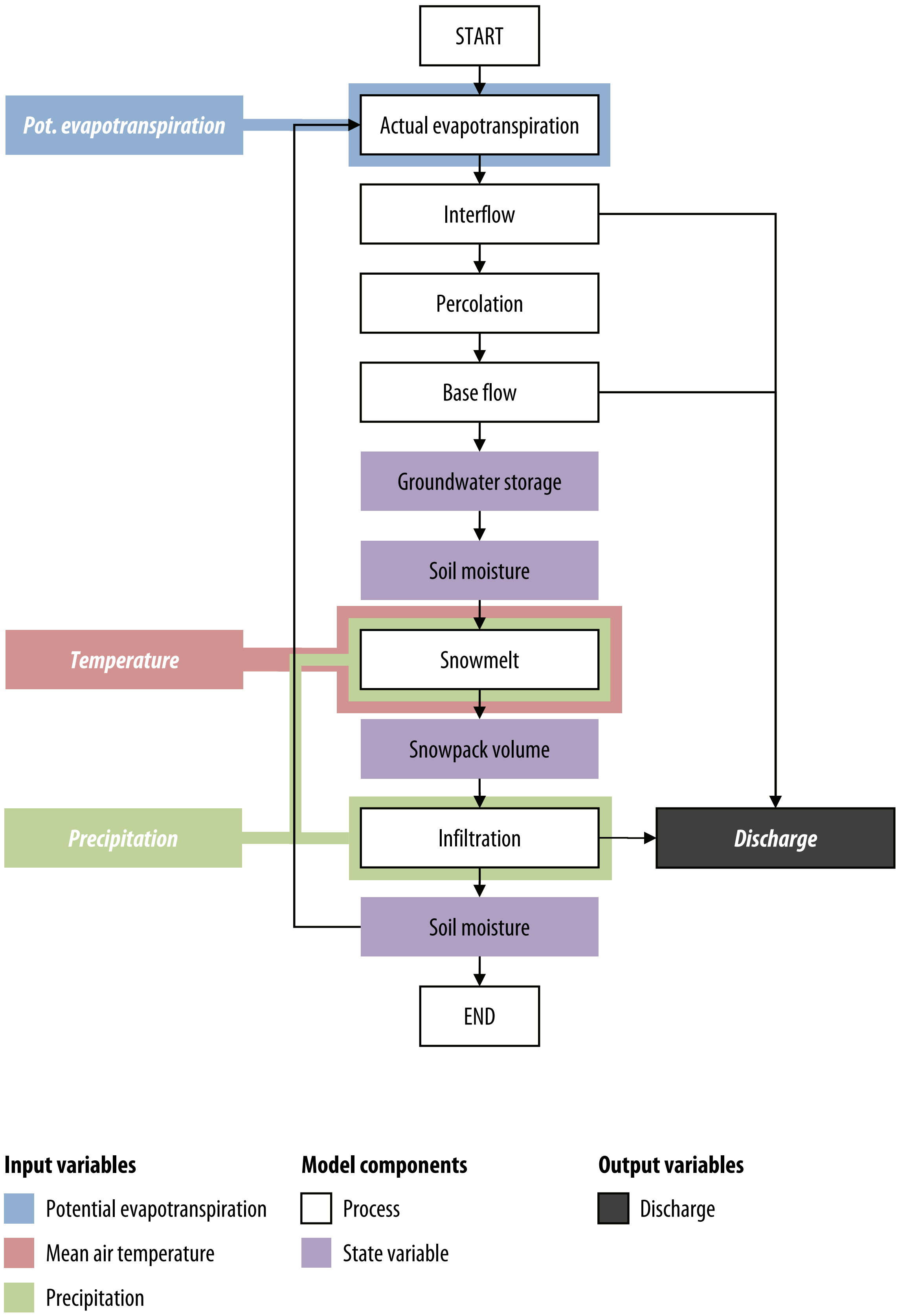


Figure 4.2: A single iteration of the hydrological model.

4.4.1 Actual evapotranspiration

After Wood *et al.* (1992), Equation 13 demonstrates the calculation of actual evapotranspiration at time t, $ET_{P,t}$, computed for a reference crop according to the FAO Penman-Monteith method (Equation 4), for a time-step of uniform length, Δt, in terms of the potential evapotranspiration at time t, $ET_{A,t}$, the soil moisture content at the end of the previous time-step, $W_{t-\Delta t}$, the soil moisture at saturation, W_c, and an exponent controlling the shape of the response, b_2.

$$ET_{A,t} = \begin{cases} ET_{P,t} \cdot \left(1 - \left(1 - \frac{W_{t-\Delta t}}{W_c}\right)^{\frac{1}{b_2}}\right), & W_{t-\Delta t} < W_c \\ ET_{P,t}, & W_{t-\Delta t} \geq W_c \end{cases} \qquad 13$$

4.4.2 Interflow and percolation

After Todini (2002), Equation 14 and Equation 15 demonstrate the calculation of the water lost from the soil moisture store due to interflow at time t, $Q_{d,t}$, and the water lost from the soil moisture store due to percolation at time t, $Q_{p,t}$, respectively, for a time-step of uniform length, Δt.

$$Q_{d,t} = D_S \cdot \left(\frac{W_{t-\Delta t}}{W_c}\right)^{c_1} \qquad 14$$

$$Q_{p,t} = I_S \cdot \left(\frac{W_{t-\Delta t}}{W_c}\right)^{c_2} \qquad 15$$

In both Equation 14 and Equation 15, $W_{t-\Delta t}$ is the soil moisture content at the end of the previous time-step and W_c is the soil moisture capacity at saturation. D_s, c_1, c_2 and I_s are parameters.

4.4.3 Base flow

This model assumes that 'base flow', Q_b, emanates from a reservoir of arbitrary dimensions storing a volume of water, S, exhibiting a non-linear relationship between storage and discharge defined by the parameters a and b (Equation 16) and recharged by percolation, Q_p (Equation 17).

$$Q_b = a \cdot S^b \tag{16}$$

$$\frac{\mathrm{d}S}{\mathrm{d}t} = Q_p - Q_b \tag{17}$$

This study implements the discrete-time solution to Equations 16 and 17 developed by Moore and Bell (2002) under conditions of non-negative recharge and a quadratic recession curve (Wittenberg, 1999) (Equation 18).

$$Q_{b,t} = \begin{cases} \left(Q_{b,t-\Delta t}^{-\frac{1}{2}} + \Delta t \cdot \mathrm{k}^{\frac{1}{2}}\right)^{-2}, & Q_p = 0 \\ Q_{p,t}\left(\dfrac{\left(\frac{Q_{b,t-\Delta t}}{Q_{p,t}}\right)^{\frac{1}{2}} + \tanh\left[\Delta t \cdot \left(Q_{p,t} \cdot k\right)^{\frac{1}{2}}\right]}{1 + \left(\frac{Q_{b,t-\Delta t}}{Q_{p,t}}\right)^{\frac{1}{2}} \tanh\left[\Delta t \cdot \left(Q_{p,t} \cdot k\right)^{\frac{1}{2}}\right]}\right)^{2}, & Q_p > 0 \end{cases} \tag{18}$$

Equation 18 demonstrates the calculation of base flow at the current time-step, $Q_{b,t}$, for a time-step of uniform length, Δt, in terms of the base-flow at the previous time-step, $Q_{b,t-\Delta t}$, the percolation at the current time-step, $Q_{p,t}$, and parameter $k = \frac{a^2}{4}$.

4.4.4 Snow accumulation and ablation

The snow accumulation and ablation sub-model assumes that, at time t, precipitation P_t falls as snow if the average air temperature T_t is equal to or less than an assumed threshold temperature of phase change, T_0. In the event that $T_t \leq T_0$ for a coincident observation of $P_t > 0$, all of the precipitation adds to a snowpack of volume $V_{s,t}$. Even if the snowpack is of non-zero volume, no melt-water discharges from the snowpack. If the average air temperature exceeds the threshold temperature, the snowpack melts by an amount linearly proportional to the difference between the average air temperature and the threshold temperature, with constant of proportionality *M*, referred to herein as the melting rate. Should melting of the snowpack occur, both precipitation and snowmelt ($Q_{s,t}$) infiltrate the soil during the infiltration step of the model, i.e. snowpack melt-water does not immediately run off the land surface.

Equation 19 and Equation 20 describe the snow accumulation and ablation process symbolically for the discharge and snowpack volume, respectively.

$$Q_{s,t} = \begin{cases} 0, & T_t \le T_0 \\ \min\left(V_{s,t}, M(T_t - T_0)\right), & T_t > T_0 \end{cases} \quad \mathbf{19}$$

$$V_{s,t} = \begin{cases} V_s + P_t, & T_t \le T_0 \\ \max\left(0, V_{s,t} - M(T_t - T_0)\right), & T_t > T_0 \end{cases} \quad \mathbf{20}$$

4.4.5 Direct runoff

Accounting for the loss of water from the soil moisture store due to actual evapotranspiration, $ET_{A,t}$, interflow, $Q_{d,t}$, and percolation, $Q_{p,t}$, by updating the soil moisture at the end of previous time-step, $W_{t-\Delta t}$ (Equation 21), the hydrological model used in this study computes direct runoff via implementation of the variable infiltration capacity water balance model described by equations 1, 2, 3a and 3b of Wood *et al.* (1992) subject to correction of equation 3b by analogy to equation 18b of Liang *et al.* (1994).

$$W_t = W_{t-\Delta t} - ET_{A,t} - Q_{d,t} - Q_{p,t} \qquad \textbf{21}$$

The variable infiltration capacity water balance model assumes that the capacity of the land surface to store water at time *t*, i_t, varies in space according to a distribution defined by the maximum infiltration capacity, i_m, the unsaturated area at time *t*, A_t, and the parameter b_1 (Equation 22).

$$i_t = i_m \cdot \left(1 - (1 - A_t)^{\frac{1}{b_1}}\right) \qquad \textbf{22}$$

The parameters W_c and b_1 alone define maximum infiltration capacity i_m (Equation 23), while unsaturated area A_t is, in addition, a function of the soil moisture at time *t*, W_t (Equation 24).

$$i_m = W_c \cdot (1 + b_1) \qquad \textbf{23}$$

$$A_t = 1 - \left(1 - \frac{W_t}{W_c}\right)^{\frac{b_1}{1+b_1}} \qquad \textbf{24}$$

Equation 25 gives the direct runoff produced by the saturated area of the land surface at time *t*, $Q_{r,t}$, following a precipitation input at that time, P_t.

$$Q_{r,t} = \begin{cases} P_t - W_c + W_t + W_c \cdot \left(1 - \dfrac{P_t + i}{i_m}\right)^{1+b_1}, & P_t + i \le i_m \\ P_t - W_c + W_t, & P_t + i > i_m \end{cases} \qquad 25$$

4.4.6 Total runoff

Equation 26 shows the total runoff from unit area of land surface at the end of time-step *t*, or a single iteration of the model as represented in Figure 4.2.

$$Q_t = Q_{r,t} + Q_{d,t} + Q_{b,t} \qquad 26$$

4.4.7 Calibration and validation

This study requires the specification of 59 independent instances of the hydrological model, one for each of the gauged areas shown in Figure 3.1. The model contains 11 parameters and produces values of discharge (Figure 4.1); however, the assumption of a quadratic recession curve fixes the value of b such that each instance of the hydrological model requires the assignment of values to only 10 parameters. Two independently executed and structurally different optimisation processes provide a means of doing so.

In the first optimisation process, direct search of a sweep of feasible parameter values identifies values of the threshold temperature of phase change T_0 and the melting rate M that maximise objective function f. Function f describes the similarity between historical observations of the number of days per month with snow lying, N, and estimates of those observations, $\widehat{N}$, computed by the snow accumulation and ablation sub-model for given daily input time-series of precipitation and mean air temperature assumed to correlate with N and a vector of candidate parameter values, $\hat{\theta}_1 = [T_0, M]$. f is un-weighted Euclidean sum of the Pearson product-moment correlation coefficient between time-series of historical and synthetic observations of the number of days per month with snow lying, $r_{N,\widehat{N},\hat{\theta}_1}$, the ratio of the standard deviation of the number of days per month with snow lying synthesised to the standard deviation of the number of days per month with snow lying observed, $\alpha_{N,\widehat{N},\hat{\theta}_1}$, and the ratio of the mean number of days per month with snow lying synthesised to the mean number of days per month with snow lying observed, $\beta_{N,\widehat{N},\hat{\theta}_1}$ (as in Equation 1, Equation 2 and Equation 3). The maximum value of f, indicating perfectly correlated series of synthetic and historical observations with equal mean and standard deviation, is +1, and the minimum value of f is $-\infty$.

Equation 27 (the Kling-Gupta efficiency, with notation consistent with the above substituted) summarises the behaviour of objective function *f*.

$$f(N,\widehat{N},\widehat{\theta}_1) = 1 - \sqrt{\left(r_{N,\widehat{N},\widehat{\theta}_1} - 1\right)^2 + \left(\alpha_{N,\widehat{N},\widehat{\theta}_1} - 1\right)^2 + \left(\beta_{N,\widehat{N},\widehat{\theta}_1} - 1\right)^2} \qquad \mathbf{27}$$

In the second optimisation process, a genetic algorithm hybridised with a compass search (Figure 4.3) identifies values of the remaining nine parameters that maximise objective function *g*. Function *g* describes the similarity between historical observations of mean daily discharge, Q, and estimates of those observations, $\widehat{Q}$, computed by the hydrological model for given daily input time-series of precipitation, mean air temperature and potential evapotranspiration assumed to correlate with Q and a vector of candidate parameter values that includes those obtained from maximising objective function *f*, $\widehat{\theta}_2 = \{W_c, b_1, b_2, D_s, c_1, I_s, c_2, a, b, \widehat{\theta}_1\}$. Note that the value of b is fixed, and is not found by optimisation. Function *g* is un-weighted Euclidean sum of the Pearson product-moment correlation coefficient between time-series of historical and synthetic observations of discharge, $r_{Q,\widehat{Q},\widehat{\theta}_2}$, the ratio of the standard deviation of synthetic observations to the standard deviation of historical observations, $\alpha_{Q,\widehat{Q},\widehat{\theta}_2}$, and the ratio of the mean of synthetic observations to the mean of historical observations, $\beta_{Q,\widehat{Q},\widehat{\theta}_2}$, subject to constraint of the bias in the mean and the deviation between the fifth percentiles of the historical and synthetic time-series of discharge, ϵ. If $\left|\beta_{Q,\widehat{Q},\widehat{\theta}_2} - 1\right|$ and ϵ are within tolerances τ_β and τ_ϵ, respectively, the maximum value of *g*, indicating perfectly correlated series of synthetic and historical observations with equal mean and standard deviation, is +1, and the minimum value of *g* is -∞. If either $\left|\beta_{Q,\widehat{Q},\widehat{\theta}_2} - 1\right|$ or ϵ is not within tolerance, *g* returns -∞.

Equation 28 summarises the behaviour of objective function *g*.

$$g\left(Q,\hat{Q},\hat{\theta}_2\right) = \begin{cases} -\infty, & (\epsilon > \tau_\epsilon) \vee \left(\left|\beta_{Q,\hat{Q},\hat{\theta}_2} - 1\right| > \tau_\beta\right) \\ 1 - \sqrt{\left(1 - r_{Q,\hat{Q},\hat{\theta}_2}\right)^2 + \left(1 - \alpha_{Q,\hat{Q},\hat{\theta}_2}\right)^2 + \left(1 - \beta_{Q,\hat{Q},\hat{\theta}_2}\right)^2}, & (\epsilon \le \tau_\epsilon) \wedge \left(\left|\beta_{Q,\hat{Q},\hat{\theta}_2} - 1\right| \le \tau_\beta\right) \end{cases} \quad \textbf{28}$$

See §3 for details regarding the construction of the time-series of precipitation, potential evapotranspiration, mean air temperature, and mean daily discharge necessary for calibration and validation.

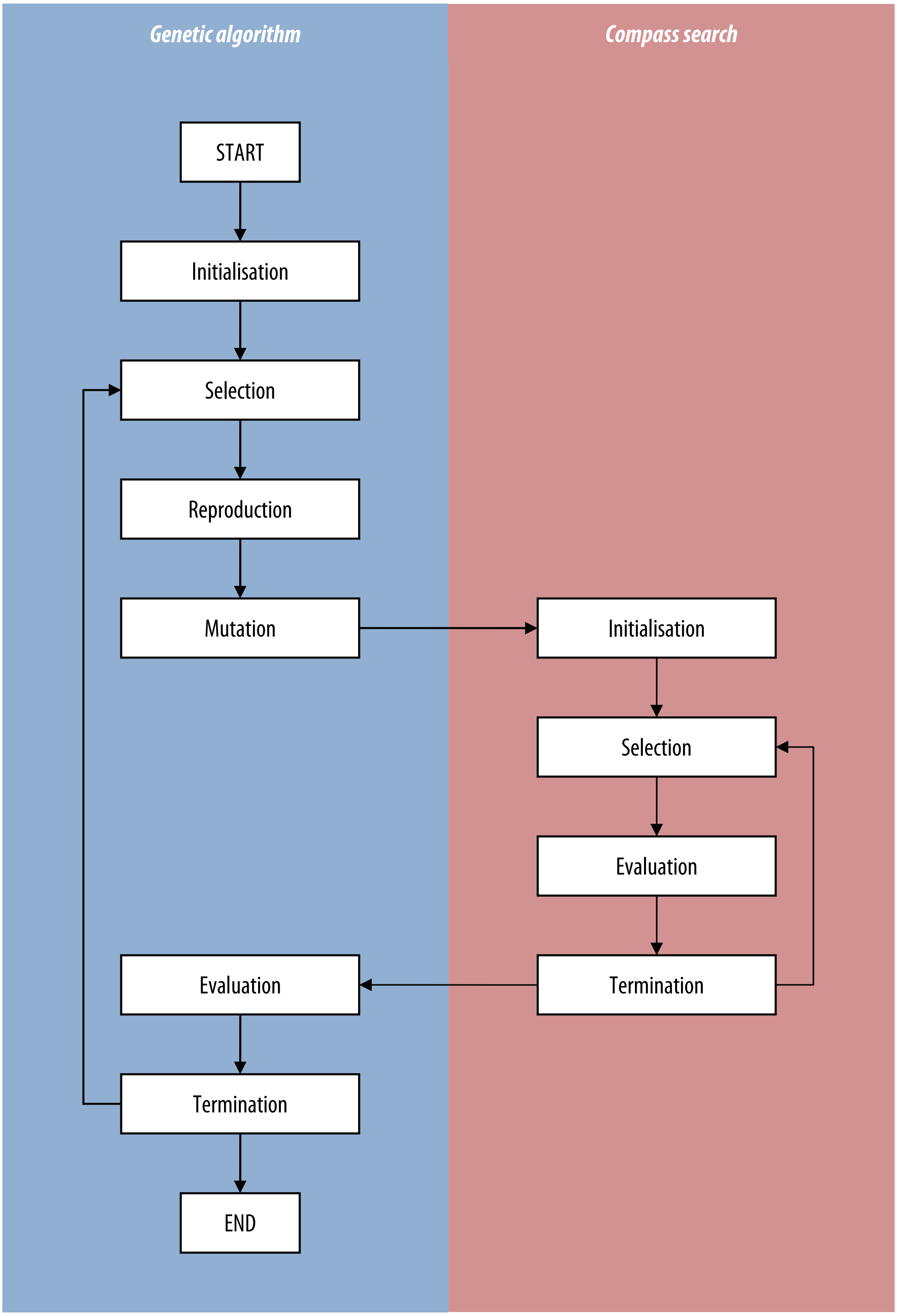


Figure 4.3: The structure of a single iteration of the calibration algorithm, showing the main processes of the genetic algorithm and the embedded compass search.

4.5 Results

4.5.1 Flow gauge locations selected for calibration and validation

To select sites for hydrological simulation, the largest gauged area within each river basin in Figure 3.2 having records of mean daily discharge was found using the UK Hydrometric Register (Marsh and Hannaford, 2008) and assumed representative of the overall basin. This yielded the 59 gauged areas shown in Figure 3.1.

For each station, a calibration time-series was constructed as the longest contiguous series of whole water years (starting October 1) congruent with the precipitation data developed according to the methodology described in §3.3.1. A validation set was constructed as the second-longest such series at each station. Note that some stations had but one such series, and so did not have sufficient river flow data remaining to construct a verification dataset.

Table 4.1 shows the values of the mean, standard deviation, maximum, and minimum of mean daily discharge for calibration datasets, including the area gauged within each river basin and the record length used, while Table 4.2 shows the same statistics computed for the validation dataset.

Gauge	River	Location	Area (km²)	Discharge ($m^3 s^{-1}$)				Record length (years)
				Mean	Std. Dev.	Min.	Max.	
3003	Oykel	Easter Turnaig	330.7	16.3	23.4	0.4	404.9	25
4001	Conon	Moy Bridge	961.8	53.4	40.8	9.5	604.8	27
6008	Enrick	Mill of Tore	105.9	3.3	5.1	0.0	76.9	23
8006	Spey	Boat o Brig	2861.2	65.0	51.2	11.3	1089.0	42
11001	Don	Parkhill	1273.0	20.8	19.0	3.6	327.5	33
12002	Dee	Park	1844.0	47.7	48.1	3.7	744.3	30
15006	Tay	Ballathie	4587.1	167.6	131.5	23.1	1965.0	37
16004	Earn	Forteviot Bridge	782.2	28.5	29.4	2.1	350.1	26
18003	Teith	Bridge of Teith	517.7	25.3	28.3	2.5	311.0	30
19001	Almond	Craigiehall	369.0	6.0	8.9	0.4	147.2	38
21009	Tweed	Norham	4390.0	79.4	84.0	7.4	1335.2	40
23001	Tyne	Bywell	2175.6	43.2	61.8	2.5	1117.0	21
24001	Wear	Sunderland Bridge	657.8	10.4	15.6	1.4	354.4	15
25001	Tees	Broken Scar	818.4	17.6	24.6	2.8	410.5	10
27009	Ouse	Skelton	3315.0	48.2	58.3	3.9	609.0	9
27025	Rother	Woodhouse Mill	352.2	4.3	5.6	0.6	86.1	27
27035	Aire	Kildwick Bridge	282.3	6.8	9.4	0.3	107.3	22
28009	Trent	Colwick	7486.0	85.0	73.0	14.7	981.7	42
30001	Witham	Claypole Mill	297.9	1.7	1.9	0.0	31.6	37
30004	Lymn	Partney Mill	61.6	0.5	0.5	0.1	8.6	15
31002	Glen	Kates Br and King St Br	341.9	1.2	1.9	0.0	23.6	29
32004	Ise Brook	Harrowden Old Mill	194.0	1.5	1.8	0.1	21.4	14
33002	Bedford Ouse	Bedford	1460.0	10.5	13.5	0.0	132.0	30
34006	Waveney	Needham Mill	370.0	1.9	3.5	0.2	89.8	26
36006	Stour	Langham	578.0	2.9	4.0	0.1	50.3	31
37008	Chelmer	Springfield	190.3	1.0	1.5	0.1	23.8	31
39001	Thames	Kingston	9948.0	63.3	66.8	0.0	581.0	42
40003	Medway	Teston	1256.1	11.7	20.7	0.0	281.9	29
40011	Great Stour	Horton	345.0	3.3	2.7	0.7	28.9	17
41006	Uck	Isfield	87.8	1.1	2.1	0.1	32.8	24
41027	Rother	Princes Marsh	37.2	0.5	0.8	0.1	17.7	22
42004	Test	Broadlands	1040.0	10.8	4.8	4.5	32.8	22
43007	Stour	Throop	1073.0	14.1	16.1	1.1	169.5	30
45001	Exe	Thorverton	600.9	16.0	18.7	0.4	263.8	42
47001	Tamar	Gunnislake	916.9	22.3	28.8	0.6	482.3	42
50001	Taw	Umberleigh	826.2	18.4	24.1	0.2	352.5	42
50002	Torridge	Torrington	663.0	15.6	22.7	0.1	338.5	37
52005	Tone	Bishops Hull	202.0	3.1	3.7	0.2	46.7	30
52010	Brue	Lovington	135.2	1.8	2.5	0.1	45.5	33
53006	Frome (Bristol)	Frenchay	148.9	1.7	2.7	0.1	53.5	38
54001	Severn	Bewdley	4325.0	60.5	62.6	6.0	600.3	42
54002	Avon	Evesham	2210.0	16.7	20.5	1.7	370.2	42
54008	Teme	Tenbury	1134.4	14.5	17.4	0.6	201.1	42
55023	Wye	Redbrook	4010.0	71.5	74.3	3.4	646.2	29
56001	Usk	Chain Bridge	911.7	27.2	33.2	1.6	585.4	38
60010	Tywi	Nantgaredig	1090.4	41.3	47.3	1.1	657.4	24
62001	Teifi	Glan Teifi	893.6	28.9	31.4	0.7	373.6	32
67015	Dee	Manley Hall	1019.3	31.0	30.6	2.7	521.0	42
68001	Weaver	Ashbrook	622.0	5.7	6.6	0.4	59.5	23
69007	Mersey	Ashton Weir	660.0	12.7	15.3	1.9	401.0	26
71001	Ribble	Samlesbury	1145.0	33.4	45.4	1.9	672.9	21
72004	Lune	Caton	983.0	37.1	51.0	1.2	811.3	24
72007	Brock	U/S A6	32.0	0.9	1.3	0.0	31.3	24
76007	Eden	Sheepmount	2286.5	54.4	61.8	5.5	750.4	22
78003	Annan	Brydekirk	925.0	29.7	33.6	1.3	410.3	35
79006	Nith	Drumlanrig	471.0	17.0	22.6	0.6	342.1	34
84005	Clyde	Blairston	1704.2	39.4	43.8	5.8	568.8	20
85001	Leven	Linnbrane	784.3	42.6	29.6	3.3	192.6	30
89003	Orchy	Glen Orchy	251.2	21.8	33.5	0.4	413.2	11

Table 4.1: Details of the data used for calibration.

Gauge	River	Location	Area (km²)	Discharge ($m^3 s^{-1}$)				Record length (years)
				Mean	Std. Dev.	Min.	Max.	
3003	Oykel	Easter Turnaig	330.7	No data available				0
4001	Conon	Moy Bridge	961.8	42.5	28.7	4.9	317.2	5
6008	Enrick	Mill of Tore	105.9	No data available				0
8006	Spey	Boat o Brig	2861.2	61.9	49.7	13.8	475.6	3
11001	Don	Parkhill	1273.0	19.7	16.5	3.6	198.7	12
12002	Dee	Park	1844.0	52.4	54.0	4.2	625.8	9
15006	Tay	Ballathie	4587.1	195.5	152.6	35.8	873.2	3
16004	Earn	Forteviot Bridge	782.2	32.7	29.4	3.8	210.8	3
18003	Teith	Bridge of Teith	517.7	21.2	21.9	2.6	203.9	11
19001	Almond	Craigiehall	369.0	7.6	10.9	1.0	125.4	3
21009	Tweed	Norham	4390.0	84.9	90.8	7.6	1335.2	9
23001	Tyne	Bywell	2175.6	49.8	61.4	5.2	757.9	9
24001	Wear	Sunderland Bridge	657.8	11.6	14.4	1.2	195.9	7
25001	Tees	Broken Scar	818.4	13.9	21.2	0.3	225.9	9
27009	Ouse	Skelton	3315.0	53.7	62.9	3.7	513.8	9
27025	Rother	Woodhouse Mill	352.2	4.1	4.7	0.4	49.0	11
27035	Aire	Kildwick Bridge	282.3	5.0	6.6	0.3	64.6	7
28009	Trent	Colwick	7486.0	77.6	58.8	23.1	427.5	7
30001	Witham	Claypole Mill	297.9	2.9	2.5	0.5	28.5	3
30004	Lymn	Partney Mill	61.6	0.5	0.6	0.0	11.8	15
31002	Glen	Kates Br and King St Br	341.9	1.0	1.6	0.0	16.8	5
32004	Ise Brook	Harrowden Old Mill	194.0	1.4	1.7	0.2	16.8	10
33002	Bedford Ouse	Bedford	1460.0	15.8	17.4	1.9	219.1	5
34006	Waveney	Needham Mill	370.0	2.9	4.0	0.2	30.6	3
36006	Stour	Langham	578.0	2.6	3.3	0.3	26.7	4
37008	Chelmer	Springfield	190.3	1.9	2.6	0.3	27.1	2
39001	Thames	Kingston	9948.0	No data available				0
40003	Medway	Teston	1256.1	9.9	16.4	0.9	198.8	5
40011	Great Stour	Horton	345.0	2.9	2.7	0.5	28.0	16
41006	Uck	Isfield	87.8	1.0	1.6	0.1	22.0	9
41027	Rother	Princes Marsh	37.2	0.5	0.6	0.1	8.1	5
42004	Test	Broadlands	1040.0	11.2	4.7	3.8	36.6	19
43007	Stour	Throop	1073.0	13.3	15.3	1.5	143.3	16
45001	Exe	Thorverton	600.9	14.8	16.7	0.4	263.8	19
47001	Tamar	Gunnislake	916.9	21.6	27.0	1.4	276.5	10
50001	Taw	Umberleigh	826.2	17.5	22.6	0.8	337.8	10
50002	Torridge	Torrington	663.0	16.0	23.1	0.5	158.4	2
52005	Tone	Bishops Hull	202.0	2.9	3.2	0.4	38.9	10
52010	Brue	Lovington	135.2	2.7	3.2	0.3	26.3	4
53006	Frome (Bristol)	Frenchay	148.9	2.4	3.9	0.2	31.0	1
54001	Severn	Bewdley	4325.0	60.7	57.9	7.9	521.2	10
54002	Avon	Evesham	2210.0	17.7	22.0	3.6	370.2	12
54008	Teme	Tenbury	1134.4	15.5	19.4	1.0	198.8	12
55023	Wye	Redbrook	4010.0	86.0	104.2	4.9	912.6	12
56001	Usk	Chain Bridge	911.7	30.1	43.0	2.2	556.0	2
60010	Tywi	Nantgaredig	1090.4	36.9	40.7	1.9	488.1	17
62001	Teifi	Glan Teifi	893.6	27.4	25.9	2.1	230.5	9
67015	Dee	Manley Hall	1019.3	29.5	32.5	2.7	521.0	6
68001	Weaver	Ashbrook	622.0	5.4	6.3	0.7	58.9	6
69007	Mersey	Ashton Weir	660.0	No data available				0
71001	Ribble	Samlesbury	1145.0	32.6	44.3	2.1	675.0	20
72004	Lune	Caton	983.0	33.7	45.9	1.2	718.3	16
72007	Brock	U/S A6	32.0	No data available				0
76007	Eden	Sheepmount	2286.5	46.1	51.4	5.5	772.9	12
78003	Annan	Brydekirk	925.0	33.0	36.1	2.0	295.8	9
79006	Nith	Drumlanrig	471.0	18.5	24.3	0.6	231.7	12
84005	Clyde	Blairston	1704.2	46.9	53.3	3.4	581.7	12
85001	Leven	Linnbrane	784.3	47.4	32.3	7.0	144.8	7
89003	Orchy	Glen Orchy	251.2	23.1	38.2	0.6	445.1	3

Table 4.2: Details of the data used for validation.

4.5.2 Calibration performance of the snow accumulation and ablation sub-model

Observations of the number of days per month with snow falling and the number of days with snow lying per month provided a means of simultaneously calibrating the two parameters of the snow accumulation and ablation sub-model independently of the infiltration components of the hydrological model.

Figure 4.4 summarises the performance of the model in predicting monthly observations of the number of days with snow lying of over a range of candidate values for the threshold temperature of phase change and the melting rate of accumulated snow, averaged nationally. The relative stability of model performance over a wide range of values of threshold temperature (T_0) between 0 °C and 1 °C allows for flexibility in the selection of an appropriate melting rate (M). This study adopts a threshold temperature of phase change of 0.5 °C and a melting rate of 5 mm $°C^{-1}$ day^{-1} from among those parameter values yielding best performance.

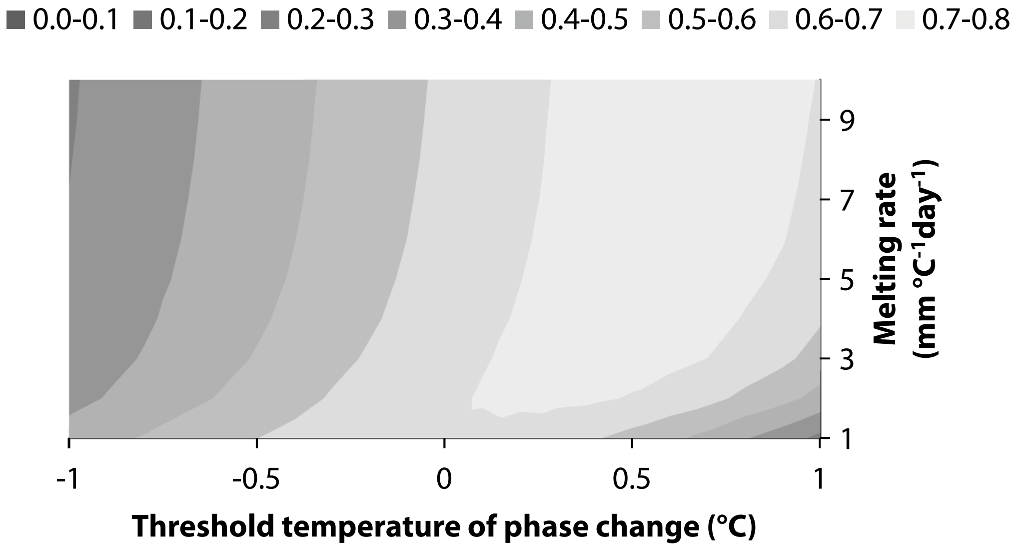


Figure 4.4: The predictive performance of the snow accumulation and ablation sub-model, in terms of KGE, against candidate parameter values.

4.5.3 Calibration performance of the hydrological model

This subsection summarises the outcomes of the calibration process.

Table 4.3 shows the same summary statistics shown in Table 4.1, computed for the output discharge time-series produced by the calibrated model in response to the inputs of the calibration input series, while Table 4.4 shows the difference between Table 4.3 and Table 4.1 as a proportion of the latter. Note that the proportional difference in the mean shown in Table 4.4 is, in this comparison, equivalent to the relative difference in the total discharge, and is therefore a metric of the 'runoff ratio' wherein small values indicate a runoff ratio close to 1, i.e. high similarity in total discharge between the compared series.

Table 4.5 summarises the performance of the hydrological model during calibration in terms of the maximum objective function value obtained for each calibration record for both daily and monthly aggregations. Values of the more conventional Nash-Sutcliffe index provide supplemental context only: they do not provide meaningful information of the merit of the calibration process.

Because the hydrological model does not include a routing component, there is no transformation of emergent hydrographs in emulation of flow through channels and reservoirs. This can result in discharge reaching the point of measurement within a given river basin more (or less) rapidly than anticipated. As a result, the calibration of some models yielded superior objective function values following displacement of the historical observations of precipitation by one day. In the tables accompanying this subsection, a row prefixed with a minus sign indicates that correlation of precipitation observed on day d with other climate variables and mean river flow observed on day $d + 1$ facilitated the achievement of superior fitness for that calibration record, i.e. the precipitation lagged by one day during successful calibration. A row prefixed with a plus sign indicates correlation of precipitation observed on day *d* + 1 with other climate variables and mean river flow observed on day *d* facilitated the achievement of superior fitness for that calibration record, i.e. the precipitation led by one day during successful calibration.

With reference to Table 4.4, for the majority of locations, calibration converged within tolerances of < 1% absolute deviation in the coefficient of runoff. Every model reproduced Q95 with < 5% absolute deviation in Q95 between historical and synthetic observations of mean daily flow. Figure 4.5 illustrates this strong agreement in Q95 between the input observations and the output of the calibrated models. A small minority of models could not converge with tolerance of < 1% absolute deviation in the coefficient of runoff, but achieved convergence within < 6% absolute deviation in the coefficient of runoff. These models still maintained < 1% absolute deviation in Q95. In the tables accompanying this subsection, a row prefixed with an asterisk indicates the adoption of a lower tolerance to facilitate convergence.

Finally, Table 4.6 shows the set of parameter values allocated for each river basin.

Calibration performance was generally very good: values of the objective function calculated from daily observations exceeded 0.65 on average across all calibration records; the application of the same metric to monthly aggregations of the daily observations yielded a mean fitness greater than 0.67, where monthly fitness exceeded daily fitness by, on average, 10%. Efficiency scores at both daily and monthly levels of analysis exceeded 0.50 in 90% of calibrations; nearly 70% exceeded 0.60 and 40% exceeded 0.70. The weakest fitness scores occurred in East Anglia and the south of England, while Scotland, Wales and the Thames region included excellent individual calibration performances as well as exhibiting very good fitness scores on aggregate.

These observations are borne out in diagnostic plots: Figure 4.6 ('a' through 'e') shows a scatter plot of estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input); Figure 4.7 ('a' through 'e') shows time-series plots of those variables, and; Figure 4.8 shows an example flow-duration curve for the River Thames at Kingston. The flow-duration curve, in particular, shows the features expected of the rules used for calibration, including strong similarity between the estimated and observed distributions around Q95 and, on average, for percentiles above this point, as these are more influential in characterising the mean and total runoff than values of discharge below Q95. This example is representative of the calibrated models, particularly the 'hinge' at Q95: because the models are 'forced' to reproduce Q95 to within 5% of the observed value, and favour accurate reproduction of mean discharge and overall water balance, extreme low flows below Q95 are often less well reproduced.

Gauge	River	Location	Discharge ($m^3 s^{-1}$)				
			Mean	Std. Dev.	Min.	Max.	Q95
3003	Oykel	Easter Turnaig	16.5	20.6	0.3	238.6	1.1
4001	Conon	Moy Bridge	53.7	40.9	1.6	438.1	12.0
6008	Enrick	Mill of Tore	3.3	4.7	0.0	48.2	0.1
8006	Spey	Boat o Brig	65.6	46.2	5.5	459.5	18.6
11001	Don	Parkhill	21.0	13.9	1.7	136.5	5.3
12002	Dee	Park	48.2	45.0	2.2	461.1	8.3
15006	Tay	Ballathie	169.3	124.6	8.8	1202.7	39.9
16004	Earn	Forteviot Bridge	28.7	25.9	0.4	294.9	3.3
18003	Teith	Bridge of Teith	26.3	24.2	0.8	204.5	4.1
19001	Almond	Craigiehall	6.1	4.6	0.2	57.9	0.9
21009	Tweed	Norham	80.1	73.5	4.1	941.0	13.7
23001	Tyne	Bywell	43.6	45.6	1.8	496.7	6.1
24001	Wear	Sunderland Bridge	10.5	13.5	1.3	164.6	1.9
25001	Tees	Broken Scar	17.8	18.8	2.3	207.6	3.9
27009	Ouse	Skelton	48.7	51.3	2.5	548.3	6.0
27025	Rother	Woodhouse Mill	4.3	3.8	0.5	47.6	1.0
27035	Aire	Kildwick Bridge	6.9	8.1	0.2	91.0	0.6
28009	Trent	Colwick	85.9	57.8	6.3	719.8	26.4
30001	Witham	Claypole Mill	1.7	1.5	0.1	26.7	0.3
30004	Lymn	Partney Mill	0.5	0.5	0.0	10.6	0.2
31002	Glen	Kates Br and King St Br	1.2	1.6	0.0	26.9	0.0
32004	Ise Brook	Harrowden Old Mill	1.5	1.6	0.0	27.0	0.3
33002	Bedford Ouse	Bedford	10.6	12.2	0.1	221.3	1.3
34006	Waveney	Needham Mill	1.8	2.0	0.1	44.5	0.3
36006	Stour	Langham	3.0	2.9	0.1	45.5	0.5
37008	Chelmer	Springfield	1.0	0.9	0.1	10.7	0.3
39001	Thames	Kingston	64.0	58.1	0.1	550.8	6.4
40003	Medway	Teston	11.9	13.4	0.2	158.1	1.4
40011	Great Stour	Horton	3.4	1.8	0.3	21.6	1.2
41006	Uck	Isfield	1.1	1.6	0.0	17.9	0.2
41027	Rother	Princes Marsh	0.5	0.4	0.1	3.2	0.1
42004	Test	Broadlands	11.4	4.1	3.9	31.8	5.5
43007	Stour	Throop	14.2	13.4	0.3	155.6	2.5
45001	Exe	Thorverton	16.2	15.2	0.2	191.3	1.9
47001	Tamar	Gunnislake	22.5	25.7	0.3	452.0	2.1
50001	Taw	Umberleigh	18.6	20.3	0.1	281.0	1.2
50002	Torridge	Torrington	15.8	18.2	0.0	270.2	0.9
52005	Tone	Bishops Hull	3.2	2.7	0.1	28.6	0.6
52010	Brue	Lovington	1.9	2.2	0.0	32.3	0.2
53006	Frome (Bristol)	Frenchay	1.7	2.4	0.0	50.3	0.2
54001	Severn	Bewdley	61.1	48.3	0.8	474.3	10.0
54002	Avon	Evesham	16.8	10.3	0.2	132.3	3.8
54008	Teme	Tenbury	14.6	14.0	0.1	160.7	1.5
55023	Wye	Redbrook	72.1	54.8	0.6	394.0	11.4
56001	Usk	Chain Bridge	27.4	31.8	0.9	349.8	3.9
60010	Tywi	Nantgaredig	41.7	43.1	0.7	388.7	4.1
62001	Teifi	Glan Teifi	29.1	26.7	0.1	383.1	2.7
67015	Dee	Manley Hall	31.3	25.2	1.7	281.4	7.7
68001	Weaver	Ashbrook	5.7	5.6	0.6	66.6	1.2
69007	Mersey	Ashton Weir	12.8	12.3	1.6	126.5	3.0
71001	Ribble	Samlesbury	33.7	37.8	1.9	381.7	4.4
72004	Lune	Caton	37.4	45.9	0.8	520.8	3.2
72007	Brock	U/S A6	0.9	1.1	0.0	13.9	0.1
76007	Eden	Sheepmount	54.9	55.5	3.6	531.2	9.7
78003	Annan	Brydekirk	30.0	27.3	0.2	361.2	3.4
79006	Nith	Drumlanrig	17.2	19.3	0.1	234.5	1.4
84005	Clyde	Blairston	39.8	38.2	3.7	521.8	7.8
85001	Leven	Linnbrane	42.4	30.1	1.9	230.7	8.6
89003	Orchy	Glen Orchy	22.0	22.5	0.1	188.5	1.3

Table 4.3: Statistics of the calibration dataset estimated by the calibrated model.

Gauge	River	Location	Difference				
			Mean	Std. Dev.	Min.	Max.	Q95
3003	Oykel	Easter Turnaig	1.0%	-12.2%	-25.2%	-41.1%	-1.7%
4001	Conon	Moy Bridge	0.6%	0.1%	-83.5%	-27.6%	-3.6%
6008	Enrick	Mill of Tore	1.0%	-7.0%	40.1%	-37.4%	-4.7%
8006	Spey	Boat o Brig	1.0%	-9.7%	-51.6%	-57.8%	-3.9%
11001	Don	Parkhill	1.0%	-26.7%	-52.7%	-58.3%	-3.1%
12002	Dee	Park	1.0%	-6.5%	-39.3%	-38.0%	-4.8%
15006	Tay	Ballathie	1.0%	-5.3%	-61.8%	-38.8%	-4.8%
16004	Earn	Forteviot Bridge	1.0%	-12.0%	-82.2%	-15.8%	-4.6%
18003	Teith	Bridge of Teith	3.9%	-14.4%	-68.3%	-34.2%	0.7%
19001	Almond	Craigiehall	1.0%	-47.6%	-57.2%	-60.6%	-4.9%
21009	Tweed	Norham	0.9%	-12.4%	-44.7%	-29.5%	-4.8%
23001	Tyne	Bywell	1.0%	-26.3%	-27.1%	-55.5%	2.4%
24001	Wear	Sunderland Bridge	1.0%	-13.8%	-4.1%	-53.6%	-4.6%
25001	Tees	Broken Scar	1.1%	-23.6%	-17.4%	-49.4%	2.6%
27009	Ouse	Skelton	1.0%	-12.1%	-35.5%	-10.0%	-4.2%
27025	Rother	Woodhouse Mill	1.0%	-31.9%	-29.0%	-44.7%	-2.7%
27035	Aire	Kildwick Bridge	1.0%	-14.2%	-48.5%	-15.2%	-3.2%
28009	Trent	Colwick	1.0%	-20.8%	-57.5%	-26.7%	-4.9%
30001	Witham	Claypole Mill	1.0%	-20.1%	170.7%	-15.6%	-4.8%
30004	Lymn	Partney Mill	1.0%	-7.4%	-45.9%	22.8%	-5.0%
31002	Glen	Kates Br and King St Br	1.0%	-16.7%	n/a	13.9%	-4.8%
32004	Ise Brook	Harrowden Old Mill	1.0%	-11.6%	-66.4%	26.3%	-4.9%
33002	Bedford Ouse	Bedford	1.0%	-10.1%	216.1%	67.6%	-4.9%
34006	Waveney	Needham Mill	-1.7%	-43.2%	-66.9%	-50.5%	-3.1%
36006	Stour	Langham	1.0%	-27.2%	-17.2%	-9.5%	-4.8%
37008	Chelmer	Springfield	0.9%	-39.4%	-29.6%	-55.2%	-4.8%
39001	Thames	Kingston	1.0%	-13.0%	548.5%	-5.2%	-1.7%
40003	Medway	Teston	1.0%	-35.3%	330.5%	-43.9%	-4.4%
40011	Great Stour	Horton	1.0%	-34.0%	-62.6%	-25.2%	-4.3%
41006	Uck	Isfield	1.0%	-23.4%	-27.7%	-45.5%	-4.2%
41027	Rother	Princes Marsh	0.9%	-54.0%	-32.8%	-82.1%	-4.9%
42004	Test	Broadlands	5.3%	-15.5%	-13.4%	-3.0%	-1.5%
43007	Stour	Throop	1.0%	-16.5%	-76.4%	-8.2%	-4.9%
45001	Exe	Thorverton	1.0%	-18.7%	-61.2%	-27.5%	-4.9%
47001	Tamar	Gunnislake	1.0%	-10.8%	-52.4%	-6.3%	-4.3%
50001	Taw	Umberleigh	1.0%	-16.1%	-66.0%	-20.3%	-4.9%
50002	Torridge	Torrington	1.0%	-19.5%	-72.5%	-20.2%	-4.9%
52005	Tone	Bishops Hull	1.0%	-25.3%	-58.1%	-38.7%	-4.9%
52010	Brue	Lovington	1.0%	-13.1%	-75.5%	-29.1%	-2.5%
53006	Frome (Bristol)	Frenchay	1.0%	-11.2%	-68.6%	-6.0%	-4.7%
54001	Severn	Bewdley	1.0%	-22.8%	-86.6%	-21.0%	-4.8%
54002	Avon	Evesham	0.9%	-49.6%	-88.8%	-64.3%	-3.3%
54008	Teme	Tenbury	1.0%	-19.7%	-90.2%	-20.1%	-4.7%
55023	Wye	Redbrook	0.8%	-26.2%	-81.4%	-39.0%	-4.8%
56001	Usk	Chain Bridge	1.0%	-4.2%	-45.3%	-40.3%	-4.4%
60010	Tywi	Nantgaredig	1.0%	-8.8%	-30.6%	-40.9%	-2.2%
62001	Teifi	Glan Teifi	1.0%	-14.8%	-85.1%	2.5%	-4.7%
67015	Dee	Manley Hall	1.0%	-17.6%	-37.9%	-46.0%	-4.5%
68001	Weaver	Ashbrook	1.0%	-14.4%	41.0%	11.9%	-2.9%
69007	Mersey	Ashton Weir	1.0%	-19.6%	-17.2%	-68.5%	-4.6%
71001	Ribble	Samlesbury	1.0%	-16.7%	3.2%	-43.3%	-0.9%
72004	Lune	Caton	1.0%	-10.0%	-32.7%	-35.8%	0.4%
72007	Brock	U/S A6	1.0%	-16.5%	-8.5%	-55.6%	2.0%
76007	Eden	Sheepmount	1.0%	-10.3%	-34.1%	-29.2%	-1.9%
78003	Annan	Brydekirk	1.0%	-18.8%	-84.8%	-12.0%	-4.9%
79006	Nith	Drumlanrig	1.0%	-14.4%	-81.4%	-31.4%	-3.2%
84005	Clyde	Blairston	1.0%	-12.9%	-36.2%	-8.3%	-4.5%
85001	Leven	Linnbrane	-0.5%	1.7%	-43.2%	19.8%	4.6%
89003	Orchy	Glen Orchy	0.9%	-32.8%	-65.9%	-54.4%	-0.4%

Table 4.4: Difference between the calibrated model and the calibration dataset.

	Gauge	Record length (years)	NSE		KGE	
			Daily	Monthly	Daily	Monthly
	3003	25	0.43	0.88	0.66	0.86
+	4001	27	0.74	0.87	0.87	0.94
	6008	23	0.61	0.87	0.78	0.85
	8006	42	0.51	0.79	0.72	0.86
-	11001	33	0.56	0.84	0.63	0.81
	12002	30	0.60	0.89	0.78	0.92
	15006	37	0.81	0.95	0.89	0.96
+	16004	26	0.78	0.97	0.83	0.95
*	18003	30	0.64	0.89	0.75	0.83
	19001	38	0.50	0.78	0.45	0.75
	21009	40	0.55	0.76	0.72	0.64
	23001	21	0.58	0.80	0.64	0.66
	24001	15	0.36	0.61	0.62	0.51
*	25001	10	0.47	0.70	0.61	0.56
	27009	9	0.32	0.65	0.60	0.56
	27025	27	0.48	0.61	0.56	0.53
+	27035	22	0.62	0.90	0.60	0.88
-	28009	42	0.41	0.65	0.60	0.59
	30001	37	0.37	0.54	0.58	0.51
	30004	15	0.36	0.61	0.65	0.58
	31002	29	0.32	0.55	0.57	0.61
	32004	14	0.30	0.54	0.59	0.48
-	33002	30	0.07	0.54	0.48	0.47
*	34006	26	0.25	0.40	0.34	0.34
-	36006	31	0.24	0.49	0.46	0.47
	37008	31	0.31	0.43	0.41	0.38
	39001	42	0.58	0.81	0.73	0.79
	40003	29	0.46	0.62	0.53	0.56
	40011	17	0.54	0.68	0.57	0.74
	41006	24	0.28	0.58	0.51	0.48
+	41027	22	0.38	0.64	0.35	0.62
*	42004	22	0.73	0.76	0.79	0.80
-	43007	30	0.47	0.71	0.66	0.58
	45001	42	0.59	0.83	0.70	0.72
	47001	42	0.48	0.73	0.70	0.59
	50001	42	0.60	0.81	0.72	0.71
	50002	37	0.62	0.82	0.71	0.69
	52005	30	0.48	0.69	0.60	0.62
	52010	33	0.33	0.61	0.60	0.50
	53006	38	0.32	0.54	0.61	0.45
-	54001	42	0.54	0.71	0.65	0.70
	54002	42	0.46	0.66	0.42	0.62
	54008	42	0.60	0.79	0.70	0.70
	55023	29	0.66	0.85	0.68	0.85
	56001	38	0.54	0.83	0.76	0.67
	60010	24	0.74	0.93	0.84	0.88
+	62001	32	0.89	0.97	0.84	0.94
	67015	42	0.53	0.77	0.68	0.67
	68001	23	0.31	0.47	0.58	0.42
	69007	26	0.36	0.61	0.58	0.51
+	71001	21	0.33	0.77	0.58	0.62
	72004	24	0.57	0.92	0.74	0.82
+	72007	24	0.57	0.77	0.71	0.65
	76007	22	0.60	0.77	0.76	0.61
	78003	35	0.77	0.94	0.78	0.87
	79006	34	0.60	0.91	0.74	0.82
	84005	20	0.62	0.76	0.76	0.61
-	85001	30	0.89	0.96	0.94	0.98
	89003	11	0.56	0.81	0.59	0.76

Table 4.5: Hydrological model calibration fitness scores, where '-' signifies the application of a lag transform of one day to driving observations, '+' signifies the application of a lead transform of one day to driving observations, and '*' signifies relaxation of the coefficient of runoff tolerance to facilitate convergence.

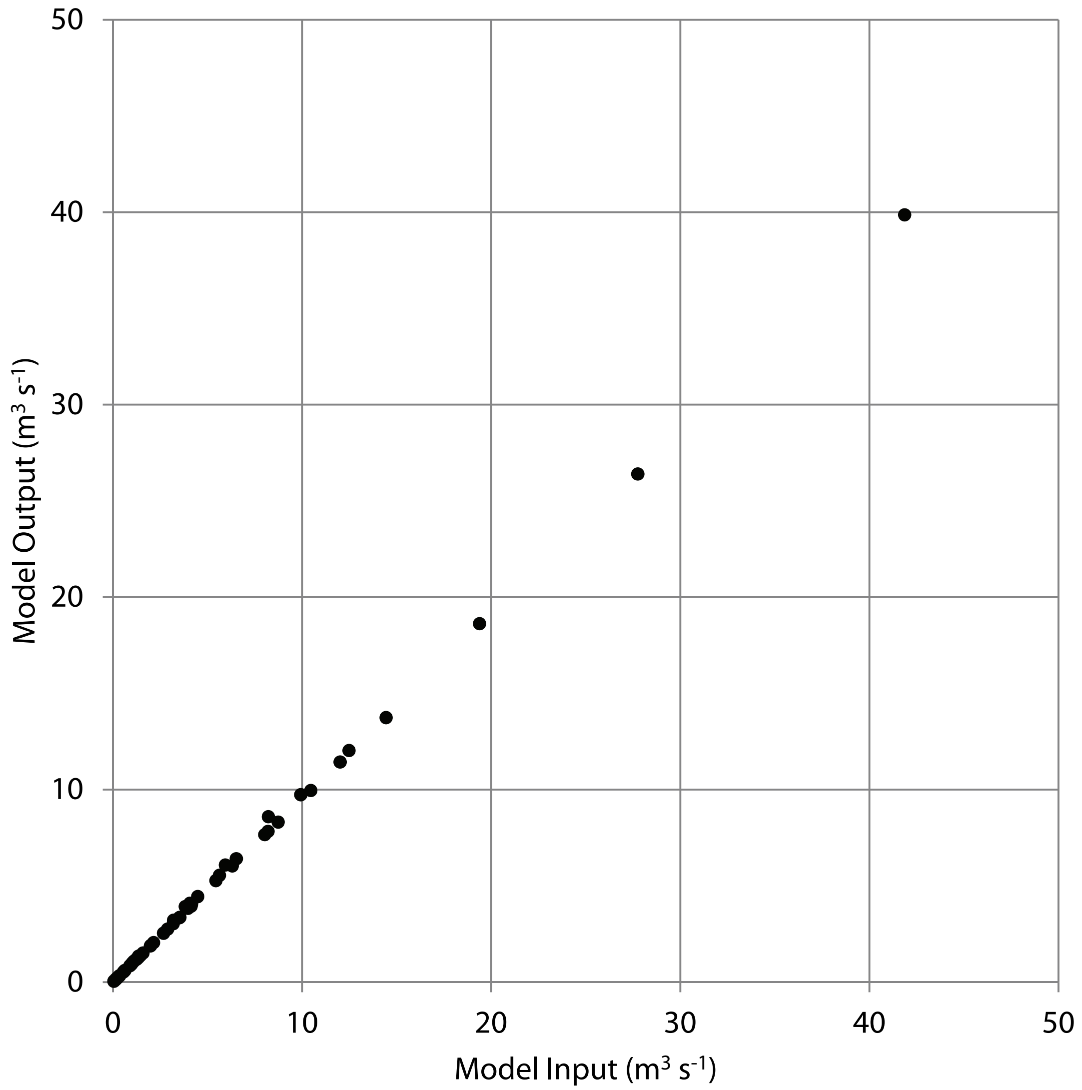


Figure 4.5: Estimated Q95 against observed Q95 (i.e. model output against model input) for the calibration dataset.

Gauge	River	Location	W_c	b_1	b_2	D_s	c_1	I_s	c_2	a
3003	Oykel	Easter Turnaig	2327.0	1.4	0.8	863.0	48.0	29.0	20.0	1471.8
4001	Conon	Moy Bridge	608.0	8.3	0.3	1194.0	3.6	37.0	0.9	929.4
6008	Enrick	Mill of Tore	1769.0	0.7	0.9	583.0	44.4	330.0	34.9	23407.7
8006	Spey	Boat o Brig	1902.0	0.8	0.3	425.0	6.9	1705.0	14.0	9385.6
11001	Don	Parkhill	2160.0	0.1	1.0	132.0	15.9	905.0	27.1	11077.8
12002	Dee	Park	1089.0	0.5	1.0	215.0	11.3	1314.0	20.5	10072.6
15006	Tay	Ballathie	1177.0	0.4	0.9	585.0	9.3	1559.0	17.2	43579.9
16004	Earn	Forteviot Bridge	1016.0	0.3	1.0	994.0	13.2	1407.0	17.7	7962.7
18003	Teith	Bridge of Teith	1846.0	0.5	0.1	29.0	8.5	907.0	26.7	99.6
19001	Almond	Craigiehall	1127.0	1.5	0.2	398.0	4.3	1112.0	8.9	8594.7
21009	Tweed	Norham	1836.0	0.4	0.8	89.0	20.5	85.0	13.6	1424.4
23001	Tyne	Bywell	1187.0	1.1	0.6	986.0	16.5	53.0	7.9	1715.1
24001	Wear	Sunderland Bridge	3117.0	0.7	0.6	1160.0	35.6	60.0	12.2	1002.5
25001	Tees	Broken Scar	3998.0	1.0	0.1	222.0	19.6	55.0	7.3	972.8
27009	Ouse	Skelton	2746.0	0.4	0.8	362.0	19.0	702.0	33.6	155482.8
27025	Rother	Woodhouse Mill	2636.0	0.4	0.8	1213.0	20.6	356.0	10.5	1202.8
27035	Aire	Kildwick Bridge	1948.0	0.9	0.8	143.0	14.7	963.0	28.8	10162.4
28009	Trent	Colwick	2571.0	0.3	0.6	184.0	8.5	953.0	15.2	11097.2
30001	Witham	Claypole Mill	2587.0	0.3	0.4	413.0	7.4	442.0	14.3	9204.9
30004	Lymn	Partney Mill	3091.0	1.3	0.2	120.0	4.1	2323.0	9.9	8687.2
31002	Glen	Kates Br and King St Br	1839.0	0.1	0.6	419.0	19.6	972.0	29.1	8343.1
32004	Ise Brook	Harrowden Old Mill	1947.0	0.7	0.4	1655.0	12.5	569.0	7.6	345.4
33002	Bedford Ouse	Bedford	2097.0	0.4	0.7	1092.0	18.6	926.0	12.9	529.2
34006	Waveney	Needham Mill	3078.0	0.2	0.7	390.0	22.5	492.0	13.5	37.4
36006	Stour	Langham	2545.0	0.6	0.3	1951.0	11.8	437.0	6.0	5781.5
37008	Chelmer	Springfield	3400.0	0.4	0.4	317.0	9.8	225.0	6.1	2619.8
39001	Thames	Kingston	1059.0	0.2	0.3	1178.0	15.8	27.0	5.2	68630.6
40003	Medway	Teston	3044.0	0.2	0.9	969.0	33.6	154.0	17.9	5817.6
40011	Great Stour	Horton	3066.0	0.1	0.5	559.0	15.7	430.0	8.8	1764.7
41006	Uck	Isfield	3630.0	0.8	0.8	129.0	11.6	884.0	27.8	9909.3
41027	Rother	Princes Marsh	3492.0	0.2	0.4	804.0	8.5	1096.0	14.4	10003.8
42004	Test	Broadlands	4000.0	0.1	0.2	683.0	42.8	41.0	2.7	444.4
43007	Stour	Throop	2813.0	0.5	0.5	673.0	15.7	712.0	9.9	4388.0
45001	Exe	Thorverton	2311.0	0.4	0.9	1260.0	20.6	1120.0	39.3	9624.5
47001	Tamar	Gunnislake	3114.0	0.6	0.9	1028.0	47.9	464.0	23.4	315.8
50001	Taw	Umberleigh	1906.0	0.3	1.0	37.0	21.9	909.0	49.6	10558.8
50002	Torridge	Torrington	1069.0	1.0	0.6	101.0	10.6	1267.0	22.4	9613.4
52005	Tone	Bishops Hull	3411.0	0.2	0.7	160.0	16.7	634.0	29.9	10989.0
52010	Brue	Lovington	2082.0	0.9	0.6	738.0	18.8	334.0	10.4	5438.8
53006	Frome (Bristol)	Frenchay	2959.0	0.7	0.8	831.0	22.0	412.0	14.3	5463.9
54001	Severn	Bewdley	2144.0	0.2	0.6	923.0	23.6	525.0	15.6	4769.4
54002	Avon	Evesham	2829.0	1.1	0.1	849.0	3.4	911.0	31.9	876.5
54008	Teme	Tenbury	1097.0	0.5	0.4	819.0	12.5	111.0	7.3	12269.3
55023	Wye	Redbrook	1437.0	0.1	0.8	411.0	22.3	88.0	13.6	6085.4
56001	Usk	Chain Bridge	2221.0	0.5	1.1	693.0	41.1	12.0	12.4	167.8
60010	Tywi	Nantgaredig	1510.0	0.3	1.1	1094.0	49.5	13.0	14.9	1912.3
62001	Teifi	Glan Teifi	801.0	0.1	0.9	1795.0	18.5	194.0	12.6	7940.1
67015	Dee	Manley Hall	2559.0	1.0	0.4	600.0	8.5	212.0	11.2	9943.8
68001	Weaver	Ashbrook	3166.0	1.0	0.4	1438.0	13.3	485.0	7.5	1252.9
69007	Mersey	Ashton Weir	3668.0	0.5	0.4	978.0	25.3	12.0	6.9	755.8
71001	Ribble	Samlesbury	2800.0	1.0	0.8	35.0	11.6	696.0	23.1	6747.1
72004	Lune	Caton	898.0	1.0	0.9	964.0	37.3	11.0	8.6	1396.2
72007	Brock	U/S A6	2146.0	0.6	0.5	79.0	46.9	10.0	12.6	2029.7
76007	Eden	Sheepmount	2947.0	0.5	0.7	999.0	41.4	42.0	13.9	906.6
78003	Annan	Brydekirk	614.0	2.2	0.4	1339.0	14.0	225.0	5.4	4705.8
79006	Nith	Drumlanrig	871.0	1.1	0.8	1192.0	32.4	52.0	10.1	3877.7
84005	Clyde	Blairston	1746.0	1.2	0.7	726.0	19.2	126.0	9.3	627.0
85001	Leven	Linnbrane	854.0	0.2	0.3	902.0	43.6	349.0	3.7	995.2
89003	Orchy	Glen Orchy	596.0	11.1	0.8	984.0	21.0	403.0	1.4	485.8

Table 4.6: The parameter values calibrated for each river basin.

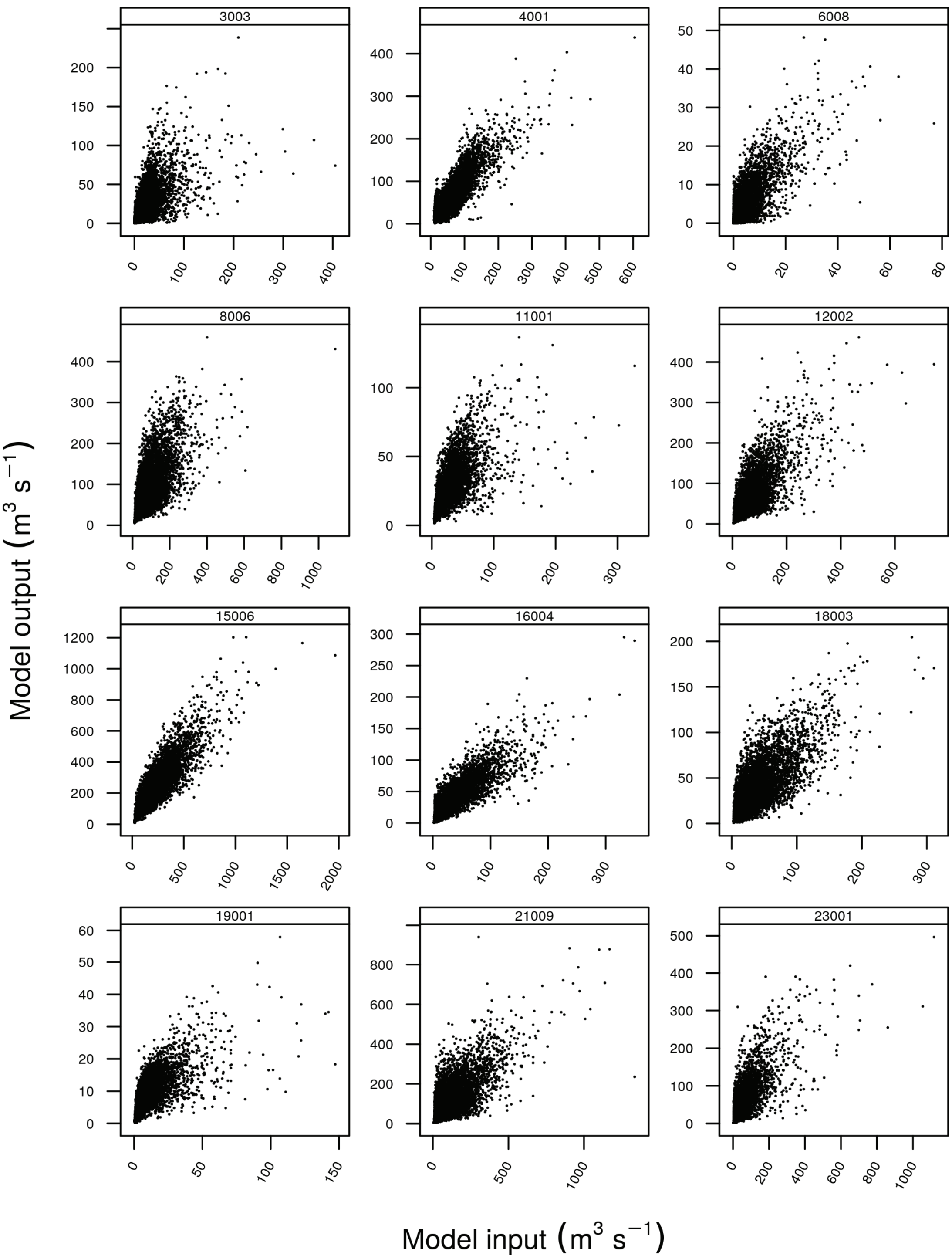


Figure 4.6a: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the calibration dataset.

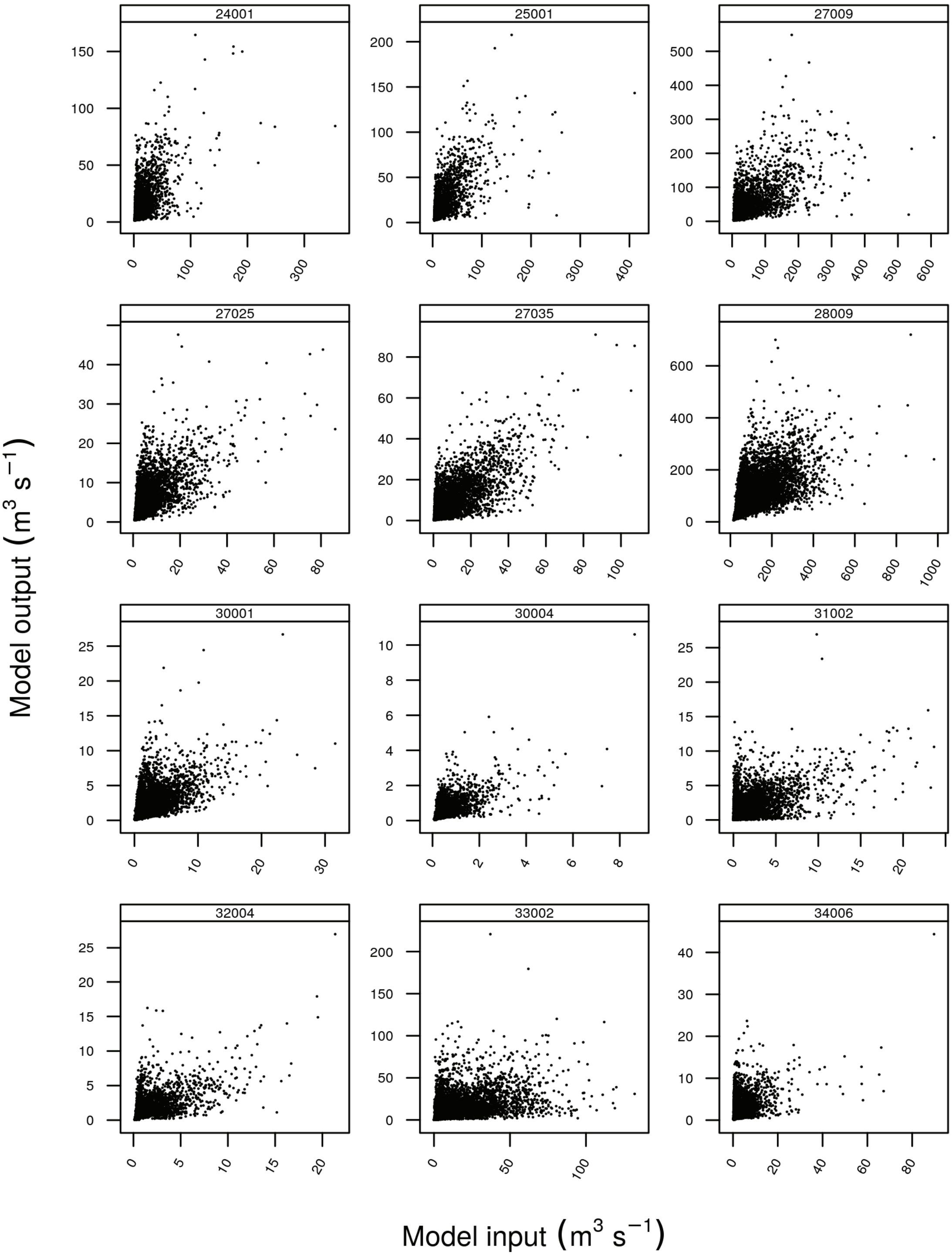


Figure 4.6b: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the calibration dataset.

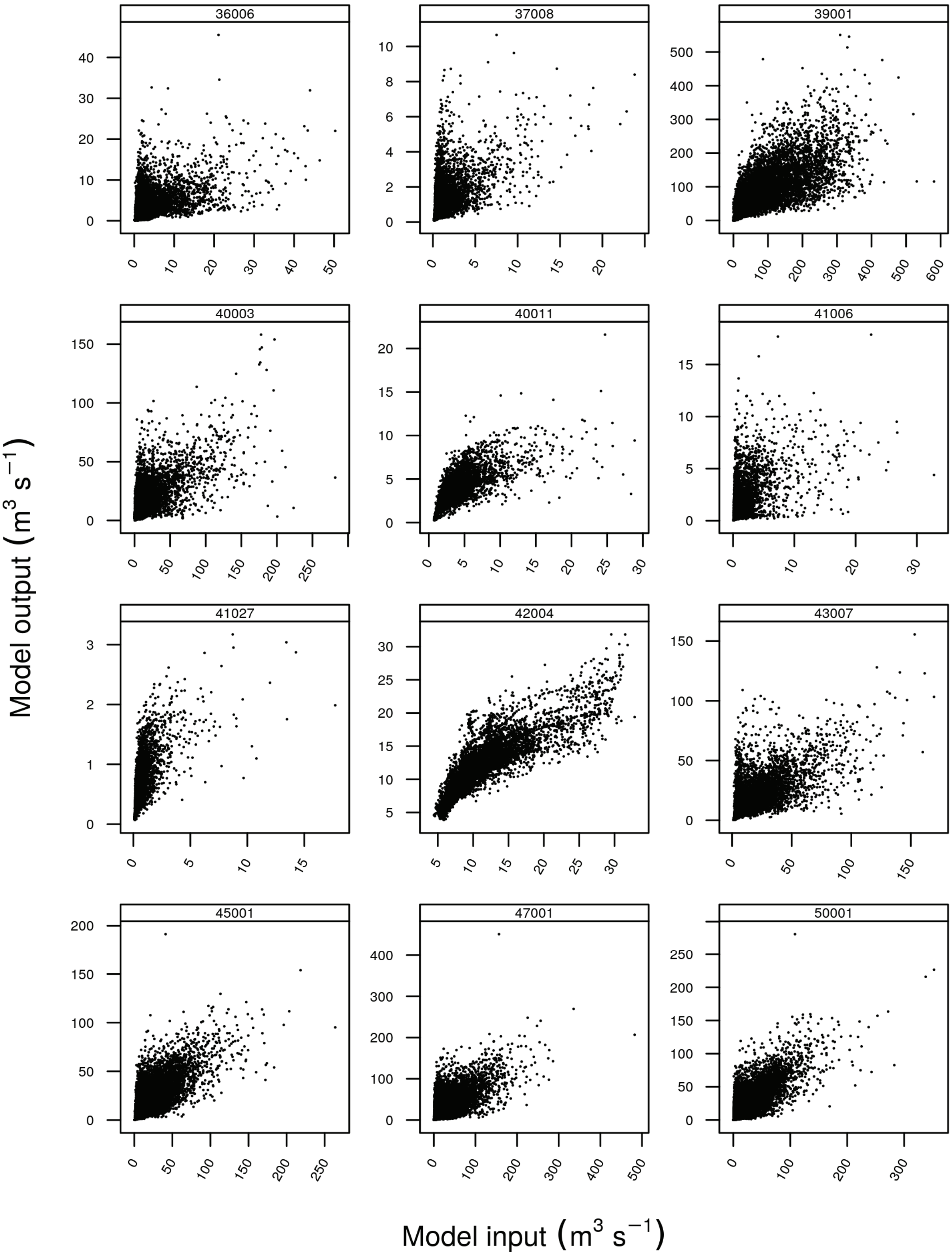


Figure 4.6c: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the calibration dataset.

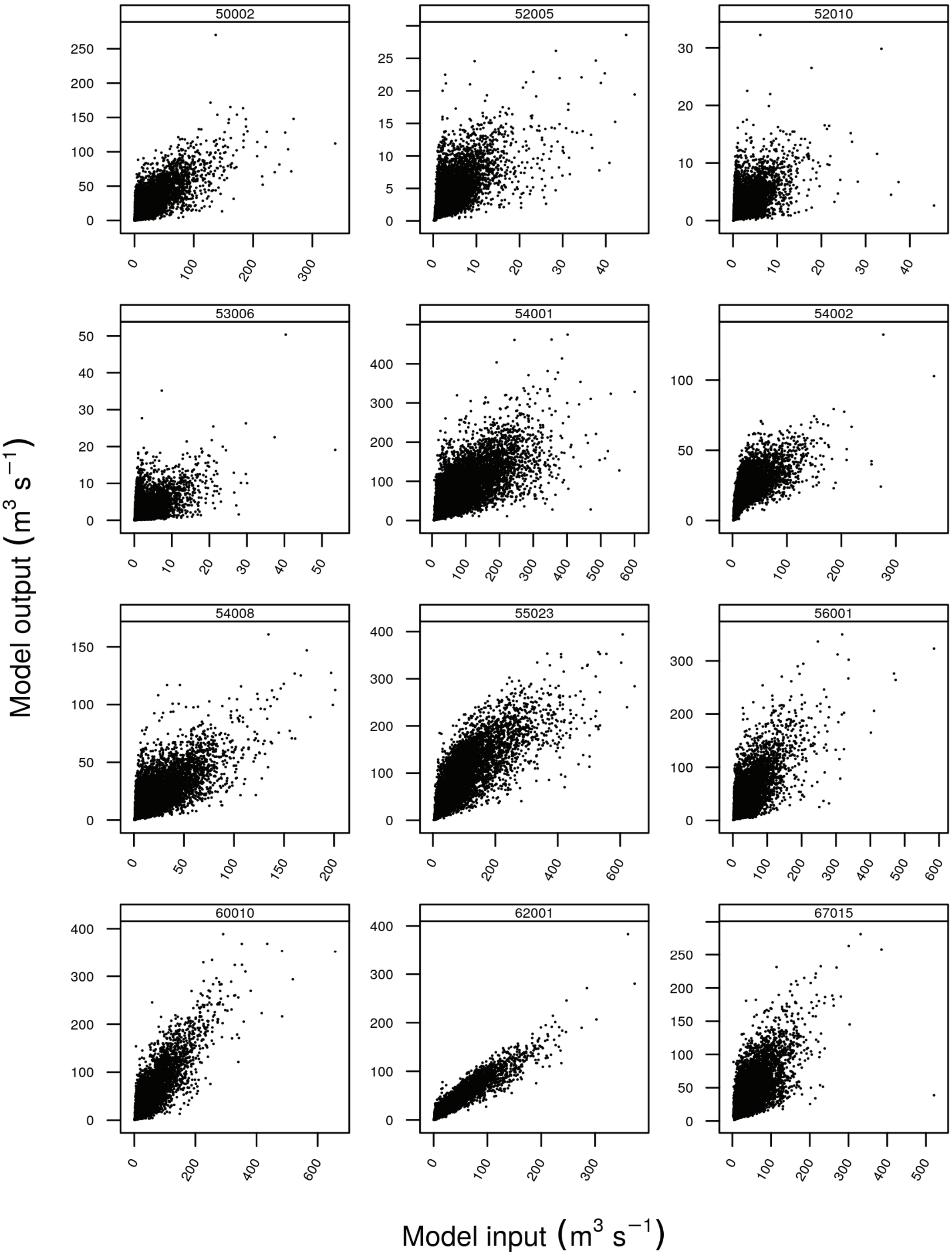


Figure 4.6d: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the calibration dataset.

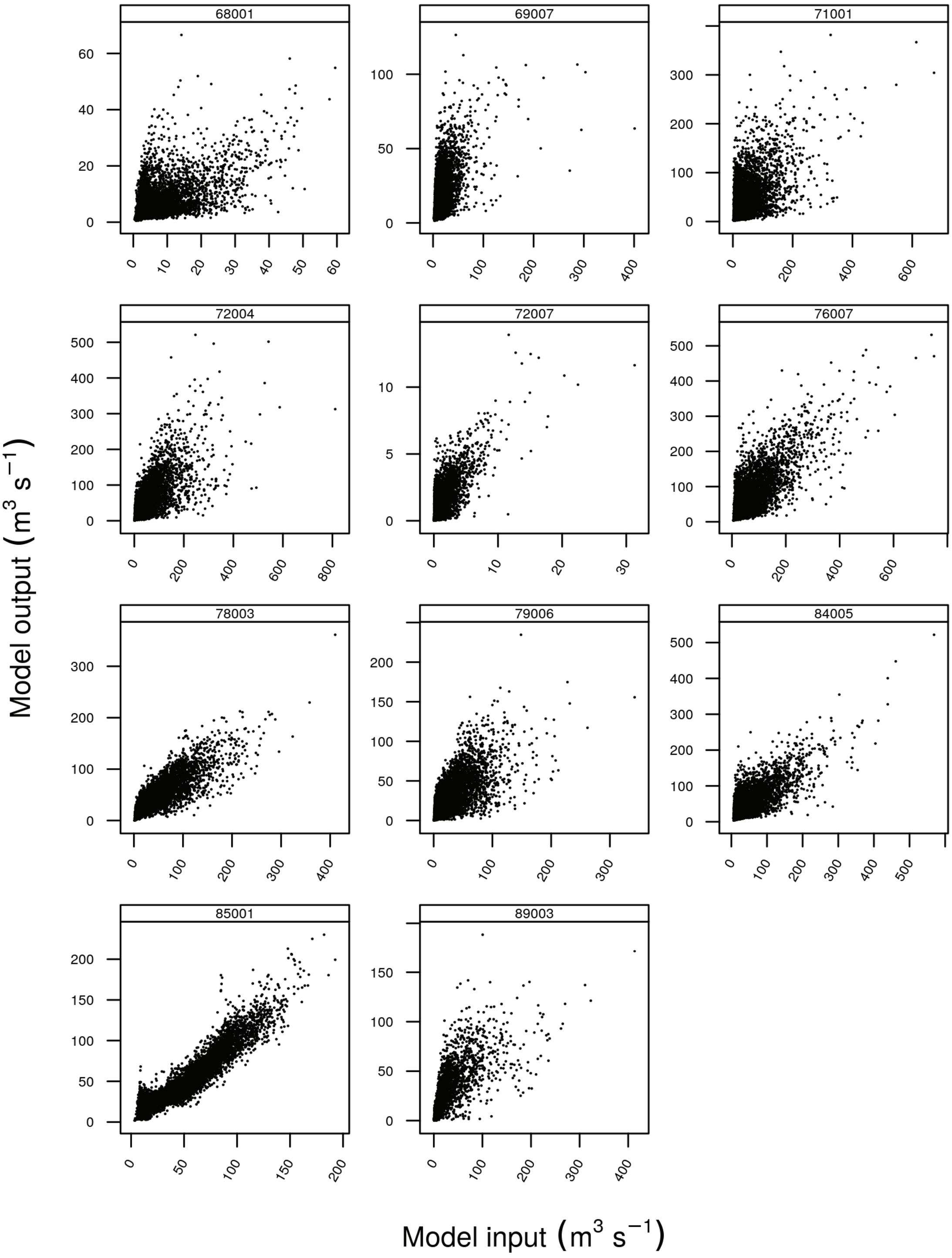


Figure 4.6e: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the calibration dataset.

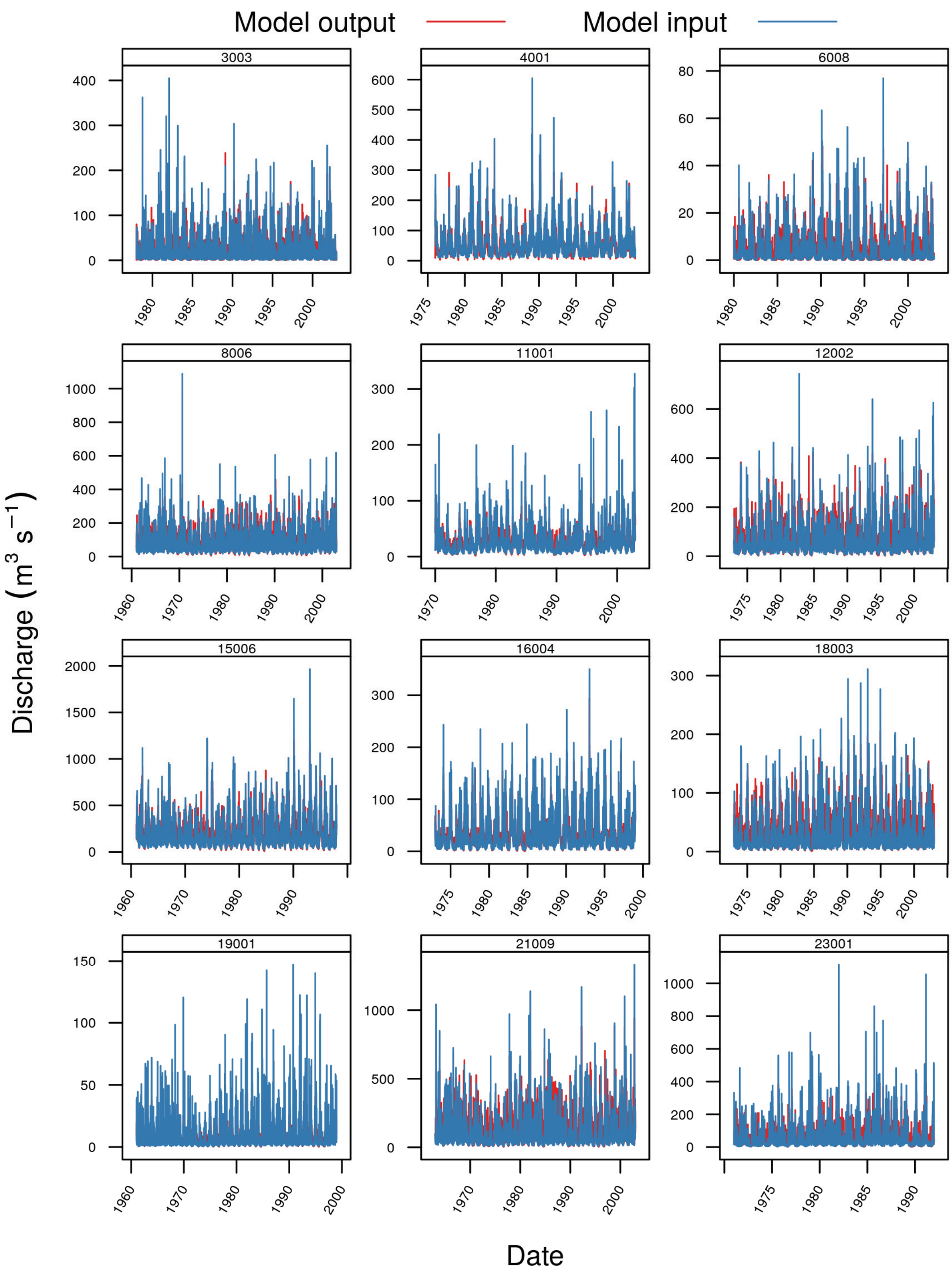


Figure 4.7a: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the calibration dataset.

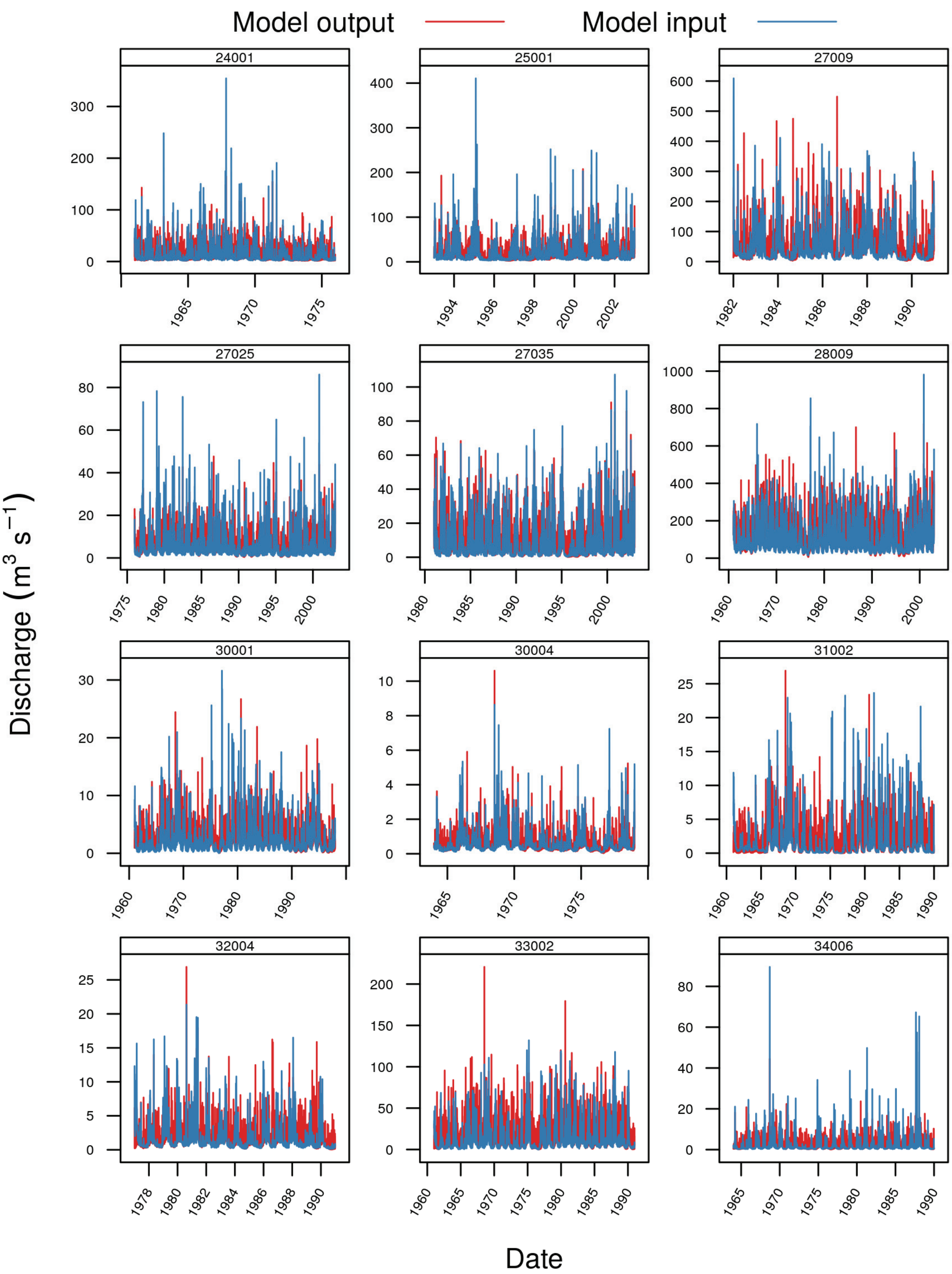


Figure 4.7b: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the calibration dataset.

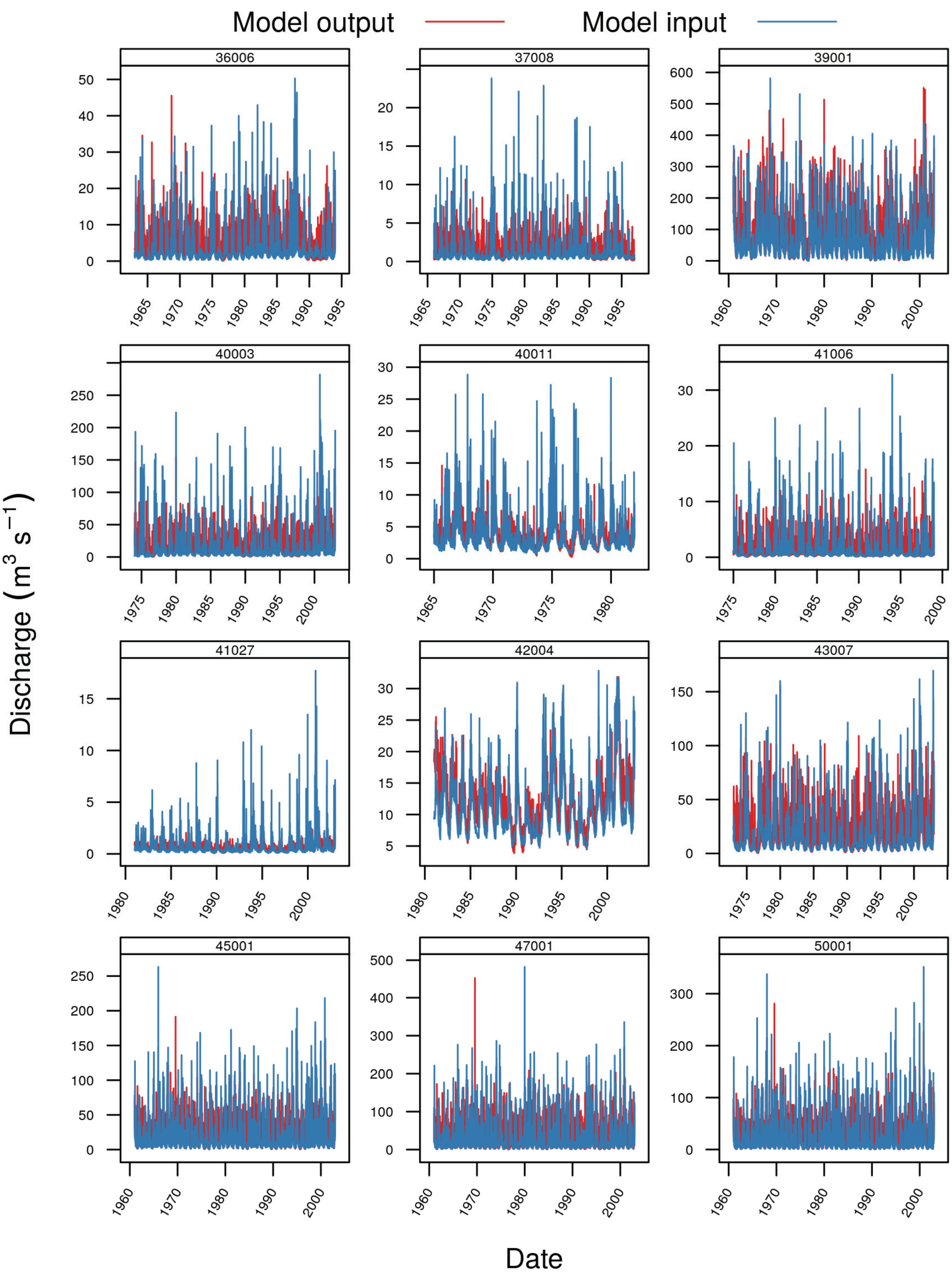


Figure 4.7c: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the calibration dataset.

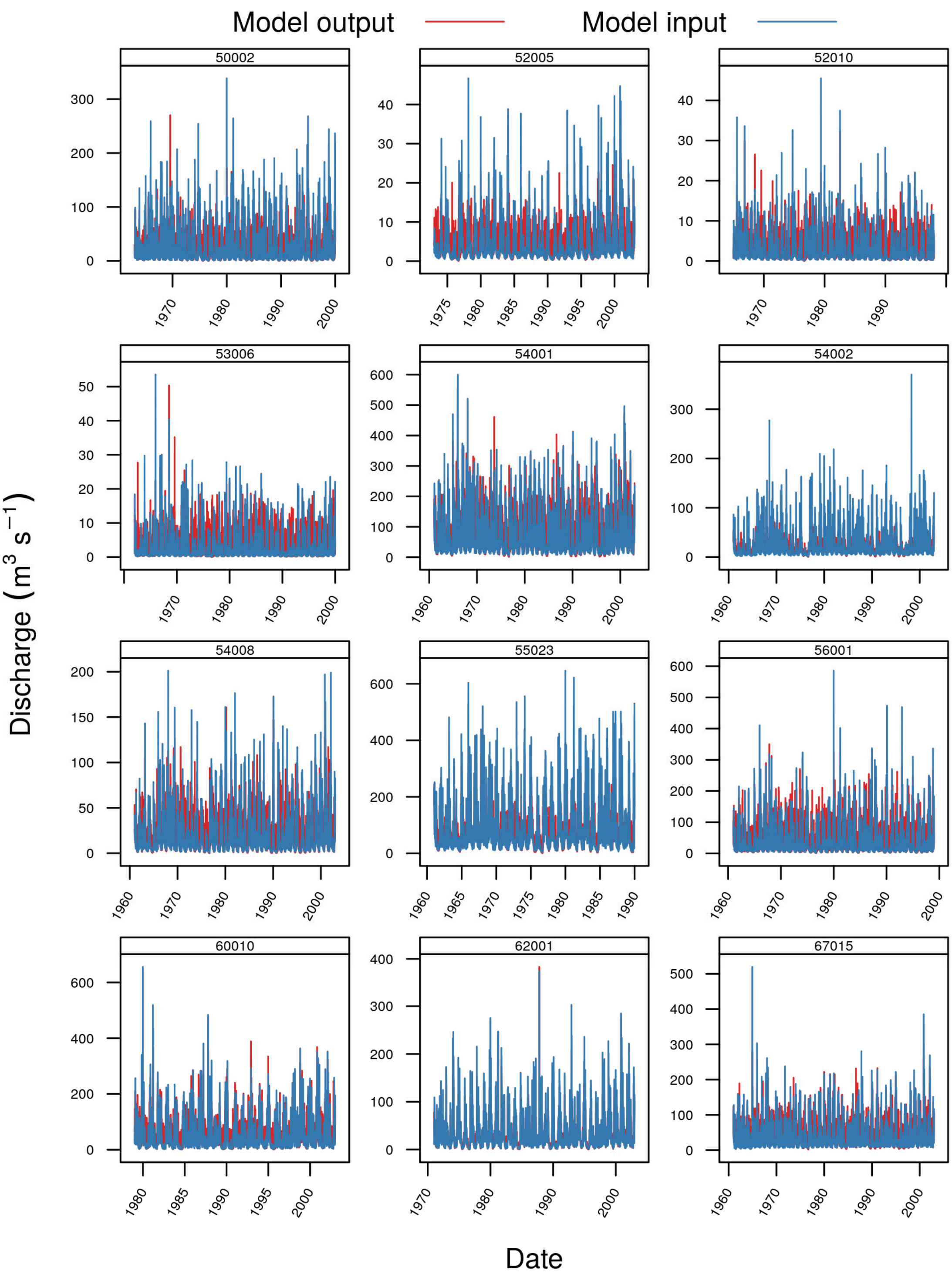


Figure 4.7d: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the calibration dataset.

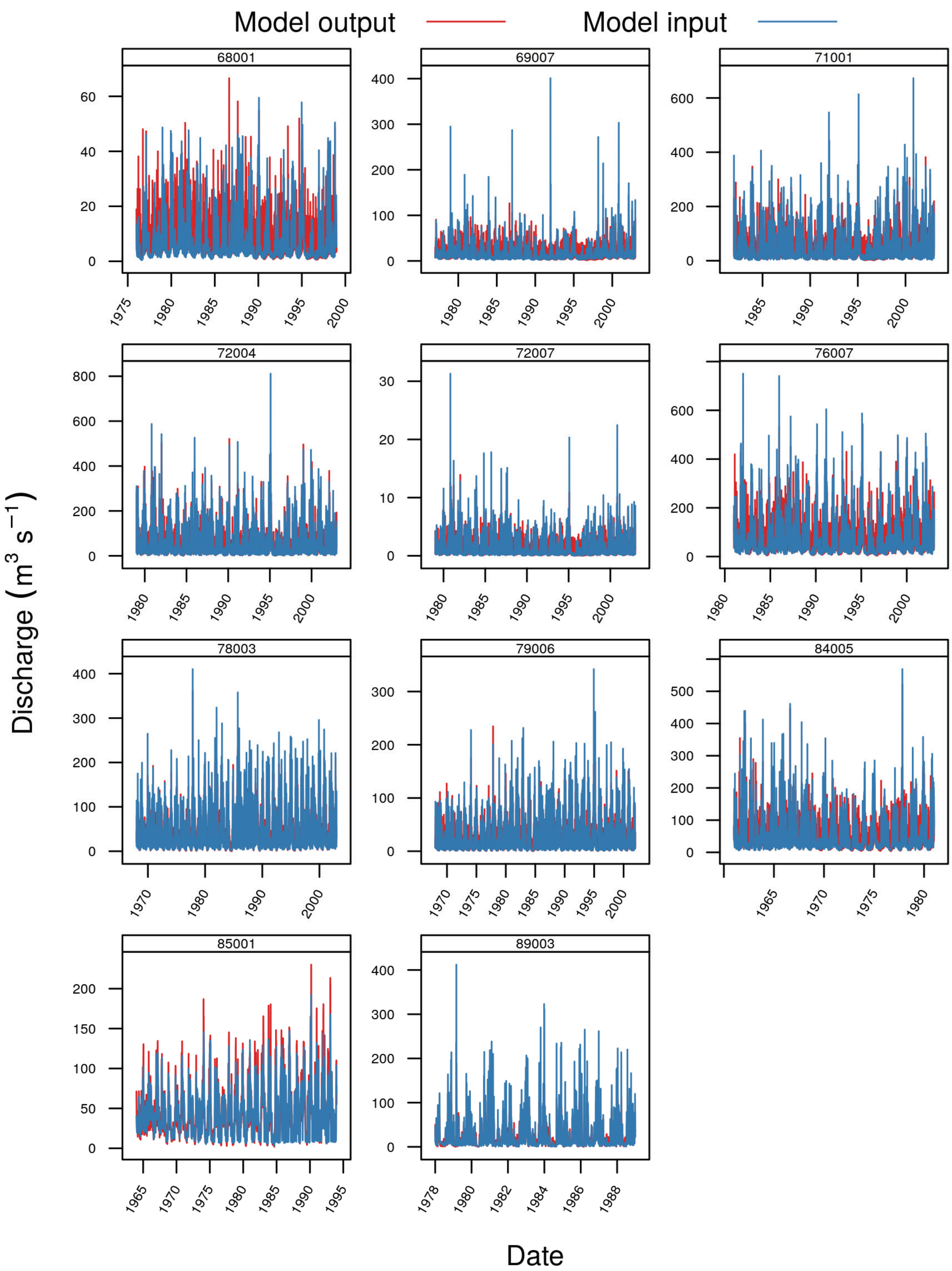


Figure 4.7e: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the calibration dataset.

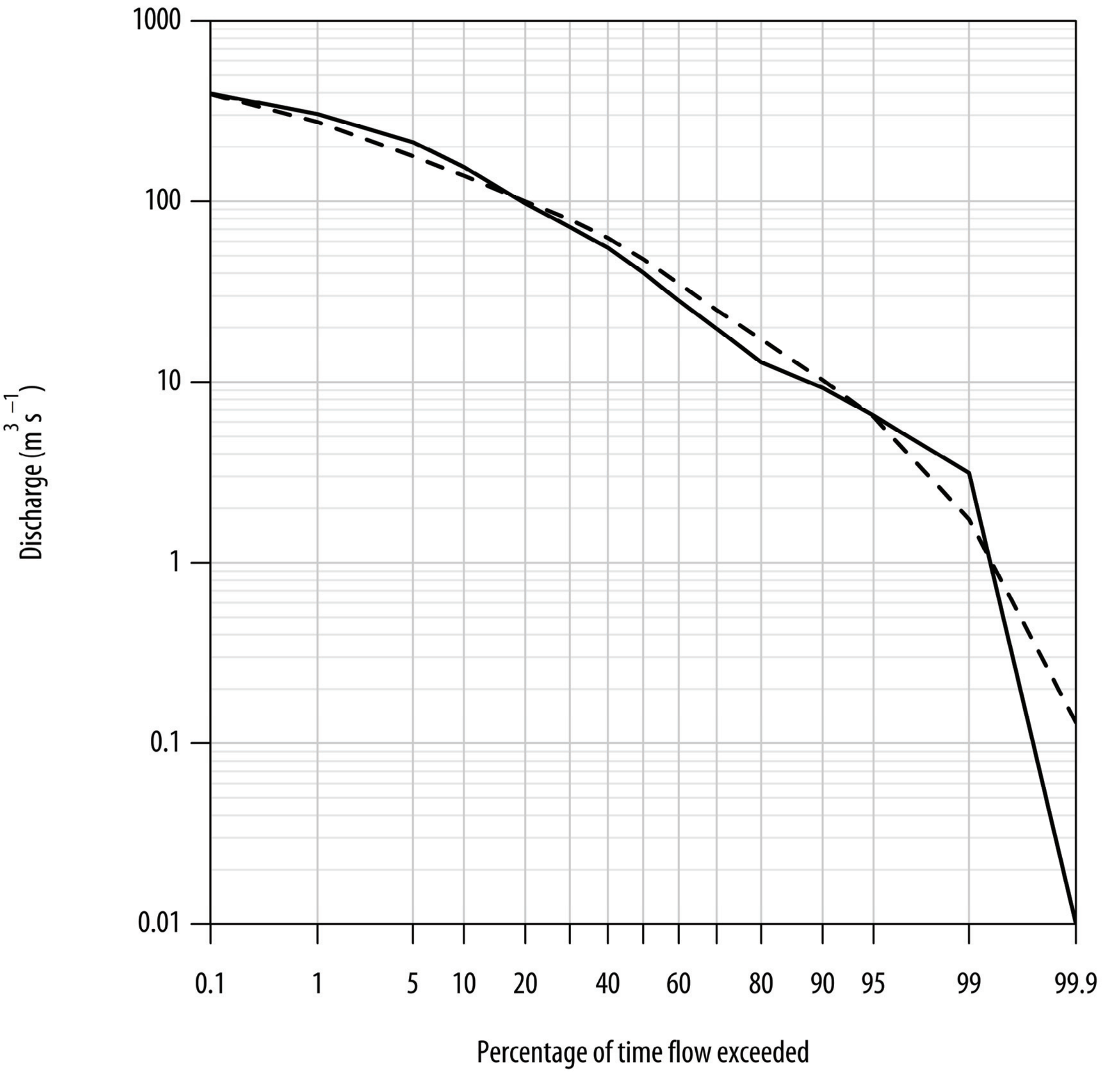


Figure 4.8: An example flow-duration curve, for the River Thames at Kingston. Values derived from historical observations are shown with a solid line; values derived from the output of the calibrated model are shown with a dashed line.

4.5.4 Validation performance of the hydrological model

Split-sample validation via assessment of the calibrated models' capacity to predict a second time-series of daily mean flows at each calibration location provides a means of testing the transferability of calibrated parameter values to events that do not occur within the calibration record. Sufficient data for the construction of a validation series, derived from the second-longest contiguous series of mean daily flows recorded at a gauge location, existed for 95% of the gauges described in §4.5.1.

Error! Reference source not found. summarises the mean predictive performance according to the administrative regions used to group calibration locations in §4.5.1 and §4.5.3. Table 4.8 shows the same summary statistics shown in Table 4.2, computed for the output produced by the calibrated model in response to the inputs of the calibration series, while Table 4.9 shows the difference between Table 4.8 and Table 4.2 as a proportion of the latter. Note that , as in §4.5.3, the proportional difference in the mean shown in Table 4.9 is a metric of the 'runoff ratio' wherein small values indicate a runoff ratio close to 1, i.e. high similarity in total discharge between the compared series.

Region	**Monthly KGE**		
	Minimum	**Mean**	**Maximum**
EA Anglian	0.14	0.40	0.60
EA Midlands	0.45	0.56	0.70
EA North East	0.61	0.65	0.69
EA North West	0.55	0.63	0.71
EA South West	0.00	0.57	0.73
EA Southern	0.39	0.54	0.64
EA Thames	No data available		
EA Wales	0.57	0.73	0.87
Scotland	0.43	0.72	0.92

Table 4.7: Hydrological model validation fitness scores by region.

In general, model validation performance is, in terms of the monthly KGE, at least as acceptable as calibration performance for the majority of simulated catchments; however, there are a few examples of relatively poor performance, wherein the predictive performance at low flows is particularly variable. Specific examples include the Frome (Bristol) at Frenchay (gauge location 53006, in the EA South West region), which struggled to reproduce Q95 from the validation dataset to such an extent that the monthly KGE was very close to zero, and the Chelmer at Springfield (gauge location 37008, in the EA Anglian region).

Figure 4.9 ('a' through 'e') shows a scatter plot of estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input), while Figure 4.10 ('a' through 'e') shows time-series plots of those variables.

These figures further explain the relatively weak validation performance at sites 37008 and 53006. In both instances, the model output was typically much less than the corresponding value in the validation dataset, with a few outlying values having the inverse of this relationship. Although the correlation was approximately 0.5 in both cases, this behaviour had a strong negative impact on the ability of the calibrated models to reproduce the standard deviations of the validation datasets.

Figure 4.11 shows an example flow-duration curve for the River Eden at Sheepmount.

Gauge	River	Location	Discharge ($m^3\ s^{-1}$)				
			Mean	Std. Dev.	Min.	Max.	Q95
3003	Oykel	Easter Turnaig	No data available				
4001	Conon	Moy Bridge	46.9	29.1	2.1	202.9	13.1
6008	Enrick	Mill of Tore	No data available				
8006	Spey	Boat o Brig	64.8	45.5	11.9	382.2	18.7
11001	Don	Parkhill	19.9	12.5	2.8	107.6	5.2
12002	Dee	Park	51.6	47.7	2.3	461.1	7.9
15006	Tay	Ballathie	195.9	133.5	30.6	827.3	46.9
16004	Earn	Forteviot Bridge	32.1	24.5	3.1	163.4	5.5
18003	Teith	Bridge of Teith	23.3	19.8	3.1	222.3	5.6
19001	Almond	Craigiehall	8.0	5.6	1.1	60.2	2.0
21009	Tweed	Norham	87.3	78.8	4.5	941.0	13.9
23001	Tyne	Bywell	46.9	48.0	1.4	449.1	6.1
24001	Wear	Sunderland Bridge	10.4	13.1	0.8	150.0	1.5
25001	Tees	Broken Scar	14.8	16.2	2.1	179.4	4.3
27009	Ouse	Skelton	51.9	56.9	2.0	689.2	5.5
27025	Rother	Woodhouse Mill	4.6	3.8	1.1	41.7	1.6
27035	Aire	Kildwick Bridge	5.7	6.7	0.5	63.3	0.7
28009	Trent	Colwick	79.2	51.6	17.6	540.4	30.9
30001	Witham	Claypole Mill	2.4	1.8	0.6	21.2	0.8
30004	Lymn	Partney Mill	0.5	0.5	0.0	6.8	0.1
31002	Glen	Kates Br and King St Br	0.7	1.1	0.0	14.5	0.0
32004	Ise Brook	Harrowden Old Mill	1.4	1.6	0.1	28.0	0.3
33002	Bedford Ouse	Bedford	15.1	13.9	1.4	129.3	2.6
34006	Waveney	Needham Mill	1.9	2.1	0.1	16.6	0.1
36006	Stour	Langham	1.9	2.3	0.1	18.7	0.2
37008	Chelmer	Springfield	1.2	0.9	0.3	7.1	0.5
39001	Thames	Kingston	No data available				
40003	Medway	Teston	8.8	11.0	0.5	140.2	1.2
40011	Great Stour	Horton	3.0	1.8	0.4	14.8	0.9
41006	Uck	Isfield	1.1	1.5	0.1	15.4	0.2
41027	Rother	Princes Marsh	0.4	0.3	0.0	2.5	0.1
42004	Test	Broadlands	11.1	3.3	2.2	27.1	6.5
43007	Stour	Throop	13.3	12.7	1.1	109.0	2.4
45001	Exe	Thorverton	15.3	14.3	0.2	191.3	2.0
47001	Tamar	Gunnislake	21.4	24.5	1.4	452.0	2.7
50001	Taw	Umberleigh	17.9	19.4	0.8	281.0	1.9
50002	Torridge	Torrington	16.4	17.8	0.4	130.2	0.8
52005	Tone	Bishops Hull	3.1	2.6	0.4	44.9	0.7
52010	Brue	Lovington	2.5	2.7	0.2	23.1	0.4
53006	Frome (Bristol)	Frenchay	0.8	1.5	0.0	11.0	0.0
54001	Severn	Bewdley	61.4	44.1	3.9	461.0	12.9
54002	Avon	Evesham	17.7	11.7	0.5	102.8	3.4
54008	Teme	Tenbury	15.5	15.2	0.1	127.4	1.5
55023	Wye	Redbrook	82.9	70.0	1.3	543.1	10.4
56001	Usk	Chain Bridge	32.0	37.4	3.3	384.5	4.7
60010	Tywi	Nantgaredig	36.1	37.2	0.5	368.6	4.7
62001	Teifi	Glan Teifi	27.6	23.2	1.3	244.4	6.2
67015	Dee	Manley Hall	29.4	23.2	5.0	281.4	8.8
68001	Weaver	Ashbrook	6.3	5.8	1.1	56.6	1.7
69007	Mersey	Ashton Weir	No data available				
71001	Ribble	Samlesbury	33.4	38.0	2.0	369.9	5.7
72004	Lune	Caton	33.7	40.4	0.9	408.3	4.1
72007	Brock	U/S A6	No data available				
76007	Eden	Sheepmount	48.8	50.3	4.2	517.7	10.1
78003	Annan	Brydekirk	32.4	28.3	0.7	211.3	4.3
79006	Nith	Drumlanrig	18.4	20.3	0.1	156.1	1.4
84005	Clyde	Blairston	47.1	43.9	2.2	371.0	8.7
85001	Leven	Linnbrane	45.5	32.2	5.3	188.7	10.4
89003	Orchy	Glen Orchy	23.0	23.6	0.4	195.8	1.8

Table 4.8: Statistics of the validation dataset estimated by the calibrated model.

Gauge	River	Location	Difference				
			Mean	Std. Dev.	Min.	Max.	Q95
3003	Oykel	Easter Turnaig	No data available				
4001	Conon	Moy Bridge	10.4%	1.4%	-57.0%	-36.0%	49.6%
6008	Enrick	Mill of Tore	No data available				
8006	Spey	Boat o Brig	4.8%	-8.4%	-14.0%	-19.6%	13.0%
11001	Don	Parkhill	0.8%	-24.7%	-19.9%	-45.9%	-5.5%
12002	Dee	Park	-1.4%	-11.7%	-45.3%	-26.3%	-13.0%
15006	Tay	Ballathie	0.2%	-12.5%	-14.5%	-5.3%	2.4%
16004	Earn	Forteviot Bridge	-1.8%	-16.6%	-17.3%	-22.5%	16.9%
18003	Teith	Bridge of Teith	9.8%	-9.8%	18.4%	9.0%	16.2%
19001	Almond	Craigiehall	5.7%	-48.9%	12.6%	-52.0%	35.6%
21009	Tweed	Norham	2.8%	-13.2%	-40.9%	-29.5%	-2.7%
23001	Tyne	Bywell	-5.8%	-21.8%	-72.5%	-40.7%	-13.4%
24001	Wear	Sunderland Bridge	-9.6%	-9.3%	-32.7%	-23.4%	-25.0%
25001	Tees	Broken Scar	6.7%	-23.4%	578.4%	-20.6%	221.5%
27009	Ouse	Skelton	-3.4%	-9.6%	-44.6%	34.1%	-24.4%
27025	Rother	Woodhouse Mill	12.4%	-19.9%	157.8%	-14.9%	86.7%
27035	Aire	Kildwick Bridge	13.6%	0.8%	91.8%	-2.1%	35.2%
28009	Trent	Colwick	2.1%	-12.3%	-24.0%	26.4%	6.8%
30001	Witham	Claypole Mill	-16.9%	-29.8%	9.4%	-25.6%	2.5%
30004	Lymn	Partney Mill	-6.9%	-18.8%	-32.9%	-42.4%	-30.5%
31002	Glen	Kates Br and King St Br	-36.2%	-30.2%	-99.1%	-13.4%	-97.1%
32004	Ise Brook	Harrowden Old Mill	-1.9%	-8.7%	-41.5%	66.5%	-21.8%
33002	Bedford Ouse	Bedford	-4.4%	-20.2%	-27.3%	-41.0%	-5.7%
34006	Waveney	Needham Mill	-35.0%	-48.2%	-73.4%	-45.9%	-74.8%
36006	Stour	Langham	-27.9%	-28.4%	-54.8%	-30.2%	-58.5%
37008	Chelmer	Springfield	-35.0%	-64.0%	-16.3%	-73.8%	21.8%
39001	Thames	Kingston	No data available				
40003	Medway	Teston	-10.3%	-33.1%	-50.5%	-29.5%	-14.0%
40011	Great Stour	Horton	3.1%	-32.2%	-16.7%	-47.3%	-4.7%
41006	Uck	Isfield	11.7%	-4.5%	1.8%	-30.0%	-5.8%
41027	Rother	Princes Marsh	-10.7%	-48.8%	-71.4%	-69.1%	-34.0%
42004	Test	Broadlands	-1.6%	-30.7%	-41.4%	-26.1%	9.2%
43007	Stour	Throop	0.4%	-17.4%	-30.7%	-23.9%	-5.0%
45001	Exe	Thorverton	3.0%	-14.8%	-61.2%	-27.5%	10.1%
47001	Tamar	Gunnislake	-0.9%	-9.3%	-0.8%	63.5%	4.8%
50001	Taw	Umberleigh	2.5%	-14.3%	-5.5%	-16.8%	10.2%
50002	Torridge	Torrington	2.2%	-23.1%	-13.9%	-17.8%	15.2%
52005	Tone	Bishops Hull	4.7%	-20.4%	0.9%	15.7%	-3.9%
52010	Brue	Lovington	-7.2%	-17.6%	-29.4%	-12.1%	-8.6%
53006	Frome (Bristol)	Frenchay	-67.5%	-62.1%	-100.0%	-64.5%	-99.9%
54001	Severn	Bewdley	1.2%	-23.8%	-50.1%	-11.6%	3.6%
54002	Avon	Evesham	0.1%	-46.9%	-85.0%	-72.2%	-21.9%
54008	Teme	Tenbury	-0.6%	-21.6%	-85.6%	-35.9%	-13.7%
55023	Wye	Redbrook	-3.6%	-32.8%	-72.6%	-40.5%	-12.9%
56001	Usk	Chain Bridge	6.2%	-13.1%	53.2%	-30.9%	62.0%
60010	Tywi	Nantgaredig	-2.1%	-8.7%	-71.4%	-24.5%	5.1%
62001	Teifi	Glan Teifi	0.7%	-10.5%	-38.2%	6.0%	38.8%
67015	Dee	Manley Hall	-0.1%	-28.5%	82.7%	-46.0%	88.0%
68001	Weaver	Ashbrook	16.9%	-8.1%	62.8%	-3.9%	50.8%
69007	Mersey	Ashton Weir	No data available				
71001	Ribble	Samlesbury	2.3%	-14.2%	-3.6%	-45.2%	25.1%
72004	Lune	Caton	0.1%	-12.1%	-28.3%	-43.2%	24.1%
72007	Brock	U/S A6	No data available				
76007	Eden	Sheepmount	5.8%	-2.2%	-22.7%	-33.0%	6.6%
78003	Annan	Brydekirk	-1.8%	-21.6%	-64.5%	-28.6%	2.3%
79006	Nith	Drumlanrig	-0.3%	-16.6%	-81.4%	-32.6%	7.7%
84005	Clyde	Blairston	0.4%	-17.5%	-35.6%	-36.2%	22.2%
85001	Leven	Linnbrane	-4.0%	-0.5%	-24.3%	30.3%	14.6%
89003	Orchy	Glen Orchy	-0.6%	-38.2%	-27.1%	-56.0%	25.8%

Table 4.9: Difference between the calibrated model and the validation dataset.

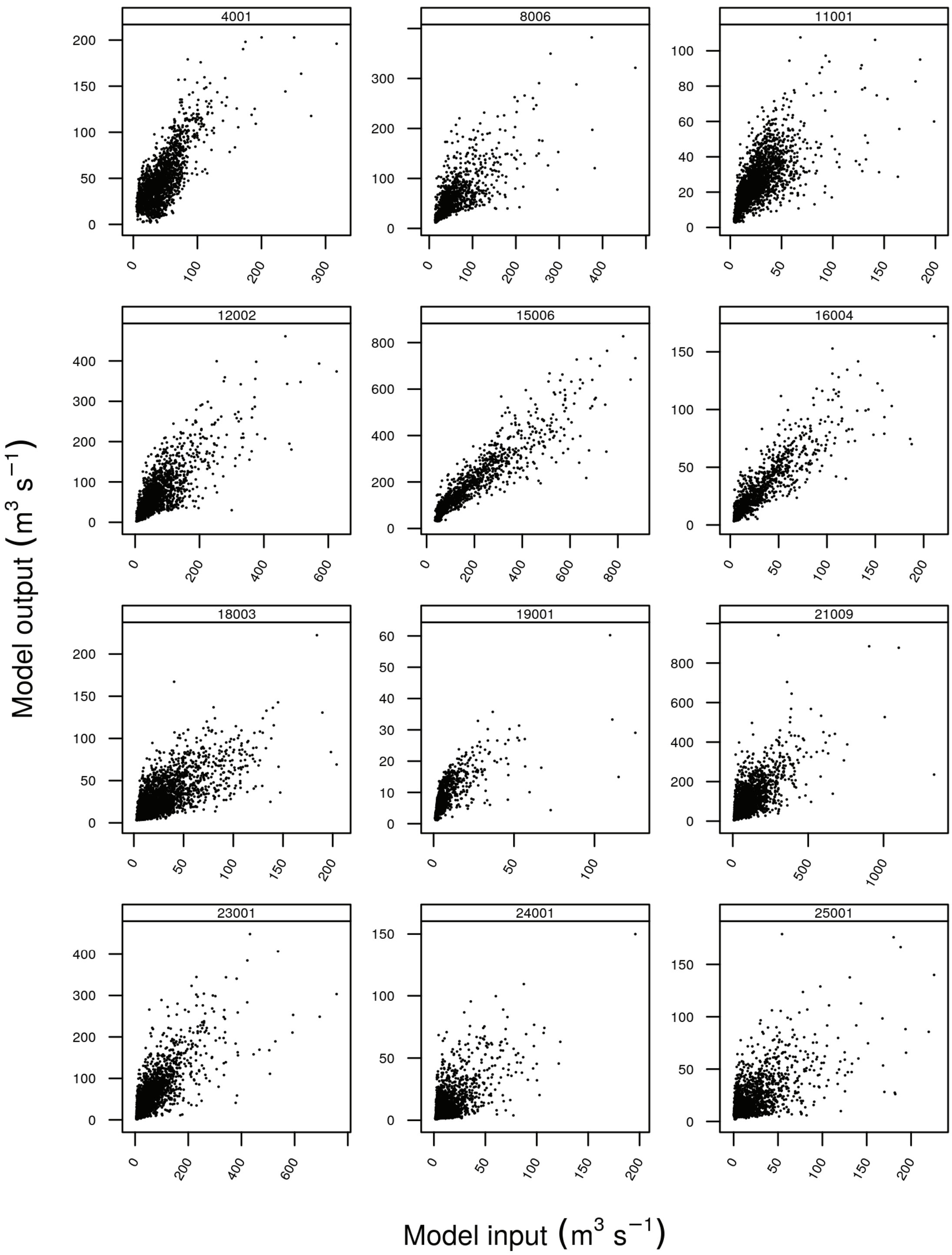


Figure 4.9a: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the validation dataset.

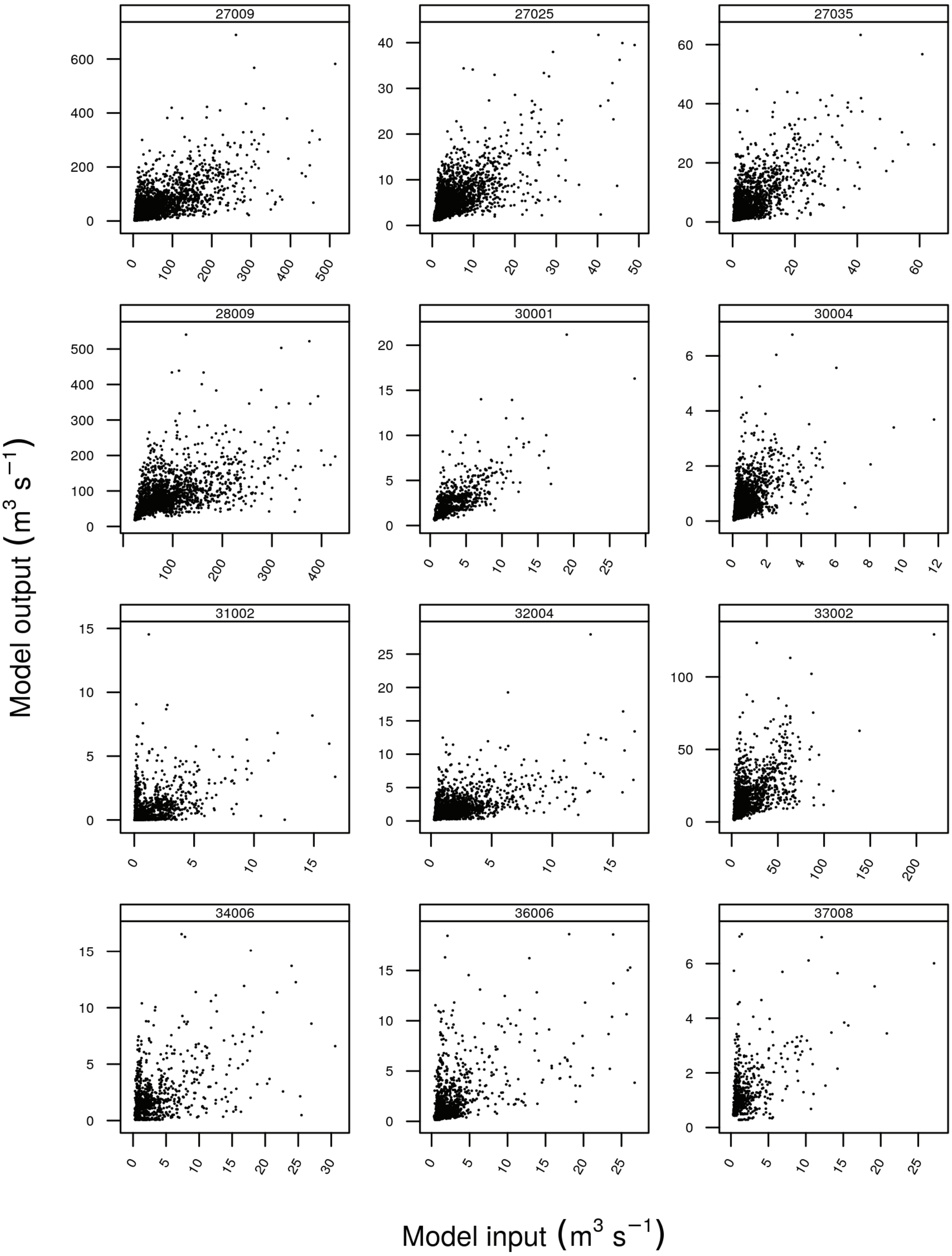


Figure 4.9b: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the validation dataset.

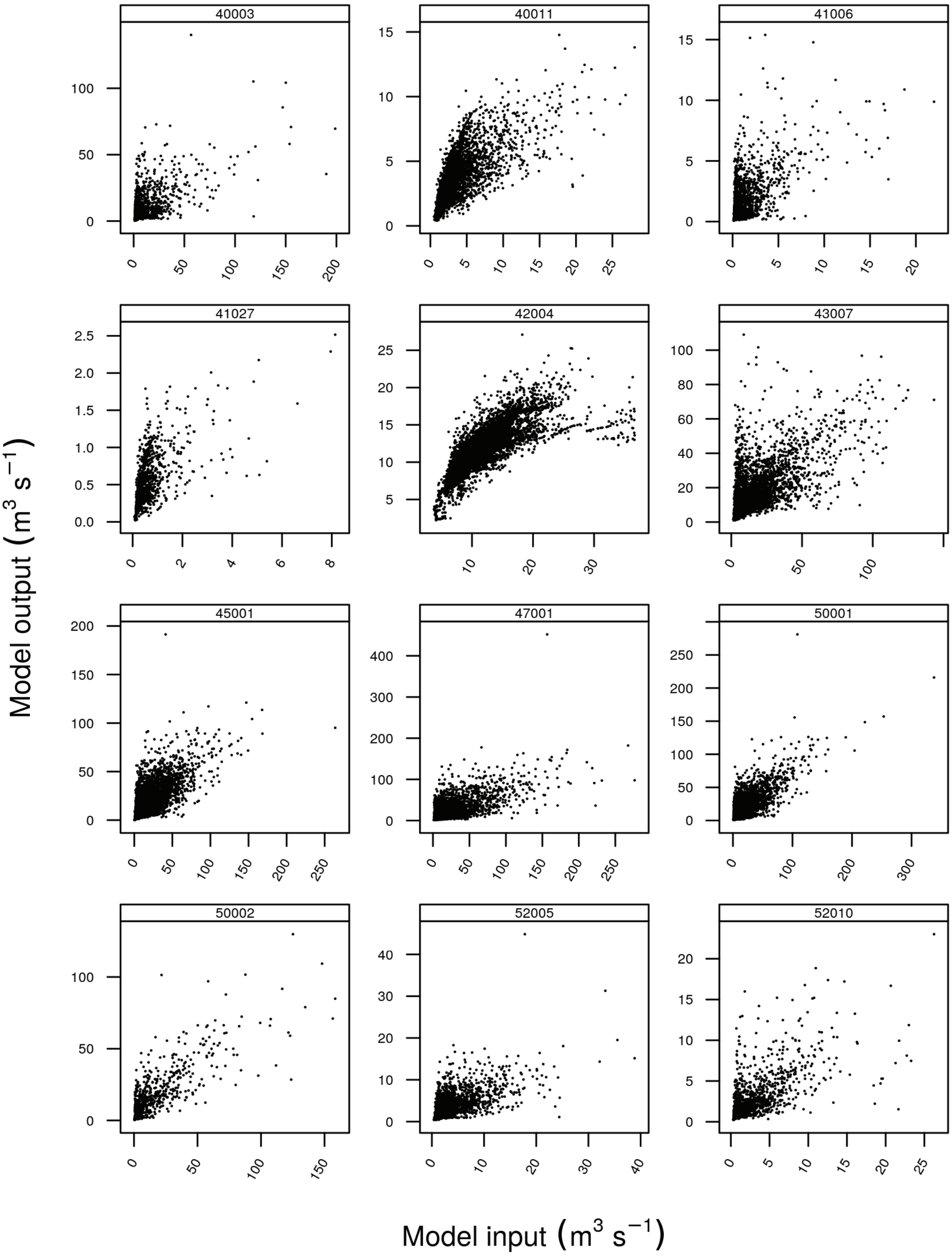


Figure 4.9c: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the validation dataset.

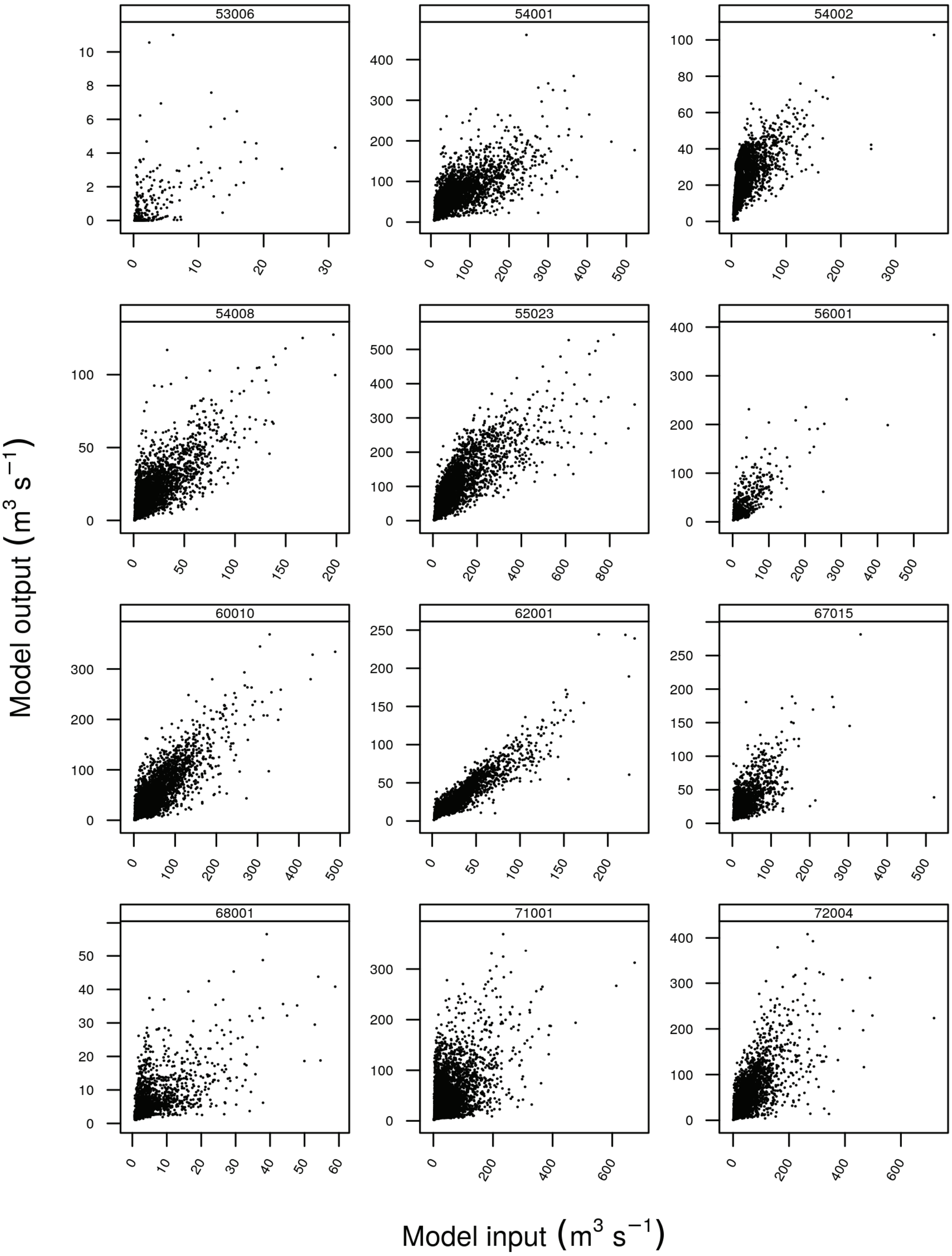


Figure 4.9d: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the validation dataset.

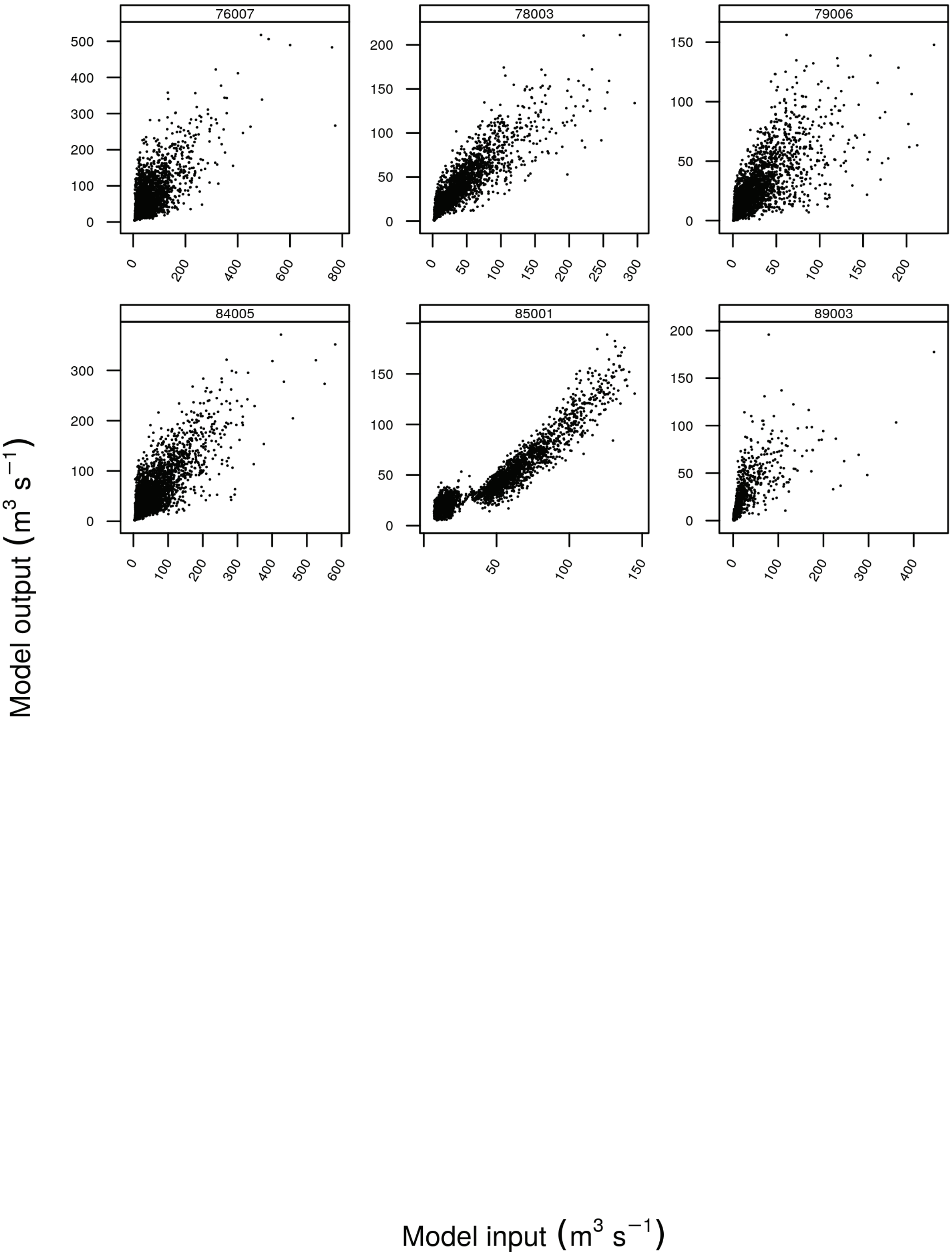


Figure 4.9e: Estimated mean daily discharge against observed mean daily discharge (i.e. model output against model input) for the validation dataset.

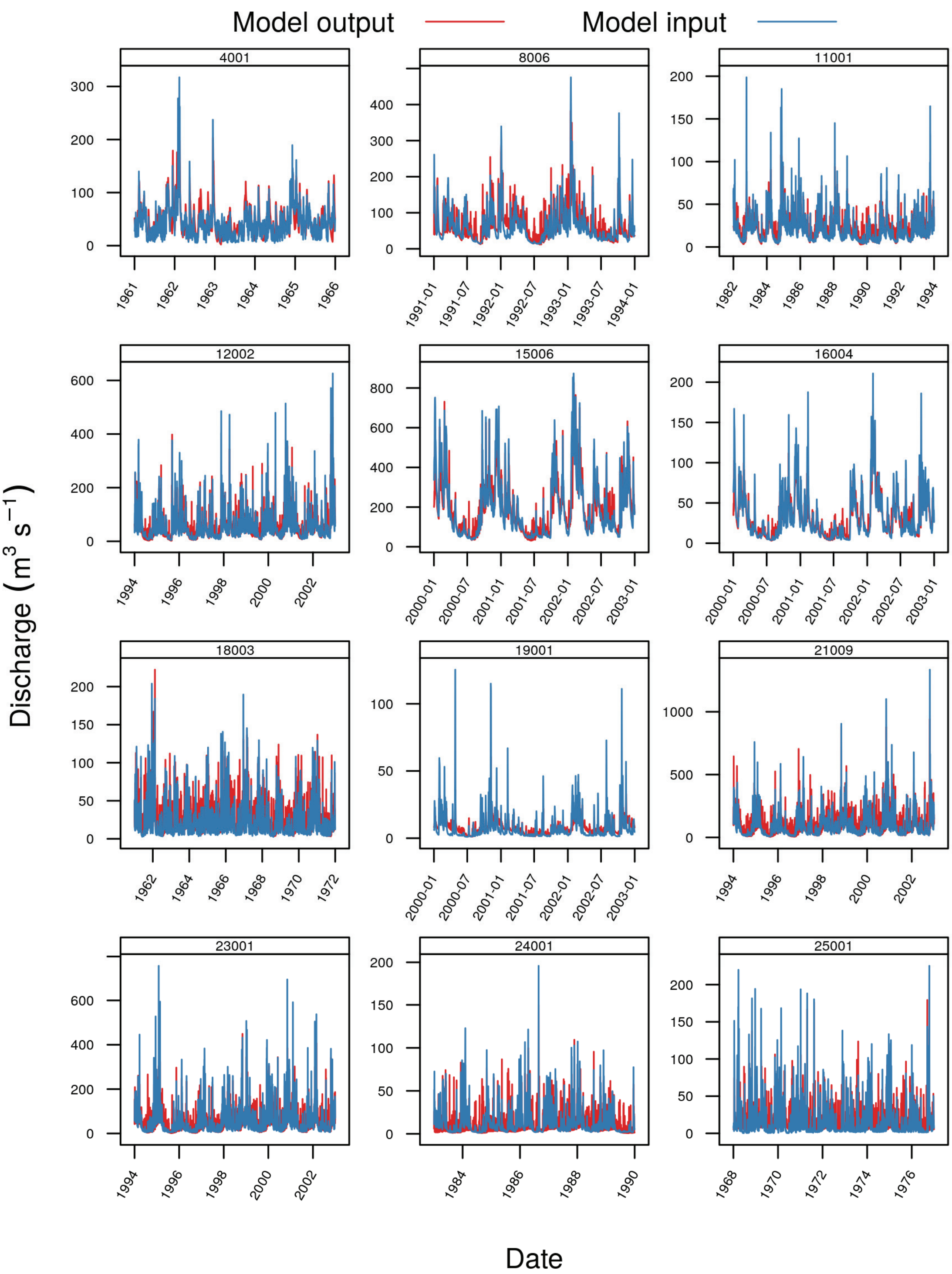


Figure 4.10a: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the validation dataset.

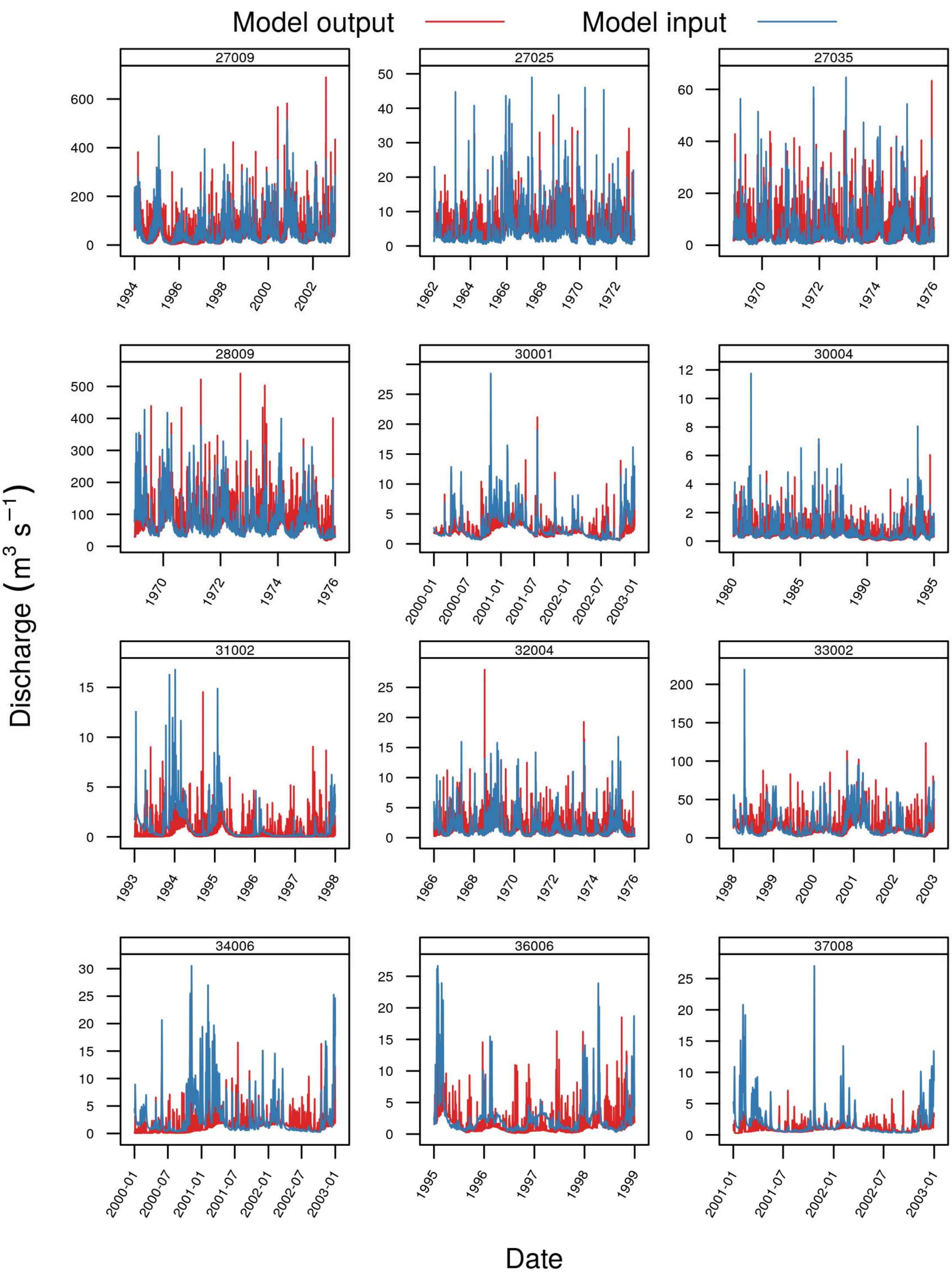


Figure 4.10b: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the validation dataset.

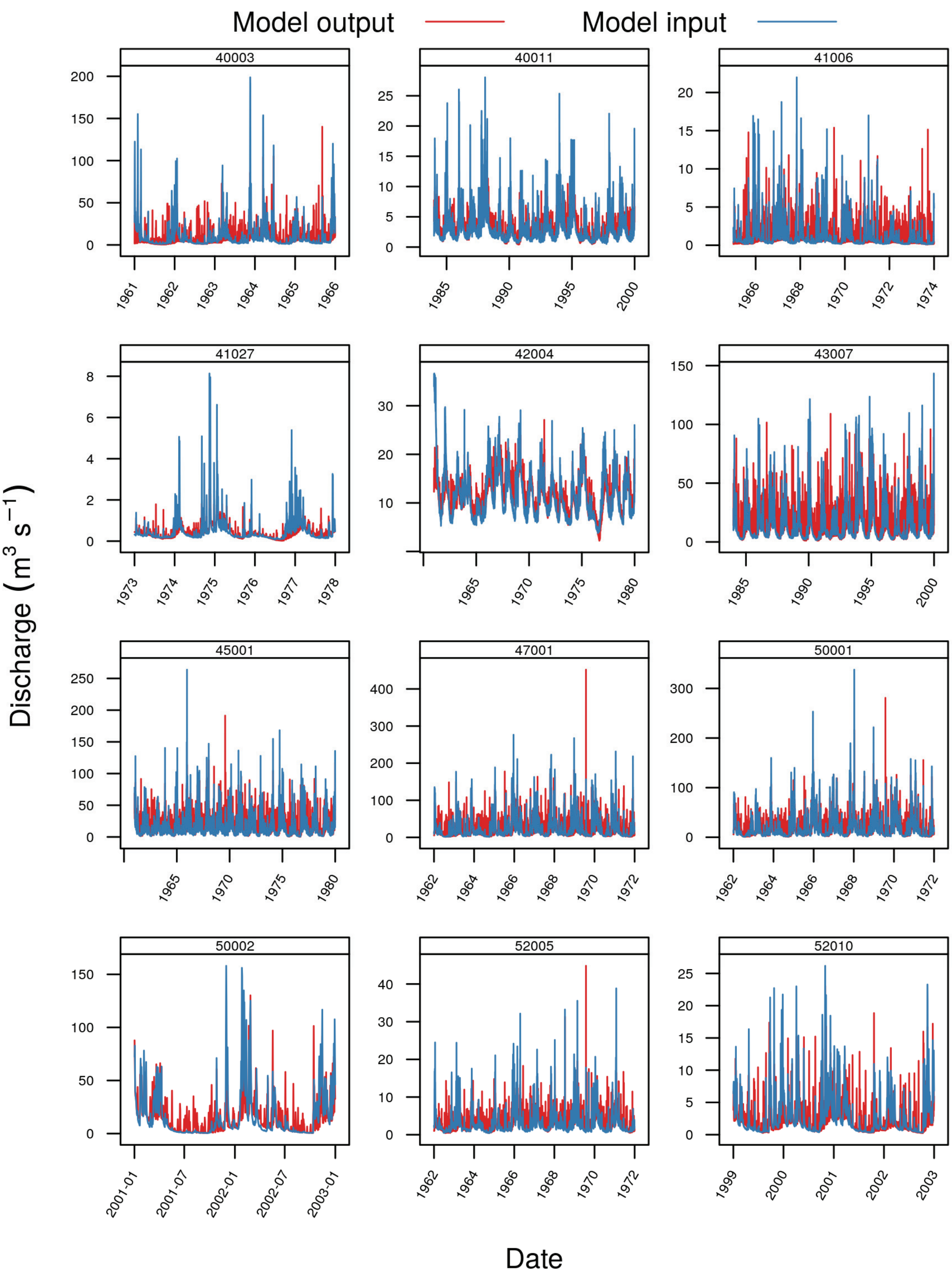


Figure 4.10c: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the validation dataset.

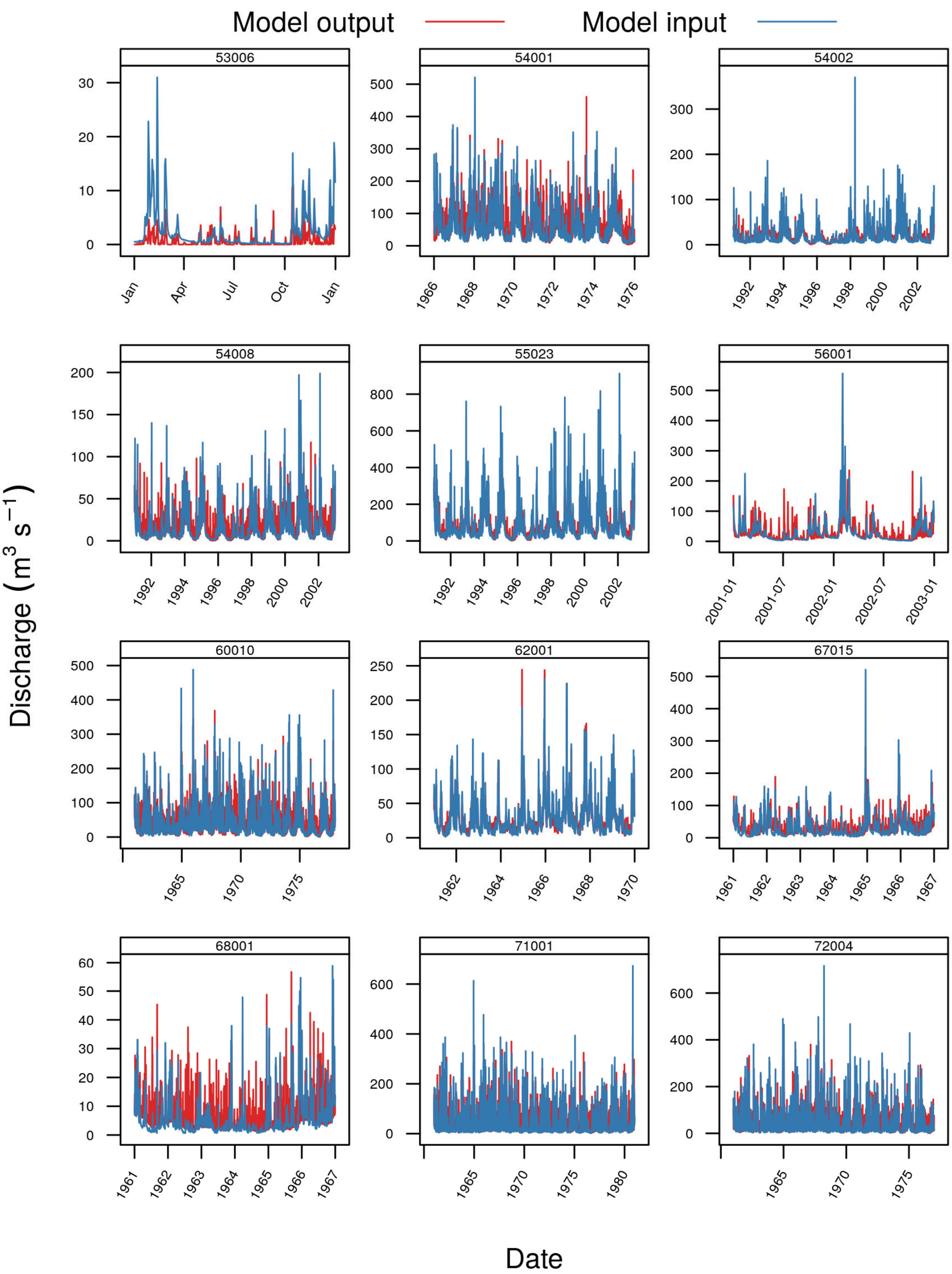


Figure 4.10d: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the validation dataset.

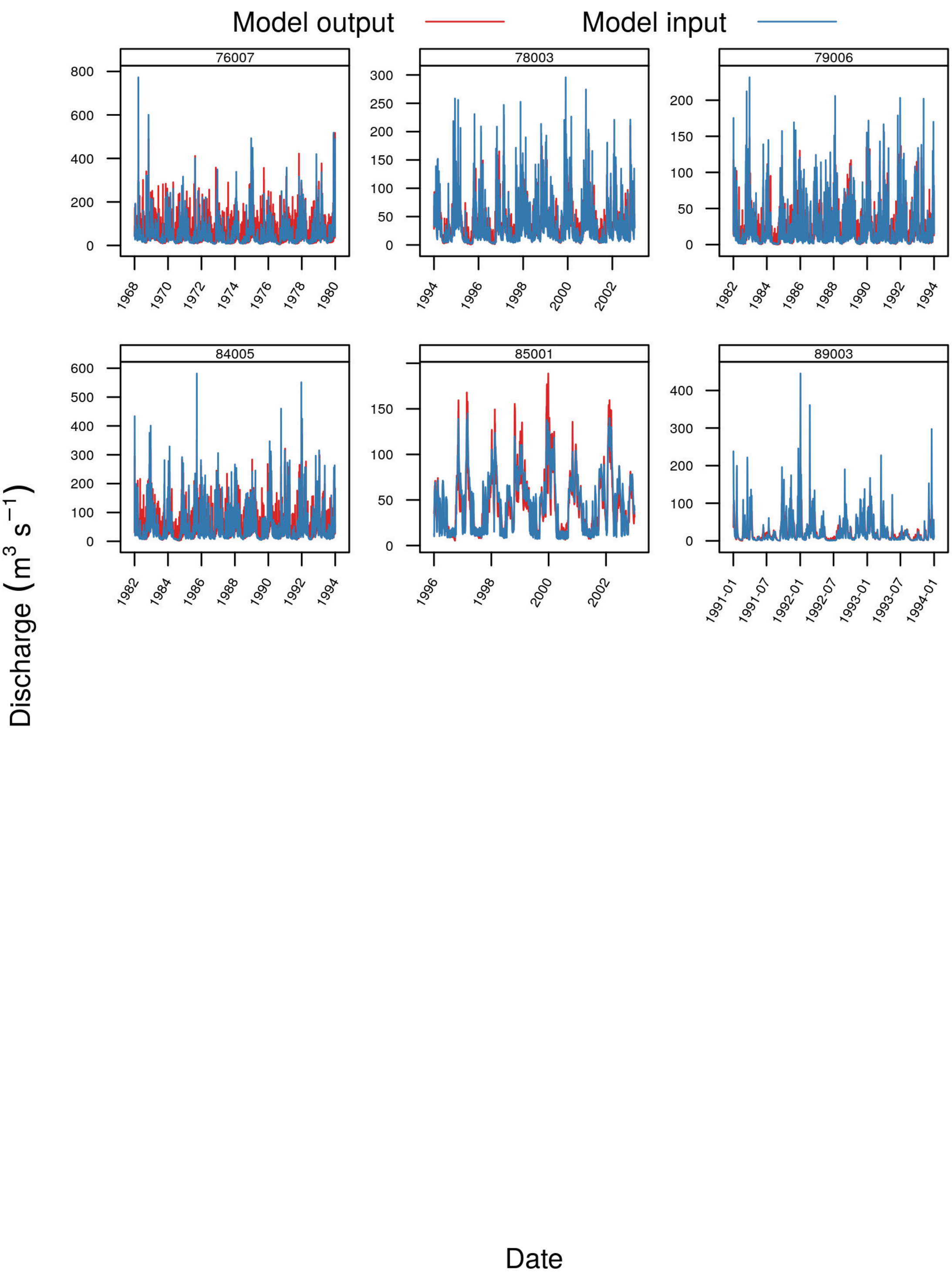


Figure 4.10e: Estimated mean daily discharge and observed mean daily discharge (i.e. model output against model input) against date for the validation dataset.

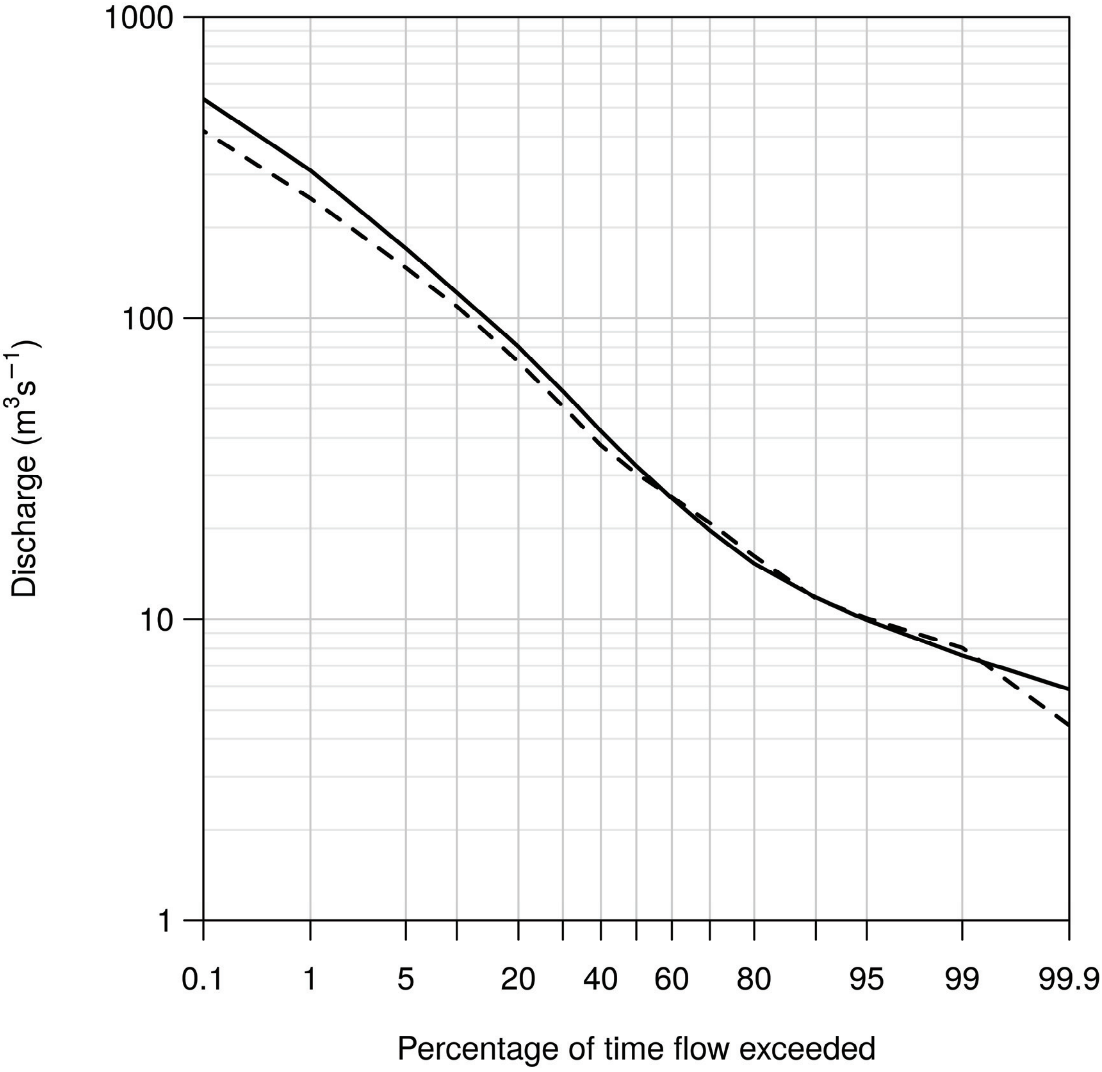


Figure 4.11: An example flow-duration curve, for the River Eden at Sheepmount. Values derived from historical observations are shown with a solid line; values derived from the output of the calibrated model are shown with a dashed line.

4.5.5 Projected changes in river flow

This subsection summarizes changes in synthetic river flow projected in 72 basins nationwide between the 1961-1990 control period and the 2020s, 2050s and 2080s. Simulation of the control period 1961-1990 produced 100 model runs of length 30 years under conditions of historical atmospheric composition, while simulation of the 2020s, 2050s and 2080s each consisted of 1000 model runs of length 30 years under conditions of the SRES A1B emissions scenario.

Table 4.10 illustrates that, on average across all simulated basins, 90% of model runs projected incremental decreases in annual river flows throughout the 21st Century; the breakdown by season presented in Table 4.11 indicates that river flow decreases most in summer (June-July-August; JJA), followed by autumn (September-October-November; SON), and, finally, spring (March-April-May; MAM), and that, at the 90% probability level, national average river flow increases in winter (December-January-February; DJF).

Table 4.12 summarizes the proportion of basins exhibiting a decrease in annual flow. On average, and at the 10% probability level, between 80% and 90% of basins exhibit negative changes in annual river flow: a proportion that decreases between the 2020s and 2080s. At the 90% probability level, the proportion of basins exhibiting negative changes in river flow decreased overall between the 2020s and the 2080s, but increased in the 2050s. Table 4.13 disaggregates these data by season, suggesting that a majority of basins exhibited negative change in river flow in spring, summer and autumn of the 2020s, 2050s and 2080s at both the 10% and 90% probability levels. In winter, a majority of basins exhibited negative changes in river flow on average and at the 10% probability level, but river flow increased in a majority of basins at the 90% probability level.

Spatial disaggregation of changes in river flow in spring (Figure 4.12), summer (Figure 4.13), autumn (Figure 4.14) and winter (Figure 4.15) demonstrates a clear pattern in the distribution of changes in river flow across Great Britain that incorporates seasonal and inter-decadal variation, generally exhibiting the latter as an exacerbation of changes occurring by the 2020s.

In spring, the spatial pattern is one of diminished river flows across England, particularly the north east, east, south, southeast and parts of the southwest. East Anglia appears particularly vulnerable by the 2020s at the 10% probability level, and in the 2050s and 2080s at the 90% probability level. Where decreases in river flow occur by the 2020s, they range from ≤ -34% at the 10% probability level to ≤ -4% at the 90% probability level. A few basins in Scotland, Wales, and the north and east of England exhibit increases in river flow of up to ≤ +3% on average, and up to ≤ +4% at the 90% probability level by the 2020s; however, the majority of these basins express either a decrease in flows, or no change in flow, on average. This pattern intensifies in the 2050s and 2080s, leading to changes in river flow between ≤ -63% and ≤ +8% at the 10% probability level and between ≤ -34% and ≤ +10% at the 90% probability level.

At the 90% probability level, changes in summer flow are negative in all basins in the 2020s, 2050s and 2080s. Decreases in the 2020s range from between ≤ -29% and ≤ -6% at the 10% probability level and between ≤ -25% and ≤ -3% at the 90% probability level, increasing to between ≤ -54% and ≤ -14% at the 10% probability level and between ≤ -40% and ≤ -9% at the 90% probability level by the 2080s. Typically, decreases in river flow are greater in magnitude in the south and east of England and central Wales than elsewhere in Great Britain, but basins in the northeast and southwest of England also exhibit large decreases in river flow. The northwest of Great Britain experiences the smallest decreases in flow.

Changes in autumn river flows are more variable in space and between decades than those in spring and summer. In particular, larger increases of up to ≤ +8% at the 10% probability level and ≤ +9% at the 90% probability level occur by the 2020s in west Scotland, while basins across the south of England experience decreases of up to ≤ -29% at the 10% probability level and ≤ -23% at the 90% probability level. By the 2080s, changes in river flow range from between ≤ -58% and ≤ +18% at the 10% probability level to between ≤ -36% and ≤ +21% at the 90% probability level.

Winter river flows express similar spatial patterns of change to those evident in autumn, except that decreases in flow appear distributed across East Anglia and the south of England, while increases in flow occur in coastal Wales, and the northeast and northwest of England, as well as more broadly across the whole of Scotland. Changes are relatively uniform in the 2020s, being between ≤ -33% and ≤ +14% at the 10% probability level and between ≤ -18% and ≤ +17% at the 90% probability level, but intensify by the 2050s and, similarly, the 2080s, to between ≤ -57% and ≤ +37% at the 10% probability level and between ≤ -36% and ≤ +40% at the 90% probability level.

Scenario	P10	Mean	P90
2020s	-8	-6	-4
2050s	-17	-13	-9
2080s	-21	-15	-10

Table 4.10: Average percent change in annual river flow with respect to the 1961-1990 baseline climate.

Scenario	Season	P10	Mean	P90
2020s	MAM	-7	-5	-3
	JJA	-14	-12	-9
	SON	-9	-7	-5
	DJF	-3	-1	1
2050s	MAM	-13	-9	-5
	JJA	-28	-24	-21
	SON	-20	-16	-12
	DJF	-7	-2	2
2080s	MAM	-15	-9	-4
	JJA	-36	-30	-24
	SON	-25	-19	-14
	DJF	-9	-2	3

Table 4.11: Average percent change in seasonal river flow with respect to the 1961-1990 baseline climate.

Scenario	P10	Mean	P90
2020s	87	84	74
2050s	87	84	79
2080s	85	80	73

Table 4.12: Percentage of rivers exhibiting a decrease in annual river flow.

Scenario	Season	P10	Mean	P90
2020s	MAM	96	90	74
	JJA	100	100	100
	SON	90	90	81
	DJF	63	57	40
2050s	MAM	92	89	82
	JJA	100	100	100
	SON	94	92	90
	DJF	63	57	44
2080s	MAM	86	79	61
	JJA	100	100	100
	SON	92	88	85
	DJF	61	54	46

Table 4.13: Percentage of rivers exhibiting a decrease in seasonal river flow.

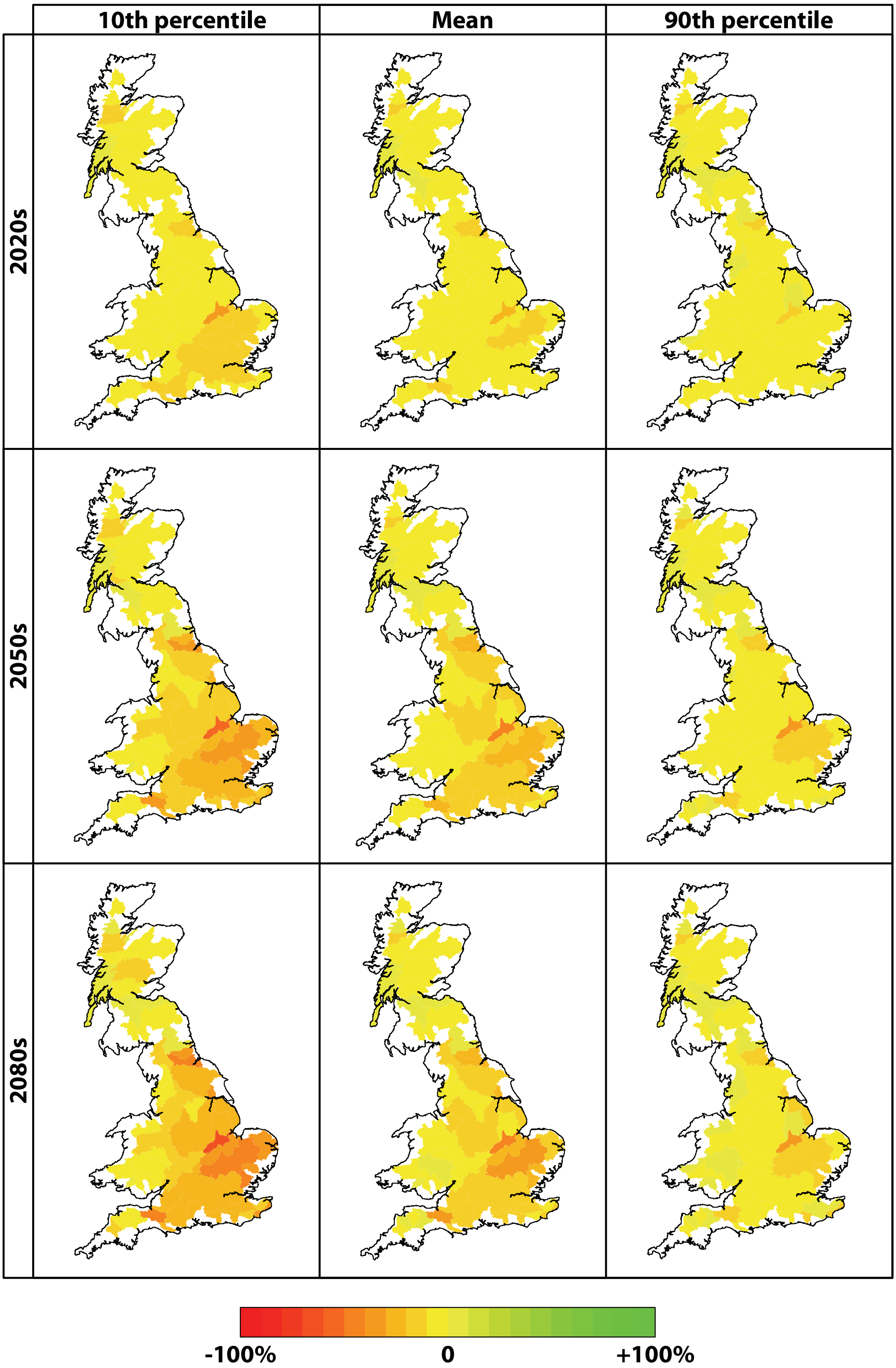


Figure 4.12: Projected changes in spring river flow.

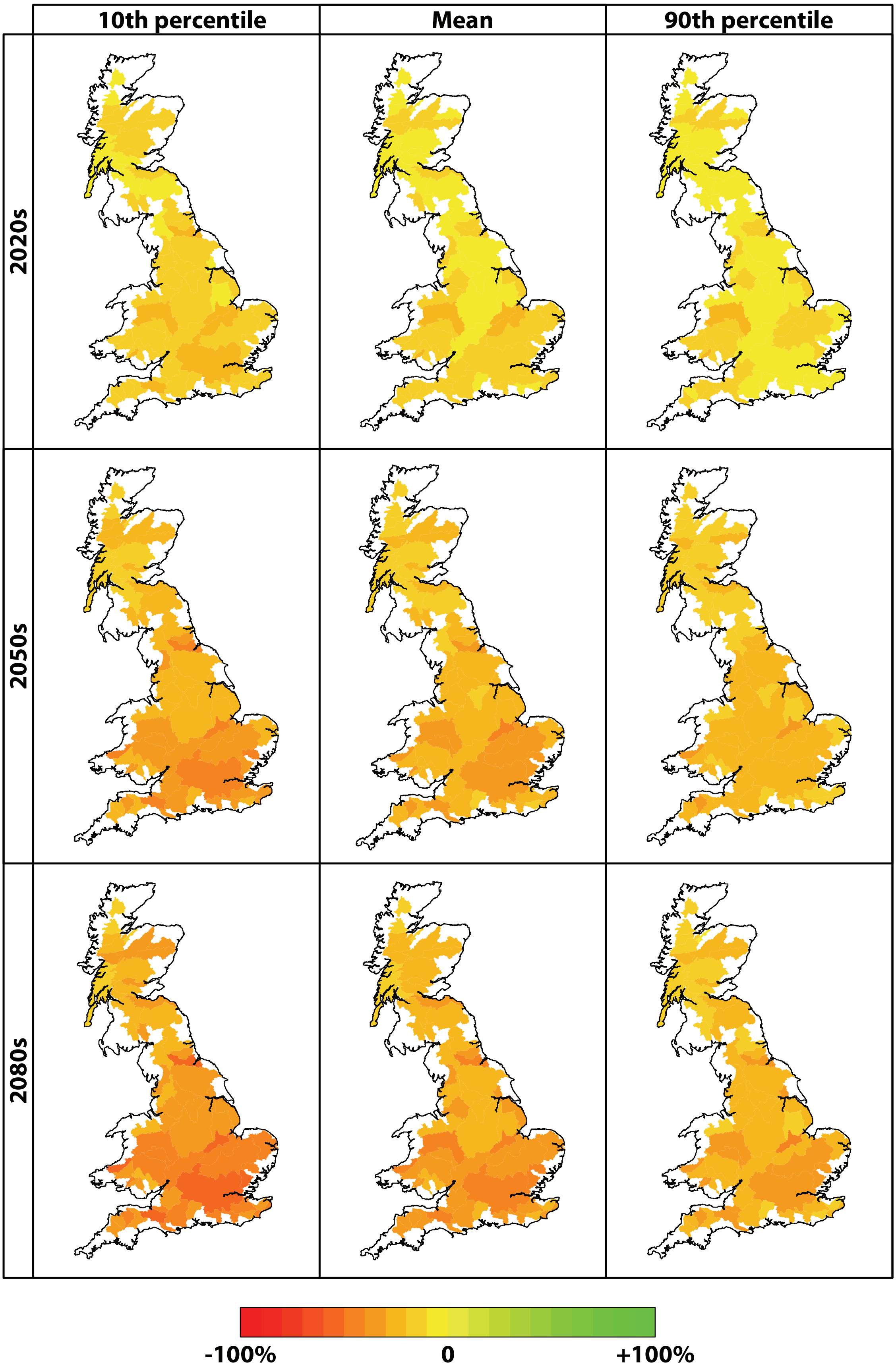


Figure 4.13: Projected changes in summer river flow.

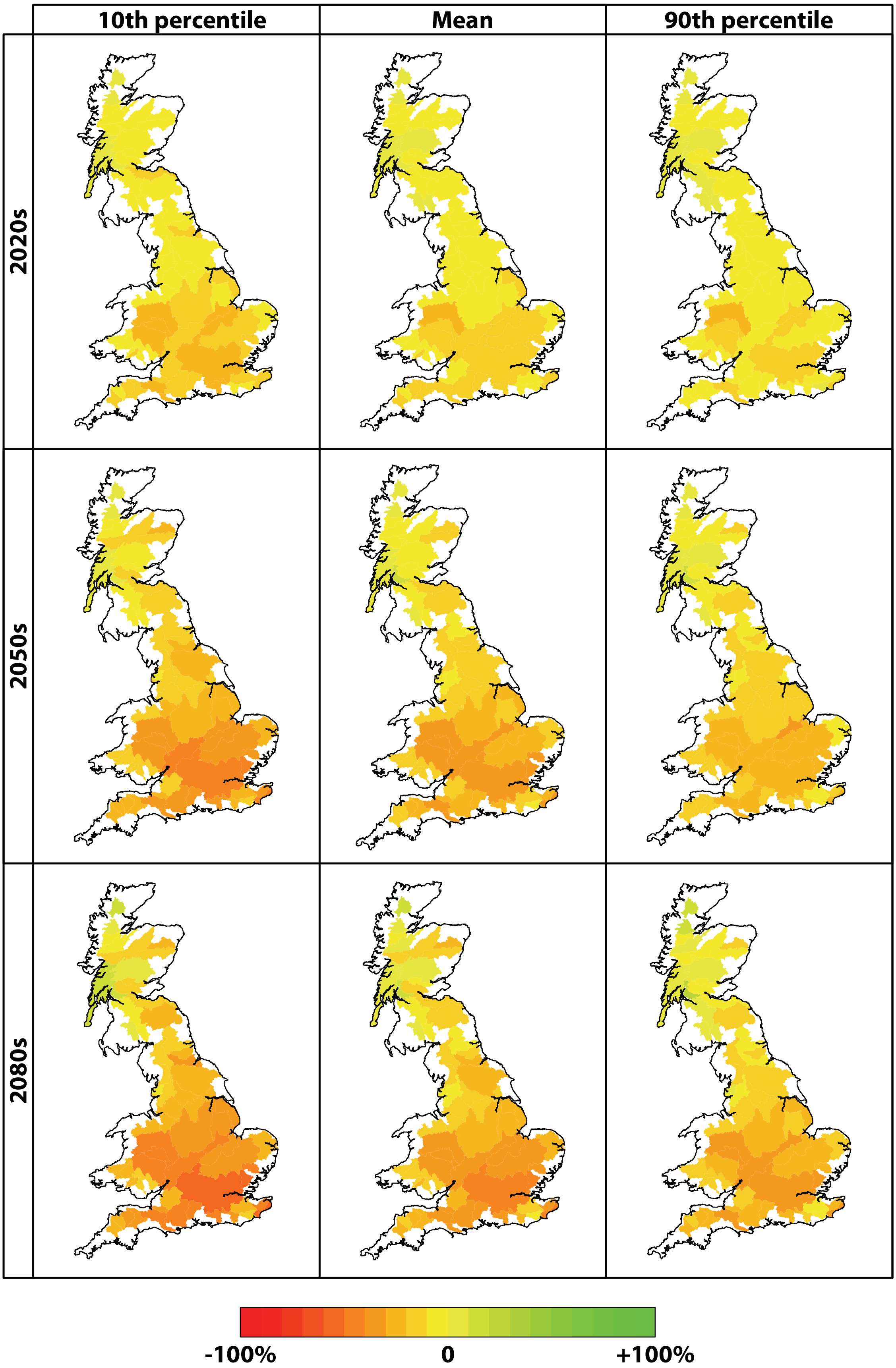


Figure 4.14: Projected changes in autumn river flow.

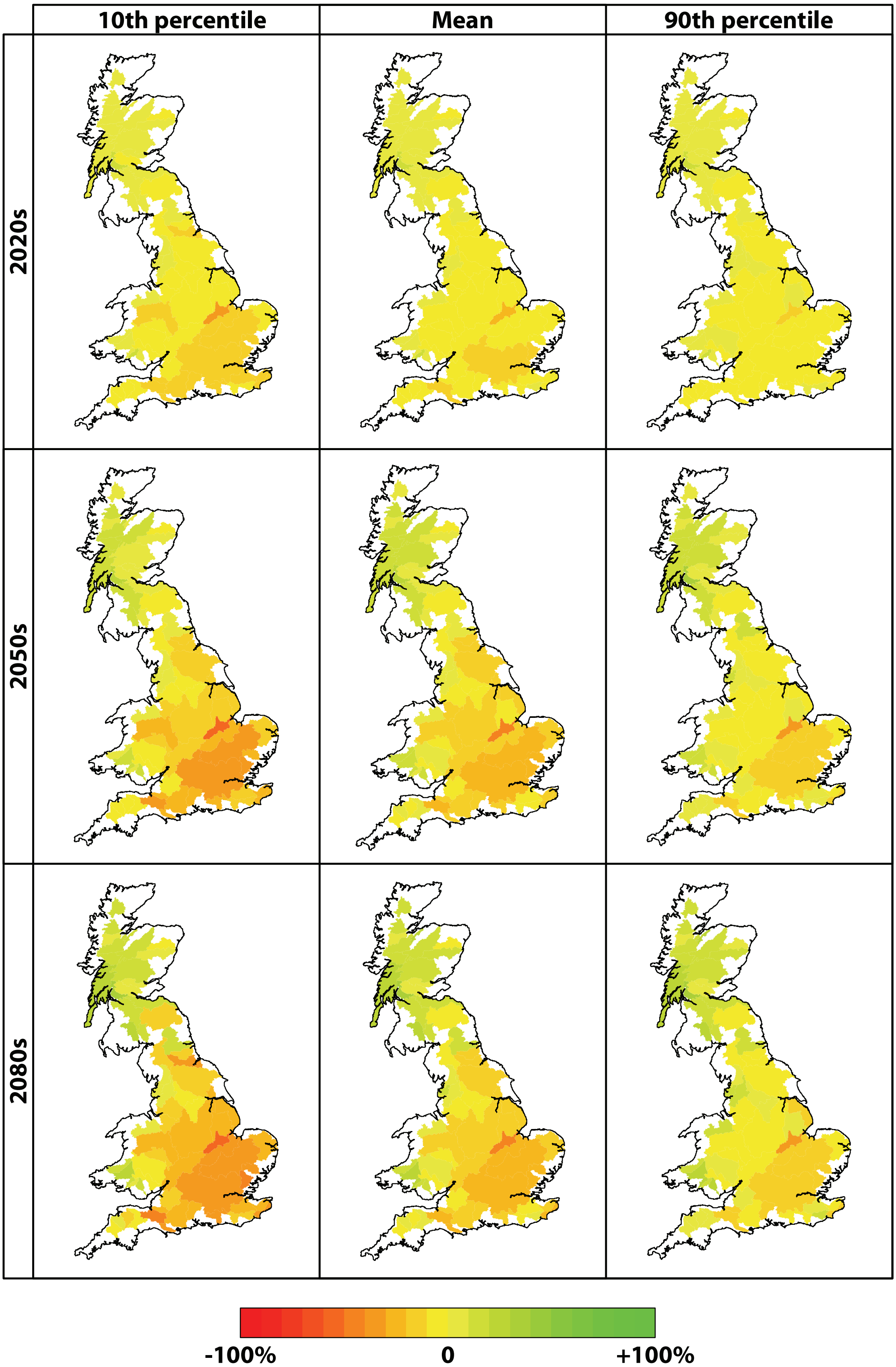


Figure 4.15: Projected changes in winter river flow.

4.5.6 Projected changes in Q95

This subsection summarizes changes in Q95, the fifth percentile of river flow, projected in 72 basins nationwide between the 1961-1990 control period and the 2020s, 2050s and 2080s. Simulation of the control period 1961-1990 produced 100 model runs of length 30 years under conditions of historical atmospheric composition, while simulation of the 2020s, 2050s and 2080s each consisted of 1000 model runs of length 30 years under conditions of the SRES A1B emissions scenario.

Table 4.14 illustrates that, on average across all simulated basins, 90% of model runs projected incremental decreases in Q95 throughout the 21st Century; the breakdown by season presented in Table 4.15 indicates that Q95 decreases most in autumn, followed by summer, winter, and, finally, spring.

Table 4.16 summarizes the proportion of basins exhibiting a decrease in Q95. By the 2020s, 98% of basins exhibit decreases at the 10% probability level, while 94% show decreases at the 90% probability level. By the 2080s, this range contracts: Q95 decreases in 97% of basins at the 10% probability level, and 95% of basins at the 90% probability level. The seasonal disaggregation of these data (Table 4.17) evidences decreases in Q95 across all basins at both the 10% and 90% probability levels in the 2020s, 2050s, and 2080s in summer and autumn. Spring shows nearly universal decreases also: only a single basin shows an increase in spring Q95, and then only at the 90% probability level in the 2020s and 2080s. In winter, changes in Q95 are somewhat more variable, decreasing by the 2020s in 90% of basins at the 10% probability level, and in 81% of basins at the 90% probability level. These proportions become 89% at the 10% probability level and 85% at the 90% probability level by the 2080s.

Spatial disaggregation of changes in Q95 in spring (Figure 4.16), summer (Figure 4.17), autumn (Figure 4.18) and winter (Figure 4.19) demonstrates a seasonally variable pattern in the distribution of changes Q95 across Great Britain.

On average, the most notable changes in Q95 observed during the spring months of the 2020s occur in Lincolnshire and the northeast of England. They range from between ≤ -83% and ≤ -3% at the 10% probability level to between ≤ -51% and ≤ +1% at the 90% probability level. This pattern intensifies during the 2050s, and, by the 2080s, it shows substantial reductions in Q95 across a large proportion of England, with changes ranging from between ≤ -99% and ≤ -3% at the 10% probability level to between ≤ -84% and ≤ +1% at the 90% probability level.

The pattern of change is similar in summer as to spring, but exhibits more widespread reductions in Q95 by the 2020s in Wales, Scotland and the southeast and southwest of England. All basins show decreases in Q95 in the 2020s, 2050s and 2080s that are, on average, of greater intensity than those observed in spring, and range from between ≤ -88% and ≤ -13% at the 10% probability level to between ≤ -57% and ≤ -10% at the 90% probability level. By the 2080s, reductions in Q95 are severe across large swathes of Great Britain, ranging from between -100% and ≤ -40% at the 10% probability level to between ≤ -90% and ≤ -26% at the 90% probability level.

In autumn, the majority of decreases observed in Q95 are even greater in magnitude than those that occur in summer and, by association, spring; however, basins in the east of Scotland experience changes in Q95 of notably lesser magnitude throughout the 2020s, 2050s and 2080s. By the 2020s, decreases range from between ≤ -90% and ≤ -2% at the 10% probability level to between ≤ -65% and ≤ -3% at the 90% probability level. Considerable decreases are widespread by the 2080s, and range from between ≤ -100% and ≤ -7% at the 10% probability level to between ≤ -94% and ≤ -7% at the 90% probability level.

The most diverse changes in Q95 occur in winter: although decreases similar in magnitude to those observed in other seasons remain across England, there are lesser decreases and even substantial increases in Q95 projected in coastal Wales and throughout Scotland by the 2020s, 2050s and 2080s. Changes range from between ≤ -86% and ≤ +17% at the 10% probability level to between ≤ -60% and ≤ +31% at the 90% probability level in the 2020s and from between ≤ -100% and ≤ +43% at the 10% probability level to between ≤ -90% and ≤ +53% at the 90% probability level in the 2080s.

Scenario	P10	Mean	P90
2020s	-31	-24	-18
2050s	-51	-41	-33
2080s	-61	-49	-39

Table 4.14: Average percent change in Q95

with respect to the 1961-1990 baseline climate.

Scenario	Season	P10	Mean	P90
2020s	MAM	-22	-15	-10
	JJA	-38	-30	-23
	SON	-41	-32	-26
	DJF	-25	-18	-13
2050s	MAM	-37	-27	-20
	JJA	-60	-49	-41
	SON	-65	-55	-48
	DJF	-41	-31	-23
2080s	MAM	-45	-33	-22
	JJA	-72	-60	-50
	SON	-76	-64	-56
	DJF	-51	-38	-29

Table 4.15: Average percent change in Q95, by season

with respect to the 1961-1990 baseline climate.

Scenario	P10	Mean	P90
2020s	98	97	94
2050s	97	97	95
2080s	97	97	95

Table 4.16: Proportion of rivers exhibiting a decrease in Q95.

Scenario	Season	P10	Mean	P90
2020s	MAM	100	100	97
	JJA	100	100	100
	SON	100	100	100
	DJF	90	86	81
2050s	MAM	100	100	100
	JJA	100	100	100
	SON	100	100	100
	DJF	89	86	81
2080s	MAM	100	100	97
	JJA	100	100	100
	SON	100	100	100
	DJF	89	88	85

Table 4.17: Proportion of rivers exhibiting a decrease in Q95, by season.

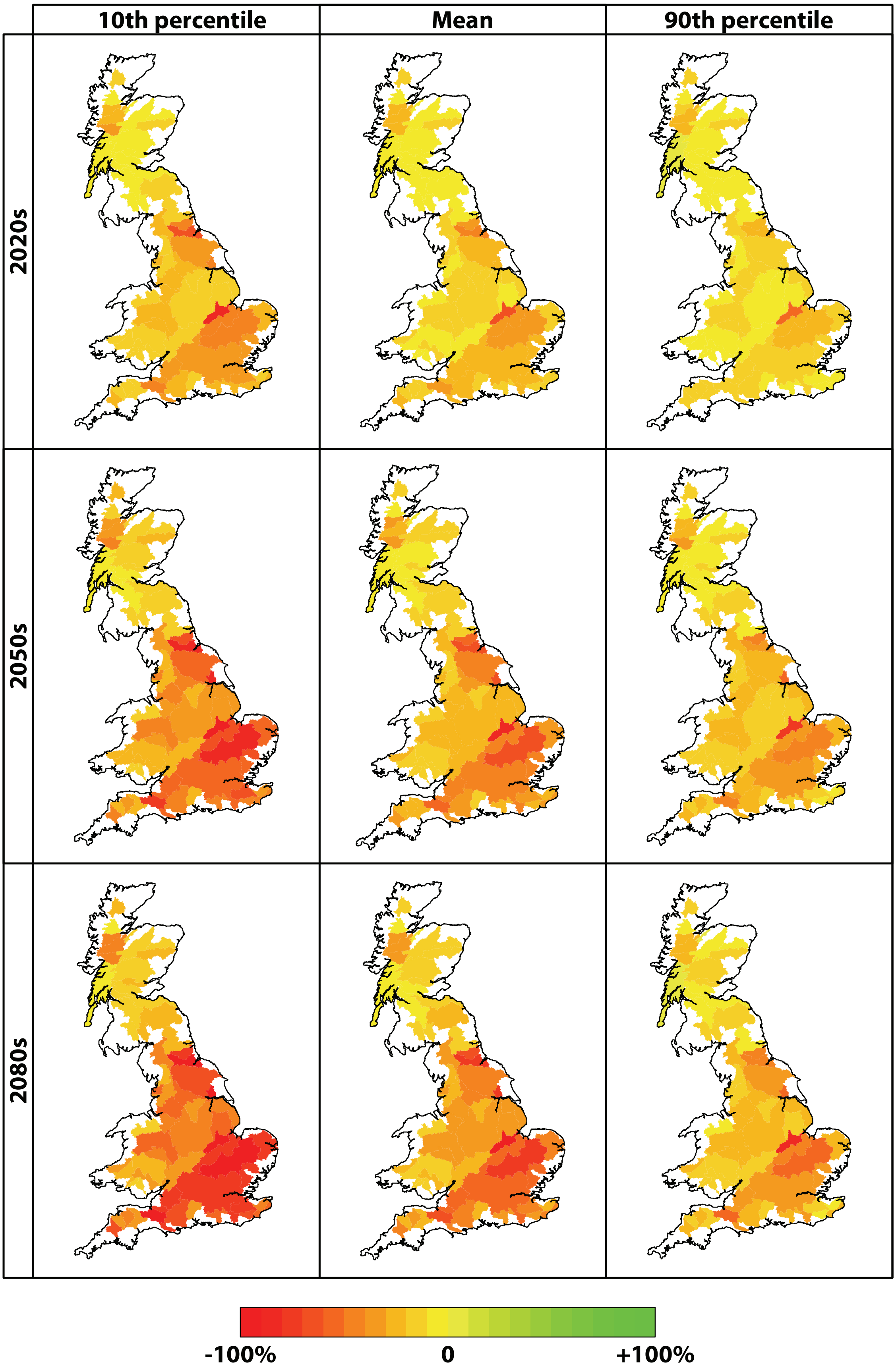


Figure 4.16: Projected changes in spring Q95.

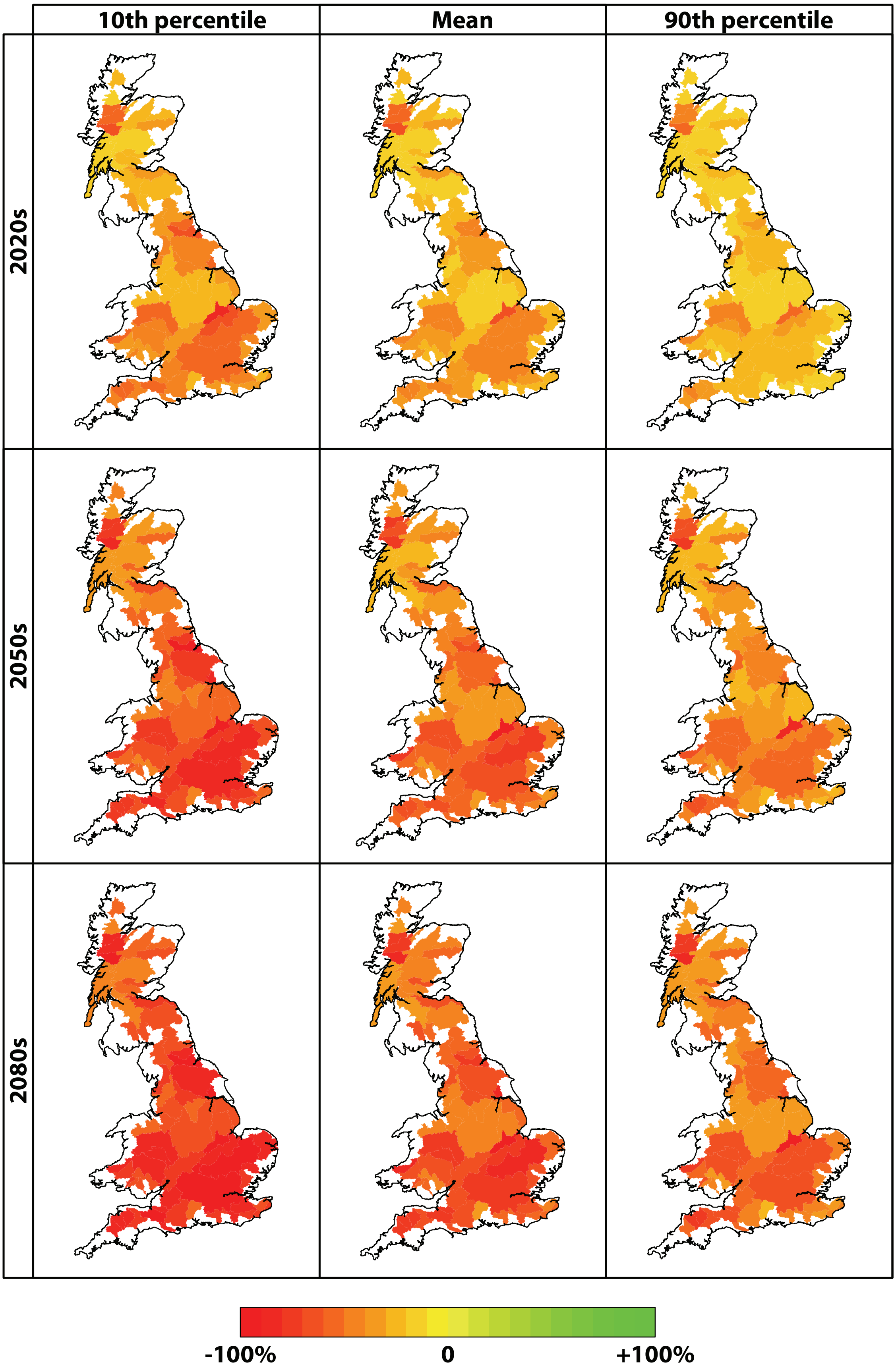


Figure 4.17: Projected changes in summer Q95.

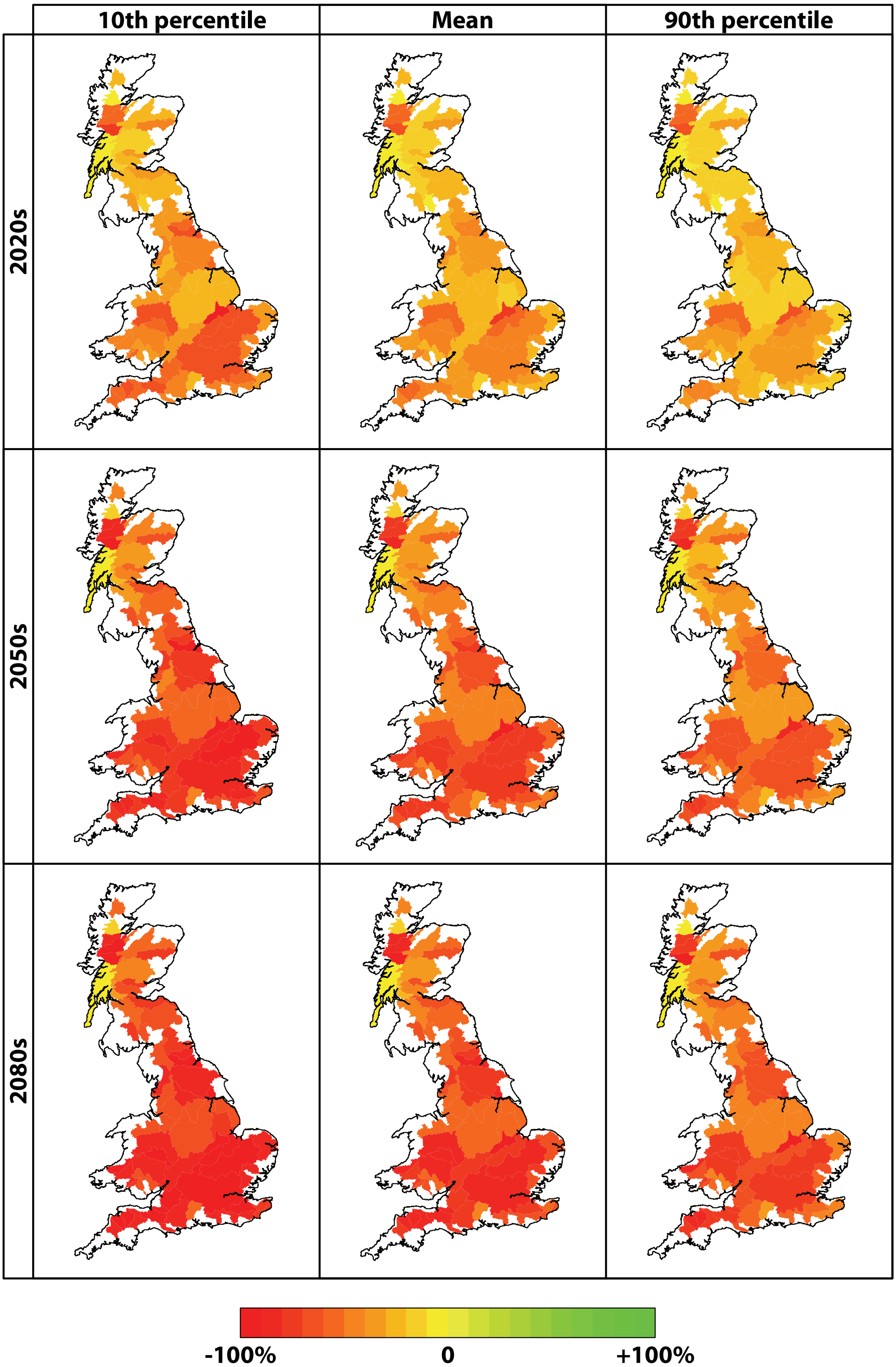


Figure 4.18: Projected changes in autumn Q95.

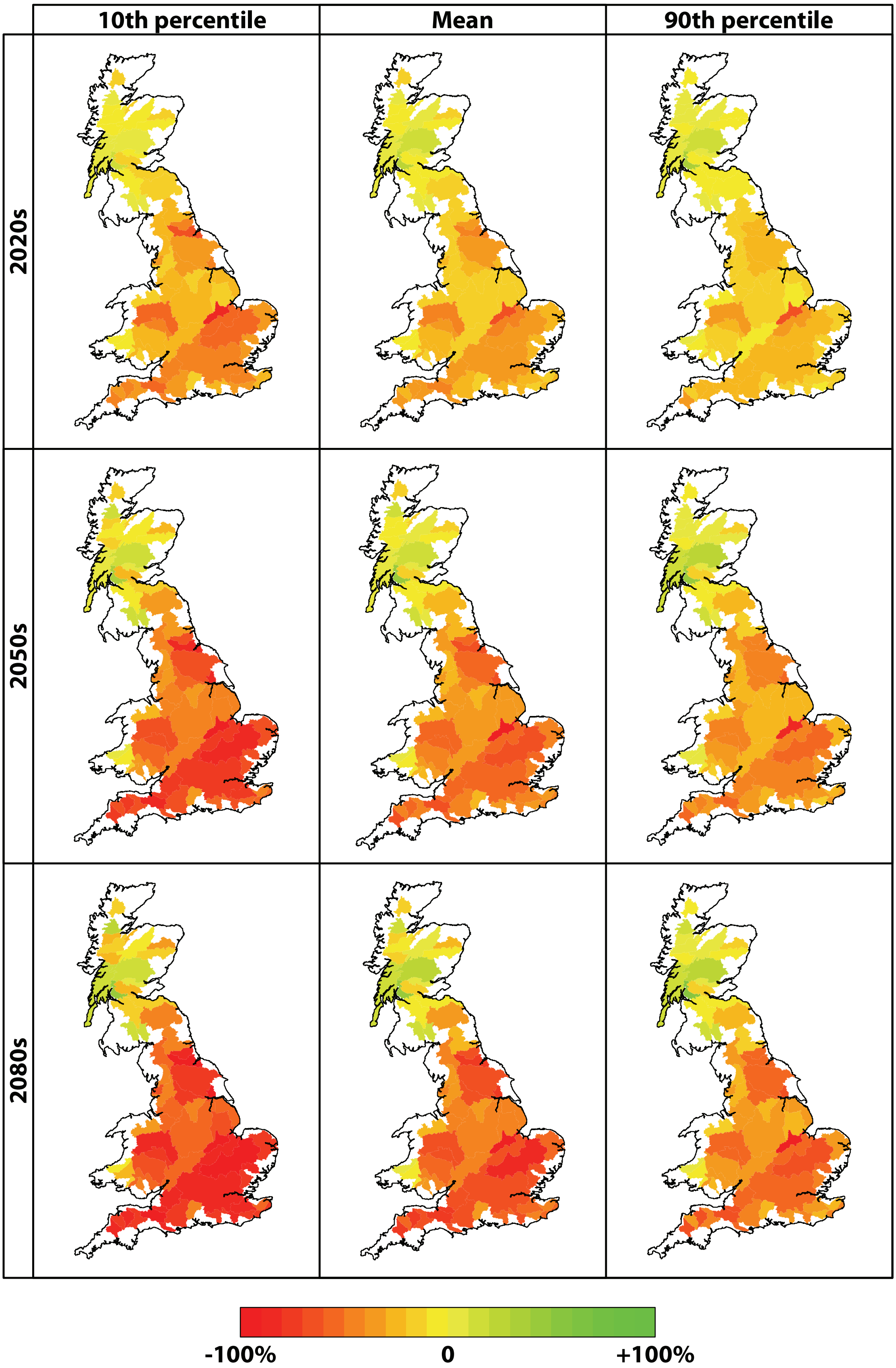


Figure 4.19: Projected changes in winter Q95.

4.6 Discussion

4.6.1 Current findings

Ninety percent of simulations demonstrated a decrease in mean average daily flow (ADF) and Q95 both nationally and in the majority of modelled catchments by the 2020s that persisted and became more acute in the 2050s and 2080s. Decreases in ADF and Q95 were more severe, and affected a larger proportion of catchments, in summer and autumn, respectively. Decreases in ADF outweighed increases in ADF until the 2080s, when a majority of rivers exhibited an increase in winter ADF, leading to a small increase in ADF nationally at this probability level.

4.6.2 Projected changes in river flow

The magnitude and direction of projected changes in ADF vary across Great Britain; however, the magnitude and frequency of decreases in ADF is, on average, greater than the magnitude and frequency of increases in ADF, and there are some clear spatiotemporal trends. As a result, national annual average ADF decreases incrementally over time (Table 4.10), as increases in winter ADF across Scotland and Wales are unable to offset relatively massive decreases in summer ADF in the south and east of England, and more modest but widely distributed reductions in ADF in spring and autumn. With reference to other large- or national-scale studies of the UK, this finding is in agreement with the broader conclusions of von Christierson *et al.* (2012), and correspondingly contrary to the findings of Sanderson *et al.* (2012), who reported increases in winter runoff exceeding decreases in summer runoff, and thus increasing annual total runoff, throughout the 21st Century.

Changes in the summer months dominate the overall pattern of seasonal change: 90% of model runs for the 2020s, 2050s and 2080s exhibited reduced summer ADF for all rivers (Table 4.13), suggesting that it is very likely that summer ADF will decrease across Great Britain throughout the 21st Century. This is a more consistent result, in terms of both the direction of change and the spatial pattern of change, than that provided by previous large-scale studies (e.g. Sanderson *et al.*, 2012; von Christierson *et al.*, 2012). On average, simulations suggested decreases in summer ADF comparable to changes in mean annual flow reported by von Christierson *et al.* (2012) (Table 4.11). There is a recognizable gradient in the magnitude of change in individual catchments, from the lowest impacts in the west and north of Scotland to the highest impacts in the south and east of England that persists in spring (Figure 4.12), autumn (Figure 4.14), and winter (Figure 4.15), coupled with a chronological progression in the severity of impact, from least severe in the 2020s, to most severe in the 2080s (Figure 4.13). Von Christierson *et al.* (2012) note that this spatial pattern is common to studies using precipitation time-series derived from UKCP09, although it is perhaps more noticeable across all seasons in this study than those published previously.

Although the national trend is again towards a reduction in ADF, the direction of change in individual catchments varies across Great Britain more so in spring, autumn and winter than in summer. By the 2020s, some catchments in Scotland demonstrate minor increases in spring ADF; however, decreases in ADF occur on average across Great Britain at both the 10% and 90% probability levels, suggesting that such a change is very likely. These changes persist and escalate throughout the 21st Century, with regional trends contrary to those reported by Sanderson *et al.* (2012): 90% of simulations suggest increases in spring ADF of up to ≤ +10% in Scotland and decreases of up to ≤ -36% in East Anglia by the 2080s, coincident with an average change of ≤ -4% at this probability level (Figure 4.12; Table 4.11).

This picture broadens in winter to include increases in ADF as early as the 2020s in west Wales, northwest England, and isolated rivers across the rest of England, in addition to those rivers in Scotland displaying increased ADF in spring (Figure 4.15). This pattern continues through to the 2080s. A majority of rivers display increased ADF in winter (Table 4.13), although decreases occur in catchments in the south and east of England by the 2080s. Indeed, 90% of simulations suggested that the number of rivers presenting a positive change in winter ADF in the 2020s would decrease by around 15% by the 2080s (Table 4.13), even though the average increase in winter ADF inflated from +5% to +14% in catchments exhibiting an increase. These trends are in general agreement with results from similar studies (e.g. Sanderson *et al.*, 2012; von Christierson *et al.*, 2012).

Like Sanderson *et al.* (2012) and von Christierson *et al.* (2012), the results of this study identify spatially variable changes in the direction and magnitude of autumn ADF; however, these findings are also somewhat exceptional in that they demonstrate agreement in the direction of change in as many of 90% of modeled rivers at the 90% probability level. Where negative changes in ADF occur in individual catchments, such as in the centre of England, they are similar in magnitude to, but generally less than, those observed in summer. Positive changes in ADF in individual catchments are more comparable to those occurring in spring at the 90% probability level, albeit slightly elevated in comparison.

4.6.3 Projected changes in Q95

Q95 is very likely to decrease in magnitude across the vast majority of Great Britain in spring (Figure 4.16), summer (Figure 4.17), and autumn (Figure 4.18), leading to incremental decrease in Q95 on aggregate across the nation. Even as early as the 2020s, average changes in Q95 in individual catchments range from -1% to -72%; by the 2080s, summer and autumn Q95 exhibit decreases of, on average -60% and -64%, respectively (Table 4.15).

The largest average decreases occur in summer, while autumn Q95 expresses the largest individual decreases. The south and east of England, in particular, display regional sensitivity to low flows (e.g. Figure 4.16, Figure 4.17, Figure 4.18, and Figure 4.19), although very few regions of Great Britain exhibited any resilience to future changes in low flows according to this metric. For example, 90% of model runs for the 2020s, 2050s and 2080s suggested a negative change in Q95 in all simulated watersheds in summer and autumn, and more than 90% of catchments in spring (Table 4.15). In winter: 90% of simulations suggested a decrease in Q95 in over 70% of simulated watersheds by the 2020s, persisting through the 2050s, and affecting nearly 80% of rivers by the 2080s (Table 4.17); however, the magnitude of negative change is, on balance, much greater than the magnitude of positive change.

Positive change in Q95 occurred in fewer than ten catchments, located in the west and north of Scotland and Wales. On average, increases were modest in comparison to the decrease exhibited elsewhere in the country, and limited to winter; however, some small increases in spring ADF became evident by the 2080s at the 90% probability level.

There are very few studies with which to compare changes in Q95 projected by this study. For the River Eden, Fowler *et al.* (2008) reported changes in Q95 of around -50% in spring, between -70% and -80% in summer and autumn, and perhaps +10% in winter by the 2050s. This study found decreases of lesser magnitude in the Eden catchment by the 2050s, even at the 10% probability level, as well as patterns of change in spring, summer, and autumn similar to those shown by Fowler *et al.* (2008); however, contrarily, 90% of model runs in this study identified a large negative change in winter Q95. So, whereas the findings of Fowler *et al.* (2008) suggested heightened seasonal variation in Q95, this study suggests, at the 90% probability level, a broad decrease in Q95 throughout the year and a compression of seasonality. Reynard (2010) performed a study of changes in Q95 by the 2050s across catchments in England and Wales using UKCIP02 data, showing changes of -10 – +16% in January, -20% – +5% in April, and -85% – -10% in July and October. Taking these months as proxies for winter, spring, summer and autumn, respectively, the most severe decreases occurred in the fenlands in winter, the Midlands in spring, the northwest and southwest of England, coastal Wales and the fens in summer, and across England and Wales in the autumn. This is, generally, a similar pattern to that seen in this study, albeit with less severe quantitative impacts. A further study by UKWIR (2007) for 70 catchments across the UK using a subset of UKCP09 for the 2020s reported decreases in Q95 of up to 35% at the 10th percentile in the southwest of England and increases of up to 21% in the northwest of Scotland at the 95th percentile. Such changes are similar to those seen in this study by the 2020s at the 10th percentile; however, based on the aggregations used in the UKWIR report, it is difficult to make direct comparison. Finally, the results of Rance *et al.* (2012) show, in general, decreases in Q95 across all basins modelled, the 2020s, 2050s and 2080s for three emissions scenarios in all cases except the 10th percentile for the 2020s. The magnitudes of change reach -70% in the Anglian region by the 2080s, for example. This is consistent with the findings of this study.

4.6.4 Hydrological model structure and performance

This study aimed to simulate the hydrological processes that determine the quantity of water available to meet demand via the public water supply of Great Britain undertaken using a nationally consistent and application-specific modelling approach and probabilistic projections of climate variables. The challenge peculiar to this specification is to implement a hydrological model that is flexible enough to represent the regional variability in hydrological processes exhibited across the country, reliable enough to reproduce the statistics of flow relevant to public water supply over a series of historical observations, sufficiently lightweight so as to permit the timely execution of thousands of model runs, and structurally consistent with the time-series of climate variables available to drive simulation. The conceptually lumped hydrological model employed in this study meets all of these criteria: it is capable of reproducing mean discharge, standard deviation of discharge, correlation, water balance and Q95 adequately when assessed at both daily and monthly scales, for 59 gauge locations across Great Britain, and does so with relatively short runtime.

Although evaporation is the principal process driving the hydrological response of the land surface to precipitation in the UK, large swathes of the south and east of England demonstrate reliance upon groundwater storage and other subsurface processes to support low river flows. To be fit for purpose, a model must represent both evaporation and subsurface processes adequately. As a general measure of fitness for purpose, the objective function values obtained through calibration and verification provide information on the power of the model structure, subject to a set of parameter values, to predict historical observations within and without the set of observations used to train the model.

Firstly, the model's capacity to preserve the overall proportion of precipitation returned as discharge for nearly all calibration records demonstrates the suitability of the variable infiltration capacity soil moisture balance and simple sub-model of evapotranspiration in representing the general balance of precipitation, loss of moisture through evapotranspiration loss, and discharge. This is perhaps due to the detailed potential evapotranspiration time-series prepared to drive calibration (See Chapter 4).Only a handful of models were unable to reproduce the ratio of runoff to precipitation to within 1% during calibration. There does not seem to be a pattern to the location, calibration record length, or calibration performance of those basins whose models could not meet this criterion.

Secondly, the hydrological model implements a quadratic relationship between storage and discharge from groundwater sources to simulate this, a supposition analogous to assuming that all aquifers are unconfined (Wittenberg, 1999). Although broadly acceptable for most of the highly productive aquifers in England, this is a notably poor assumption of the chalk that underlies Humberside, Lincolnshire, parts of East Anglia, the Thames basin and the South Downs; however, model performance is generally ‘acceptable’ to ‘very good’ in these areas. Exceptions are the River Waveney in East Anglia and the River Rother in Sussex (Table 4.4). Both produced reasonable scores in verification, given the available record lengths (Table 4.9). These results suggest that, at least on the basin scale, the combination of a variable infiltration capacity soil moisture balance with a nonlinear groundwater storage volume recharged by percolation and a quadratic relationship between storage and discharge facilitates reasonable approximation to the seasonal ‘slow’ flow contributed to rivers by subsurface processes. In many cases, the interflow component contributes a ‘base flow’ component in addition to that emanating from the non-linear reservoir.

The formulation used in this study is not without its limitations, however. For example, the implementation of potential evapotranspiration used implicitly assumes a uniform coverage of a hypothetical reference crop of green, well-watered grass that completely shades the ground (Allen *et al.*, 1998). To mitigate the impacts of this assumption, future estimations of potential evapotranspiration could use a model of land use to determine appropriate ‘crop coefficients’ by which to scale calculated values and thus perhaps be more representative of true land surface covering.

Preliminary testing of the hydrological model indicated a need to incorporate the seasonal disruption of hydrological processes attributable to snow accumulation and ablation, and a review of the literature suggested that the ‘degree-day’ model is suitable for application in the UK. This popular model parameterizes the processes of snow accumulation and ablation in terms of a threshold temperature of phase change, at or below which snowpack accumulates, and a rate at which snow melts when temperature exceeds the threshold temperature of phase change. Monthly observations of the number of days per month with snow lying per month facilitated the simultaneous calibration of both parameters, independently of the infiltration components of the hydrological model.

Evaluation of the model's capacity to predict the mean, standard deviation and correlation of historical observations of monthly snow coverage (in terms of the KGE), aggregated across 59 basins and assessed across broad ranges of parameter values, supports the assertion that the model is adequate for the simulation of month-to-month accumulation and ablation of snow at basin scale in the UK. For example, Figure 4.4 shows that, on average, relatively high values of KGE between 0.7 and 0.8 were obtained for a sizeable envelope of parameter values demarcated by threshold temperatures of phase change between 0 °C and 1 °C, and melting rates greater than 1 mm $°C^{-1}$ day^{-1}. Furthermore, the variability in performance with parameter values between regions suggested that a threshold temperature of phase change of 0.5 °C and a melting rate of 5 mm $°C^{-1}$ day^{-1} would provide adequate power to predict the number of days per month with snow lying in all basins.

This result is somewhat crude, but justifiable: although the performance of individual models exhibited substantial variability in their sensitivity to the values of the threshold temperature of phase change in the determination of the state of the model as either a 'freezing' day or a 'melting' day, most sensitivity is 'smeared' or 'smoothed' away when both the threshold temperature of phase change and the melting rate vary simultaneously in the calculation of the volume of snowpack. Furthermore, no strong spatial pattern correlated with, for example, latitude, emerged to support the supposition of basin-specific parameter values justified by variable radiative forcing, say. These findings are probably attributable to the use of a large number of monthly observations of the number of days per month with snow lying, which allows for more substantial error in the day-to-day accounting of snowpack volume as long as the overall, long-term, number of days per month with snow lying is reasonable. A further detail of the implementation of the snowmelt accumulation and ablation sub-model is its means of integration with the variable infiltration capacity moisture balance: if snowmelt does not occur, all precipitation accretes to the snowpack, but direct runoff still discharges, depleting the soil moisture store; if snowmelt occurs, it adds to the precipitation input of Equation 25. This has the effect of delaying the response of the land surface to precipitation without necessarily promoting a very ‘flashy’ response to melting snow, and is reasonably consistent with the drainage behaviour of frozen soils (e.g. Johnsson and Lundin, 1991), and delivers ‘good’ performance from the perspective of the integrated hydrological model.

This study incorporated two optimization procedures in order to identify reliable parameter values: the first sought parameter values that maximized the power of the snow accumulation and ablation sub-model to predict observations of the number of days per month with snow lying; the second sought parameter values that maximized the power of the hydrological model to predict observations of mean daily discharge. The former was a trivial direct search by parameter sweep, feasible because the number of parameters was small and the range of each parameter was small. The latter was significantly more complex, and applying a genetic algorithm hybridized with a compass search to optimize an objective function over seven parameters, each with a large range. A wide range of GA configurations yielded satisfactory outcomes; however, benchmarked experimentation suggested that using an un-scaled rank selector combined with a 90% chance of uniform crossover during reproduction, and a 30% probability of ‘flip’ mutation, produced satisfactorily robust optima after 1 000 elitist generations, each consisting of 400 individual genomes. The execution time varied depending on the length of the calibration record, ranging from a few minutes up to several hours. The integration of a compass search and the use of double-precision floating-point data types to represent the objective function values resulted in extremely well explored global maxima for each basin, with only three basins identifying ambiguous 'optimal' parameter value sets. These consisted of, at most, three vectors of parameter values.

Following local optimisation via the compass search, the procedure output every vector candidate of parameter values, allowing exploration of the uncertainty associated with the selection of a specific vector, and the robustness of the 'optimal' vector. In general, a very large number of parameterisations provide 'near optimal' performance, e.g. within 1%-2% of the maximum objective function value, for each basin; however, there were few, if any, opportunities to regionalise parameter values between basins, as indicated by a paucity of overlapping parameter value ranges.

The use of KGE as the core measure of fitness in this study provided a compound measure of predictive performance in terms of correlation, mean and standard deviation. Stringent constraints on the bias in the mean and the Q95 restricted the propagation of sets of parameter values that did not reproduce these quantities satisfactorily. Although no guarantee of similar performance for time-series of input data representing future climate conditions, all calibrated models performed well according to these metrics, and the majority performed similarly in validation. Exceptions include sites in the southwest of England and East Anglia, which tended to overestimate the total volume of runoff and the Q95 observed in the verification record.

Finally, this study performed sensitivity analyses with respect to parameter values: as part of the optimisation procedure, seeking 'stable' maxima, as opposed to 'peaky' local maxima; however, it does not take this further and quantify uncertainties arising from hydrological simulation, such as modelling uncertainty and parameter value uncertainty (e.g. Fung *et al.*, 2011). A more complete treatment of uncertainty would require use of multiple models of differing formulation and/or structure, and multiple ensembles of parameter values (e.g. Ajami *et al.*, 2008), but, using the available data, estimates of parameter uncertainty are possible with additional analysis of the data generated in this investigation.

4.7 Conclusions

The study described in this chapter contributes to the overall aims of this thesis, summarised in §1.3, in two ways. Firstly, it outputs coherent time-series of discharge and baseflow on spatiotemporal scales adequate for the simulation of inter-basin water transfers in a probabilistic framework, which are instrumental to the accomplishment of Objective O3 and Aim A1. Secondly, the analysis of changes in ADF and Q95 within a probabilistic framework presented herein contributes to the accomplishment of Aim A2.

The analysis suggests that Great Britain is very likely to experience incremental decreases in river flow throughout the 21st Century, exaggerated across much of England and Wales in the summer months, and mitigated only by increases of substantially lesser magnitude in flow in upland areas, such as Scotland and Wales.

Similarly, almost all basins demonstrate a decrease in Q95, the fifth percentile of river flow, which is an indicator of supply security. By the 2080s, the magnitude of change is severe in many basins, in some cases approaching ≤ -100% in ninety percent of model runs, and often exaggerated in the autumn months. This is perhaps attributable to enhanced evapotranspiration in spring and summer, leading to reduced recharge of soil moisture and subsurface storage.

To synthesise these data, a simple hydrological model, consisting of a variable infiltration capacity soil moisture balance coupled with a non-linear storage, was constructed. Based on the model's capacity to reproduce, among other metrics, the overall water balance and Q95 reliably for long historical records, it appears satisfactory for the simulation of river flow for 59 gauge locations across Great Britain.

This is attributable to a flexible model structure that includes the hydrological processes that dominate the flow regimes of the UK, and the use of a robust multi-part calibration methodology that combines global and local direct search with constrained objective functions and detailed records of the input variables of precipitation, potential evapotranspiration and mean air temperature.

Finally, while not published in its own right, outputs from the calibrated model have been found to perform satisfactorily well outside the model's design specification and are published in the peer-reviewed press (Byers *et al.*, 2015; Byers *et al.*, 2016).

5 Water resource simulation

5.1 Chapter outline

This study sought to develop and implement a framework that facilitates the risk-based planning and management of the water supply infrastructure system of the UK on a national scale using probabilistic climate change projections, and to demonstrate this methodology through its application to a case study that represents one possible future adaptation of the public water supply infrastructure system of the UK: a more integrated national network of water transfers between regions, or a 'water grid'. The study developed an abstract computational simulation model of the water supply infrastructure system of the UK containing parameterisations of key strategic water supply infrastructure components relevant to the public water supply, including river abstractions, groundwater abstractions, and reservoirs, with consideration of probabilistic hydrological constraints, empirical deterministic raw water infrastructure capacity constraints, and long-term projections of the demand for water services.

Output from the model suggests that water supply infrastructure systems in the north, east and south of England may be unable to support the level of demand for water reported by Ofwat in 2010-2011 (2011) under conditions of the 'baseline' climate. All regions except Scotland exhibit some drought impacts under scenarios of future climate representative of the 2020s, 2050s and 2080s, with the droughts of greatest severity and duration again being located in the north, east and south of England. Further results from an extension of the model that includes the transfer of water from Wales to the south and east of England suggests that transfers alone are insufficient to mitigate drought impacts in these regions.

5.2 Introduction

Water supply infrastructure systems facilitate the acquisition of water from the environment for human consumption. Highly complex, they comprise a number of natural and artificial structures and processes that interact across a wide range of spatiotemporal scales to maximise the probability that water of satisfactory quantity and quality is available to meet the demand of consumers of water at the location and time that water services are required, subject to the operational requirements of the system. Thus, a water supply infrastructure system 'fails' when the demand for water exceeds the capacity of the system to withdraw water from the environment, treat it, and deliver it to the point of consumption, as determined by properties and constraints of the system, such as its physical state, configuration, limitations, and operational constraints, and externalities that influence the quantity and quality of water available for withdrawal from the environment and the demand for water services. All determinants of performance are dynamic: the condition of components within the system deteriorates over time, the demand for water services varies with population, land use, and behaviour, and the quantity of water available for withdrawal fluctuates in response to local, regional, and global climate variability. The impacts of dynamic behaviour are complex and unpredictable; however, interventions in the configuration, operation, and maintenance of water supply infrastructure systems can mitigate dynamic behaviour that reduces the reliability of the system and/or the resilience of the system to failure. These interventions entail significant long-term costs concomitant with high risk, and can be mutually exclusive; thus, it is conventional to develop and compare portfolios of interventions that leverage the value of specific interventions against the change in the probability of failure that results from implementing that intervention. This approach is often termed 'risk-based'.

Risk-based planning and management analyses the probability and consequences of failure in a system in order to support the development of intervention strategies that modify the risk of failure in a quantifiably justified way. The methodology comprises five processes: identification of the criteria of failure and the mechanisms by which they occur; assessment of the vulnerability of the system to each failure mechanism; determination of the likelihood and consequences associated with the superposition of specific failure mechanisms upon specific components of the system; identification of interventions that reduce the risks determined, and; the definition of alternative strategies of interventions that mitigate risk. A risk-based approach to water resource planning and management therefore facilitates the quantification of the change in the probability of a specified criterion of failure, such as a shortfall of known magnitude in the capacity of the system to meet the demand for water, in response to a specific strategy of intervention to maintain and enhance the performance of the water supply infrastructure system. This methodology is of particular value in the context of the highly uncertain potential impacts of climate change.

Projections of future climate over the UK typically suggest a decrease in water availability in the southeast of England, which is also the region of greatest population density and the region of greatest anticipated growth in population. As the southeast already experiences water shortages more frequently than the rest of the UK, and population is a key determinant of the demand for water, it is possible that a decrease in water availability coupled with further population growth could lead to an unacceptable probability of failure in the region's water supply infrastructure system. Conversely, climate projections often show less negative, occasionally positive, impacts on water availability in Wales, Scotland, and the northwest of England (e.g. Murphy *et al.*, 2009; Prudhomme *et al.*, 2012; Sanderson *et al.*, 2012), particularly in the winter months, depending on the climate model and scenario used. These are all regions of the UK historically having high water availability, low population, and thus a correspondingly high surplus of water resource; thus, intervention strategies aimed at bolstering the resilience of southeast England to water shortage have long featured the notion of connecting these relatively water-affluent areas to the southeast by inter-basin water transfers, or a 'water grid', analogous to the national electricity conveyance network.

Previous studies have demurred against this strategy (e.g. Environment Agency, 2006a); however, none evaluated it comprehensively in the context of uncertain long-term projections of climate variability. This is ostensibly attributable to the computational demands of such an assessment and the limitations of the probabilistic projections available, and may influence the apparent efficacy of the 'water grid'.

This study is a step towards developing a fully risk-based approach to water management in the UK under uncertain future climates. It describes a general and scalable framework for the simulation of the water supply infrastructure system of the UK, and demonstrates the informative power of the model through comparison of the performance of two example implementations under four probabilistic projections of future climate representative of the 1961-1990 climate baseline, 2010-2039 (the '2020s'), 2040-2069 (the '2080s') and 2070-2099 (the '2080s'). The first implementation is representative of the majority of the water supply infrastructure system of Great Britain as reported in 2011 (a 'Business As Usual' or 'BAU' strategy), while the second is an extension of this BAU strategy that incorporates large-scale transfers of water resource supporting the southeast of England (a 'Water Grid' strategy).

The 'Water Grid' strategy (Figure 5.1) implements part of the national strategy for water resource published by the NRA (1994), in that it enables the transfer of water from Wales (Dŵr Cymru Welsh Water) to the Midlands (Severn Trent Water), and from there to the water resource zones of Anglian Water and/or Thames Water. A further connection enables support from Anglian Water to Thames Water.

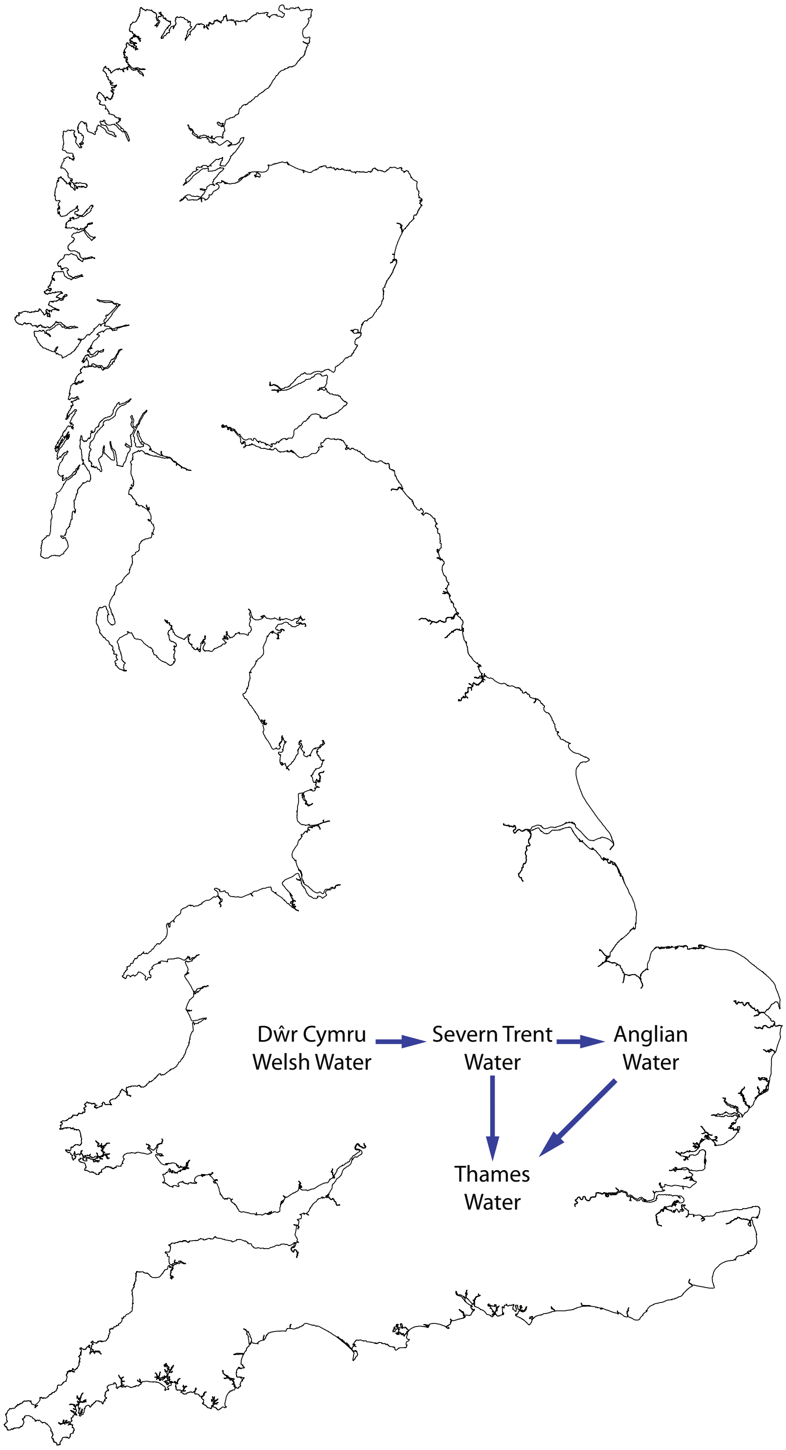


Figure 5.1: Inter-basin transfers included in the Water Grid strategy.

5.3 Data

The design of a model suitable for national-scale simulation of the UK's water supply infrastructure system under projected future climate is constrained by the availability of suitable supporting data. Firstly, the extraction of parameter values and detailed configuration data from the multitude of detailed water resource models used by undertakers into a single national-scale model would yield an extremely large and unwieldy model, which would not necessarily duplicate the behaviour of the individual models in their native development environments. Secondly, much of the detailed technical data and local knowledge informing undertakers' models of the water supply infrastructure system of the UK is sparse, unavailable or unreliable due to commercial sensitivity, national security, cost, and a general lack of transparency and rigorous data collection. This includes, but is not limited to, hydrological data for determining the state of abstractions and inflows to reservoirs, estimates of the productivity of sources and the storage capacity of reservoirs, estimates of the demand for water from the public water supply, and the connectivity, co-dependency and operating conditions of individual infrastructure elements. As a result, the design of any such model must pragmatically use what information is available and reasonably reliable.

To that end, this study collates information from a range of sources.

To drive simulation of river sources, groundwater sources and reservoir inflows, it takes as input values of mean daily discharge and baseflow output from hydrological simulation and described in §4 of this thesis.

Records of source yield and the demand for water services are extracted from undertakers' reports to regulators, which are aggregated over all water resource zones operated by a given undertaker (Ofwat, 2011; Scottish Water, 2013) (Table 5.1 and Table 5.2).

Undertaker	River sources (Ml/d)	Groundwater sources (Ml/d)
Anglian Water	100.9	788.0
Dwr Cymru	310.0	36.3
Northumbrian Water	486.8	57.8
Scottish Water	357.0	127.0
Severn Trent Water	589.2	651.2
South West Water	335.4	35.3
Southern Water	227.1	490.9
Thames Water	2 169.8	670.2
United Utilities	1 165.5	100.6
Wessex Water	5.4	312.4
Yorkshire Water	495.3	296.1

Table 5.1: Water available for use by undertaker and source type.

Undertaker	Demand (Ml/d)
Anglian Water	1 198.7
Dwr Cymru	848.8
Northumbrian Water	733.3
Scottish Water	2 095.0
Severn Trent Water	1 881.6
South West Water	442.6
Southern Water	597.3
Thames Water	2 594.6
United Utilities	1 853.2
Wessex Water	357.4
Yorkshire Water	1 346.8

Table 5.2: The demand for water by undertaker in 2010-2011.

The storage capacities of reservoirs are integrated across multiple sources, including the Public Register of Large Raised Reservoirs (Environment Agency, Personal Communication) and the Register of British Dams (Building Research Establishment, 1994). The former contains records of reservoir name, location, undertaker name and capacity for reservoirs in England and Wales, while the latter contains records of dam name, location, undertaker name and capacity for dams in England, Wales and Scotland. From inspection, both appear to be drawn from the same source data; however, neither contains sufficient data to inform simulation, lacking estimates of watershed area and environmental or compensation releases. A study of compensation flows by Gustard *et al.* (1987) contains some of this information, but it is at once insufficiently comprehensive to be the sole source of information for a national-scale study and too specific to be a general source of information for compensation flows. For these reasons, this study employs a sub-model of reservoir watershed area based on both the Public Register of Large Raised Reservoirs sources and the Register of British Dams supplemented by mapping data (Ordnance Survey, 2008; OpenStreetMap contributors, 2013) and terrain data (Ordnance Survey, 2009). This provides estimates of watershed area for each reservoir, and, when combined with data from §4 of this thesis, informs a consistent estimate of environmental flows for impounding reservoirs.

5.4 Methods

5.4.1 Model of reservoir watershed areas

As detailed in §2 of this thesis, data regarding reservoir characteristics is sparse in the UK. In particular, the watershed areas of reservoirs are generally unknown, published inconsistently, or estimated inconsistently. The model of watershed areas described herein estimates the area draining into reservoirs used for public water supply across Great Britain using a nationally consistent application of the D8 watershed estimation method (Jenson and Domingue, 1988).

The data sources for this model are the Register of Large Raised Reservoirs (Environment Agency, Personal Communication) and the Register of British Dams (Building Research Establishment, 1994), which together contain the names, indicative point locations and storage capacities of reservoirs, and OS Meridian 2 (Ordnance Survey, 2008), OpenStreetMap (OpenStreetMap contributors, 2013), which contain geometries of water features that are variably named or unnamed, and OS LandForm Profile DTM data (Ordnance Survey, 2009).

Records from the Register of Large Raised Reservoirs and the Register of British Dams include only indicative point locations of resources uninformative to watershed estimation. Thus, to develop a more suitable set of geometries, these data are associated with geometry from OS Meridian 2 and OpenStreetMap by means of spatial intersection and fuzzy text matching.

In this process, the 'location' attribute of records from the Register of Large Raised Reservoirs and the Register of British Dams are compared with the set of water feature geometries in OS Meridian 2 and OpenStreetMap: if two geometries intersect, the records are considered a 'match'. Records from the Register of Large Raised Reservoirs and the Register of British Dams unmatched following spatial intersection are matched with named geometries in OS Meridian 2 and OpenStreetMap using Levenshtein distance (Levenshtein, 1966): if the 'name' attributes of a record from the Register of Large Raised Reservoirs or the Register of British Dams matches the 'name' attributes of water features extracted from OS Meridian 2 and OpenStreetMap to within a small tolerance of edit distance, the records are considered a 'match', subject to manual inspection for gross errors.

Finally, the watershed area of each record matched with a geometry via either spatial matching or fuzzy text matching is estimated using the D8 model (Jenson and Domingue, 1988) using OS LandForm Profile DTM data (Ordnance Survey, 2009).

Figure 5.2 summarises this process.

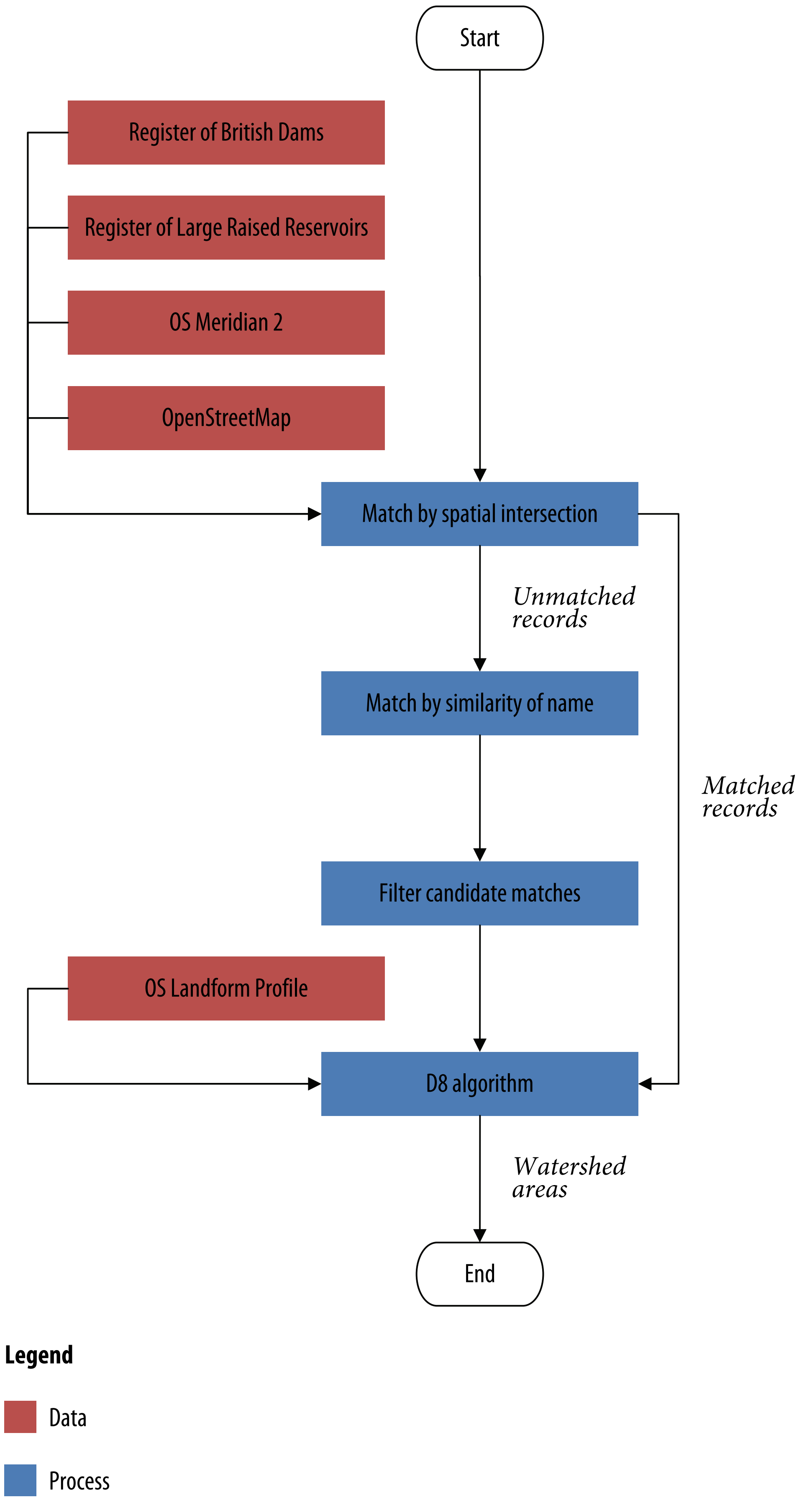


Figure 5.2: Reservoir watershed area model.

5.4.2 Model of water supply infrastructure

The model of water supply infrastructure represents the water supply infrastructure system of the UK using a bi-directed multi-graph flow network with edge properties. Each edge in the graph represents the flow of water through an infrastructure component: the properties of each edge encode the attributes of the component, and the direction of each edge denotes the direction of flow. Properly attributed, solution of such a graph as a 'flow network' provides an approximation of the water allocable from the network to meet demand at a point in time. The network is wrapped in a discrete time-step solution scheme to provide time dependence, and is therefore conceptually very similar to the models of water infrastructure used by water service undertakers.

Every edge has, as a minimum, properties of capacity, flow and weight, necessary for algorithmic solution of each graph as a flow network, and analogous to maximum allocation or demand at the current time-step, assigned allocation at the current time-step, and cost per unit allocation at the current time-step, respectively. Some edges have additional properties, such as environmental flow thresholds and reservoir storage. Vertices have no properties: they represent points at which flows between different infrastructure components interact. This facilitates estimation of the optimal allocation required from each infrastructure element in order to meet demand at the current time-step as the minimum-cost maximum-flow through the graph via successive applications of the 'push-relabel' (Goldberg, 1985) and 'cycle cancelling' (e.g. Ahuja *et al.*, 1993) algorithms using the implementations of Siek *et al.* (2001). This is embedded in a discrete-time algorithm that updates the values of edge properties and re-computes the optimal flow allocation through networks at each time-step, facilitating the estimation of allocation in the system at successive time-steps, and thus simulating the state of the system over time.

With reference to Figure 5.3, the state of each property of each edge in the model is first initialised to the values expected at time $t = 1$ (‘1. Initialise system state’). Each reservoir is initialised such that the volume of water stored is equal to the capacity of the reservoir. The network is then solved for maximum flow, i.e. the maximum water allocable from the model at the current time-step (‘2. Solve for maximum flow’), and for minimum cost, which applies logic such as preference in the quantity of water allocated from different sources (‘3. Solve for minimum cost flow’). The state of the model is output at this point. If there are additional time-steps with data remaining to be processed (‘4. Data remaining?’), the state of the model is updated (‘5. Update system state’), and execution returns to step ‘2’. If no data remain to be processed, execution terminates.

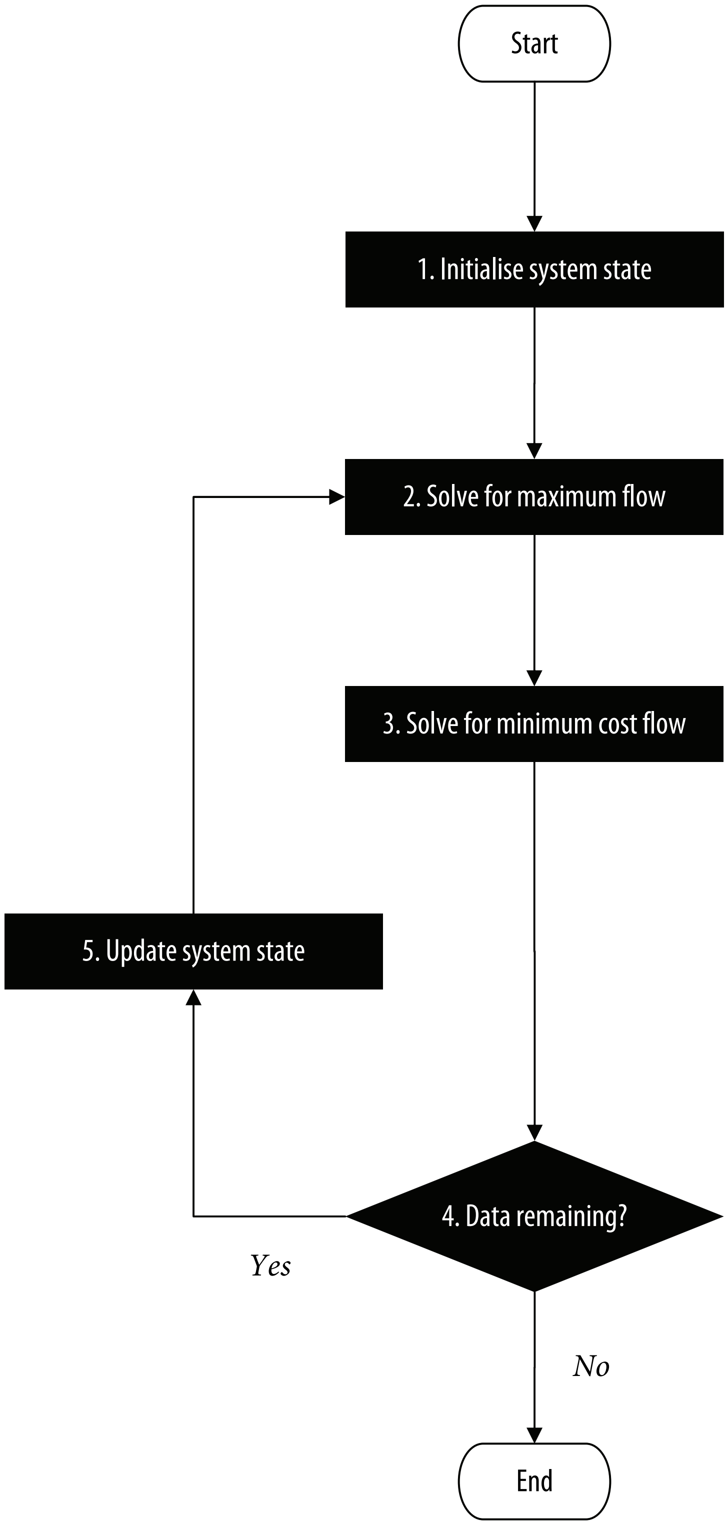
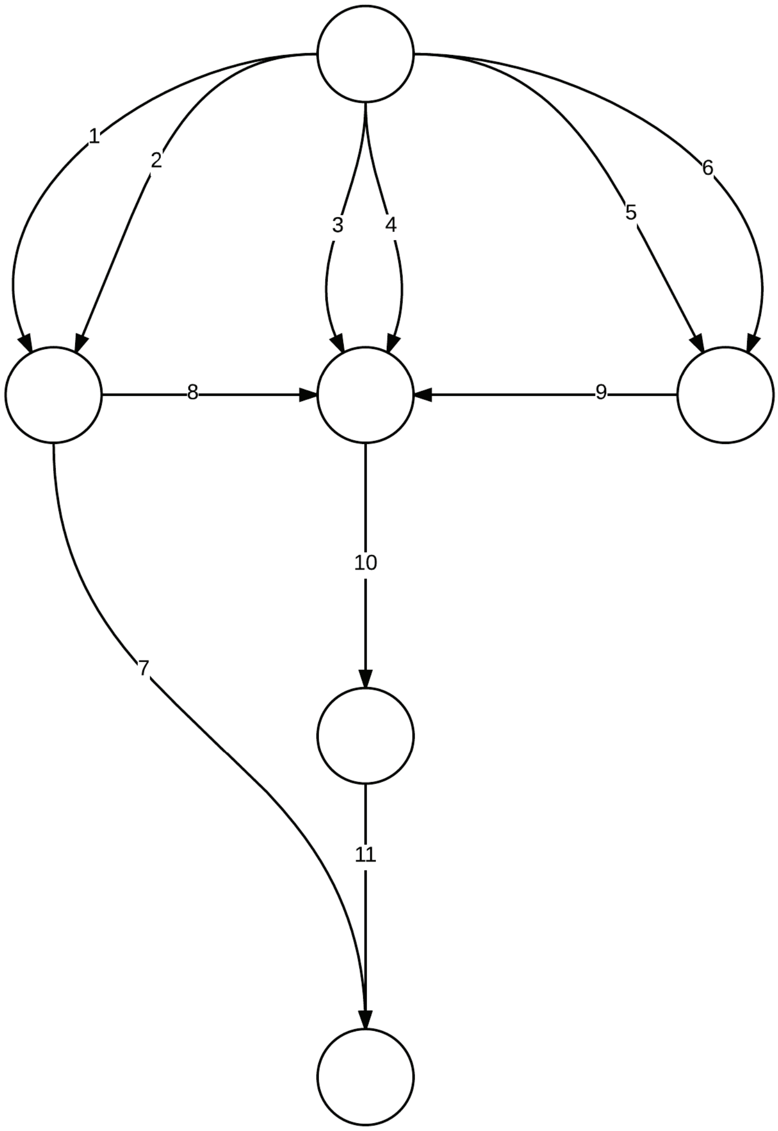


Figure 5.3: The principal steps of the discrete-time algorithm that wraps the model of water supply infrastructure, and which updates the values of edge properties and re-computes the optimal flow allocation through flow networks at each time-step.

This representation is general, able to incorporate any number and configuration of infrastructure components capable of forming a flow network; thus, its applicability is defined wholly by the data used to provide values to its attributes. Owing to the available data, the two implementations demonstrated in this study includes simplified, aggregated characterisations of the water supply infrastructure systems of the 11 water and sewerage service providers as 11 network components, each network component consisting of the same configuration of 11 edges between 6 vertices. This arrangement of edges and vertices is sufficient to represent deployable output from desalination plants, groundwater abstractions, reservoirs, river abstractions and water treatment works, inflows to reservoirs, reservoir storage, and demand for water services at the regional level.

Figure 5.4 shows one such regional sub-network without any inter-regional connections (i.e. a sub-network of the BAU strategy), while Figure 5.5 shows this abstraction realised as rivers, reservoirs, etc. and including inter-regional connections for completeness (i.e. a sub-network of the Water Grid strategy).



Edge descriptions

1	Impounding reservoir inflow
2	Impounding reservoir storage
3	Groundwater abstraction
4	Desalination plant
5	River abstraction
6	Non-impounding reservoir storage
7	Impounding reservoir compensation flow
8	Impounding reservoir allocation
9	Non-impounding reservoir allocation
10	Water treatment works deployable output
11	Demand

Figure 5.4: The arrangement of vertices (circles) and edges (arrows) in a single sub-network, representing a regional sub-network of the water supply infrastructure system of the UK in the absence of connections to other regions. Vertices represent points of interaction between flows, which are properties of edges.

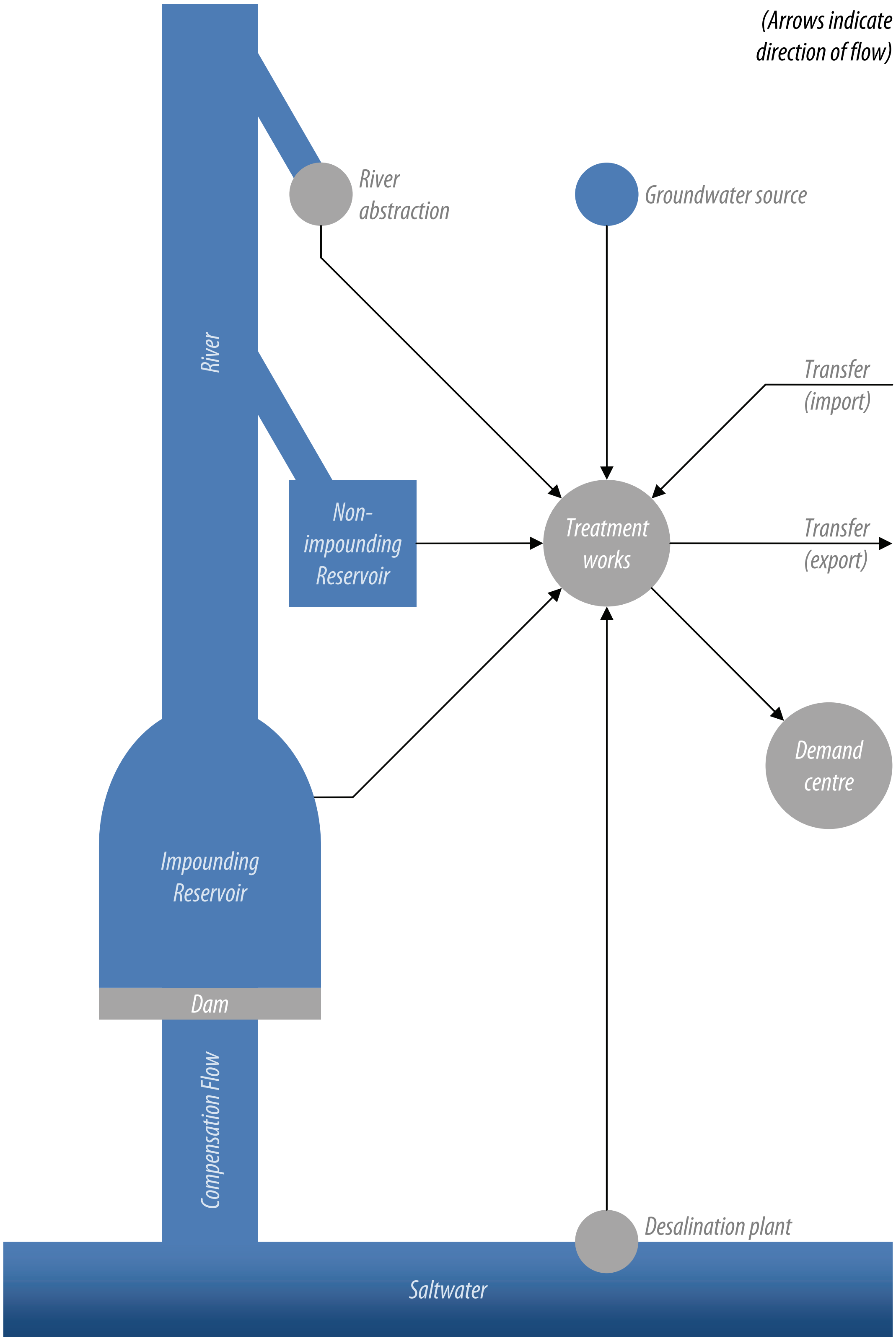


Figure 5.5: The infrastructure modelled in each regional sub-model, and their connectivity, including inter-regional import and export.

Edges representing different types of flow have different rules for determining their capacity.

Equation 29 summarises the rule determining $C_{R,i}$, the capacity of the edge representing flow arising from river abstraction in the i^{th} sub-network.

$$C_{R,i} = \begin{cases} 0, & q_{t,i} \leq q_{95,i} \\ W_{R,i}, & q_{t,i} > q_{95,i} \end{cases} \tag{29}$$

In Equation 29, $q_{t,i}$ is the discharge per unit area at time t, $q_{95,i}$ is the fifth percentile of discharge per unit area for the period 1961-1990, obtained from the model of hydrology for a catchment representative of the sub-network's source locations, and $W_{R,i}$ is the water available for use from river abstractions in the i^{th} sub-network according to the network operator's June Return (Ofwat, 2011).

Similarly, Equation 30 summarises the rule determining $C_{G,i}$, the capacity of the edge representing flow arising from groundwater abstraction in the i^{th} sub-network.

$$C_{G,i} = \begin{cases} 0, & q_{b,t,i} \leq \min{(q_{b,i})} \\ W_{G,i}, & q_{b,t,i} > \min{(q_{b,i})} \end{cases} \tag{30}$$

In Equation 30, $q_{b,t,i}$ is the baseflow per unit area at time t, $q_{b,i}$ is the baseflow per unit area for the period 1961-1990, obtained from the model of hydrology for a catchment representative of the sub-network's source locations, and $W_{G,i}$ is the water available for use from groundwater abstractions in the i^{th} sub-network according to the network operator's June Return (Ofwat, 2011).

Equation 31 summaries the rule determining $C_{I,t}$, the capacity of the edge representing impounding reservoir inflow in the i^{th} sub-network.

$$C_{I,i} = A_i \cdot q_{t,i} \qquad \textbf{31}$$

In Equation 31, $q_{t,i}$ is the discharge per unit area at the current time-step, obtained from the model of hydrology for a catchment representative of the i^{th} sub-network's source locations, and A_i is the watershed area of reservoirs receiving inflow in the i^{th} sub-network, obtained from the model of watershed areas.

Equation 32 summaries the rule determining $C_{C,t}$, the capacity of the edge representing impounding reservoir compensation flow in the i^{th} sub-network.

$$C_{C,i} = A_i \cdot q_{95,i} \qquad \textbf{32}$$

In Equation 32, $q_{95,i}$ is the Q95 per unit area, obtained from the model of hydrology for a catchment representative of the i^{th} sub-network's source locations, and A_i is the watershed area of reservoirs receiving inflow in the i^{th} sub-network, obtained from the model of watershed areas.

The capacities of the edges representing allocation from reservoirs in a given sub-network are equal to the sum of reservoir inflow and reservoir storage at the current time-step less compensation flows, and the capacities of edges representing flows arising from reservoir storage in a given sub-network are equal to reservoir storage in that sub-network at the end of the previous time-step. Reservoir storage is initialised to storage capacity obtained from the Register of Large Raised Reservoirs (Environment Agency, Personal Communication) and the Register of British Dams (Building Research Establishment, 1994), and updated at the end of each time-step.

The capacities of edges representing allocation from water treatment works have the value of positive infinity, i.e. the capacity of treatment works is unlimited. This is so that allocations made by the model reflect only water availability, and are not constrained by water treatment works capacity. Water treatment works edges are required in the model to enforce the meeting of the demand for water services from potable sources.

The capacities of the edges representing water resource arising from desalination plants and demand in the i^{th} sub-network are equal to the deployable output of desalination plants and the demand for water services in that regional sub-network, respectively, according to the network operator's June Return (Ofwat, 2011).

The weights of edges are analogous to a 'unit cost' of allocation, and thus determine the priority with which water resource is allocated across the graph network during the max-flow min-cost optimisation. In this study, edge weights are configured such that environmental flows are allocated prior to all other flows, and reservoir storage is optimised, i.e. spill is minimised. In this configuration, the maximum flow through a component is the resource allocable to meet demand in the infrastructure system the component represents, subject to environmental flow constraints, having an upper limit of the demand for water services and a lower limit of zero.

In the BAU strategy (e.g. Figure 5.4), each of the 11 regional sub-networks is independent and disconnected from every other sub-network. This represents the 11 regional sub-networks of the water and sewerage service providers of the UK in the absence of transfers between them, shown for two regional sub-networks in Figure 5.6. The sharing of water resource between regional sub-networks in the Water Grid strategy is modelled by introducing additional edges linking the initial vertices of edges that represent demand. Figure 5.7 shows the representation of a one-way transfer of water resource between two regional sub-networks using this model.

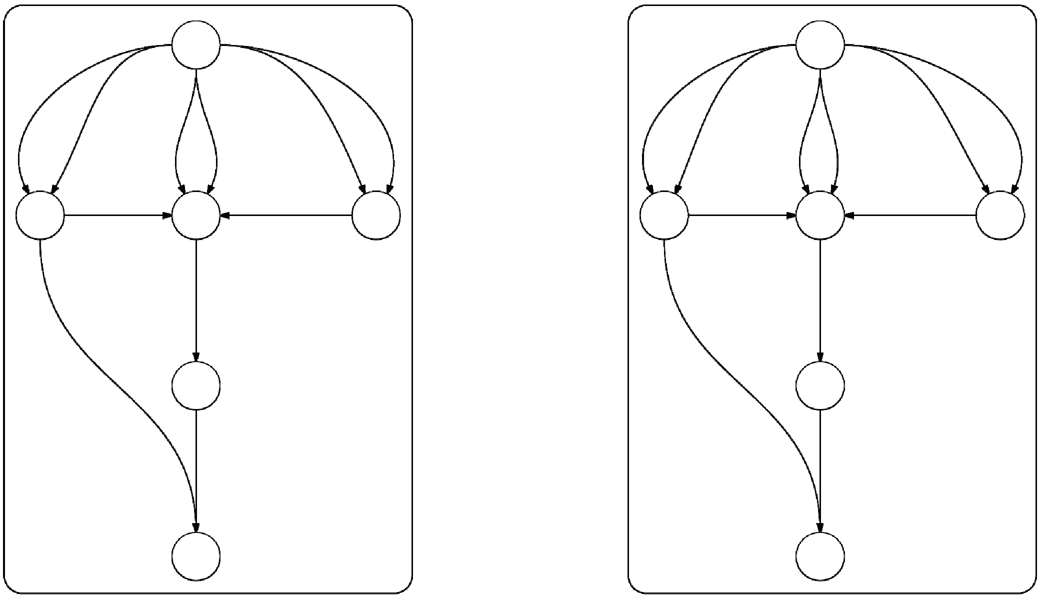


Figure 5.6: The arrangement of vertices and edges in two distinct water supply infrastructure systems (i.e. the BAU strategy).

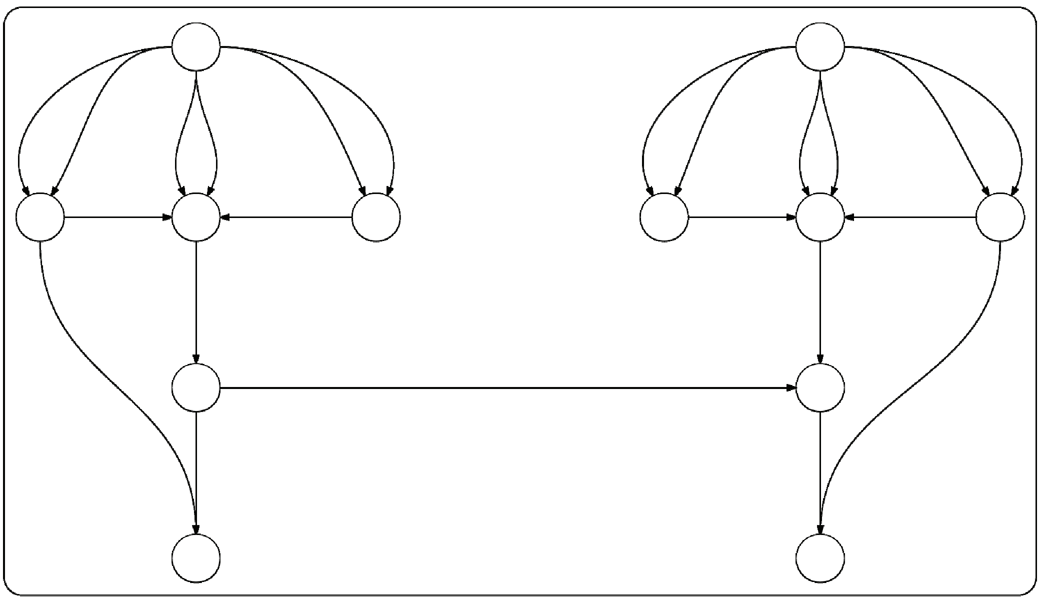


Figure 5.7: The arrangement of vertices and edges in a water supply infrastructure system formed by the addition of an edge between the two sub-graphs (i.e. the Water Grid strategy).

The capacity of the edges representing the transfer of water resource between sub-networks has the value of positive infinity, i.e. the only constraint on transferring water is the quantity of surplus water available for transfer. The edge weights of these links are assigned such that resource is allocated optimally within a 'donor' network prior to surplus resource being transferred to a 'receptor' network. As such, the model is 'locally greedy' in space, prioritising the meeting of demand locally over the meeting of demand collectively: a sub-network will not export water unless demand is satisfied in that sub-network. This behaviour is further exacerbated in that the model performs allocations based solely on the state at the current time-step: it does not look at future states in the allocation algorithm, and therefore does not consider the impact of over- or under-allocation on the long-term sustainability of the supply-demand balance. This extends the phenomenon of 'local greed' across time, as the model prioritises the 'needs of today' over the 'needs of tomorrow'.

5.4.3 Demand

For this study, the demand for water services is assumed constant for each sub-network according to Table 5.2.

5.4.4 Drought metrics used

This study defines a drought event as 'a number of consecutive months during which the accumulated deficit between the three-month moving mean monthly demand for water services and the three-month moving mean monthly water available for allocation equals or exceeds the three-month moving mean daily demand for water services'.

Duration and severity are defined per drought event: the duration of a drought event is the number of months for which aggregated deficit equals or exceeds aggregated allocation for a given event, and; the severity of a drought event is equal to the maximum aggregated deficit accumulated during a given event. The frequency of drought events is defined per time-slice as the count of events occurring during that time-slice.

5.5 Results

5.5.1 Model of watershed areas

Table 5.3 shows the watershed area estimated for each of the 11 water and sewerage providers of the UK.

Undertaker	Area (km^2)
Anglian Water	544.1
Dŵr Cymru (Welsh Water)	726.0
Northumbrian Water	681.8
Scottish Water	6 143.4
Severn Trent Water	4 622.5
South West Water	1 740.0
Southern Water	64.3
Thames Water	1 310.5
United Utilities	612.6
Wessex Water	88.9
Yorkshire Water	1 059.4

Table 5.3: Estimated watershed area by undertaker.

Scottish Water has the largest estimated watershed area, followed by Severn Trent Water. Of the other undertakers, Wessex Water and Southern Water had the smallest estimated watershed areas.

Table 5.4 shows the proportion of reservoir volume for which the model of reservoir watershed areas successfully estimated an area using the methodology outlined in Figure 5.2, summarized by water and sewerage provider.

Undertaker	Proportion (%)
Anglian Water	98.3
Dŵr Cymru (Welsh Water)	96.0
Northumbrian Water	99.5
Scottish Water	91.0
Severn Trent Water	99.5
South West Water	99.5
Southern Water	99.8
Thames Water	98.8
United Utilities	96.4
Wessex Water	98.9
Yorkshire Water	97.1

Table 5.4: Proportion of reservoir volume captured by the model of watershed area by undertaker.

For each undertaker, the model successfully estimated areas for a high proportion (over 90%) of reservoir capacity. On average, a higher proportion of reservoirs by volume were successfully modelled in England and Wales than in Scotland.

5.5.2 Model of water infrastructure

Table 5.5 shows drought event severity by undertaker, climate scenario and percentile for the 'no transfers' strategy, measured as the accumulated deficit in water allocated for sequences of months having maximum accumulated deficit greater than three months' accumulated demand.

The Scottish Water region has drought severity of 0.0 Ml/d under all climate scenarios and across all probability levels.

Under the 1961-1990 'baseline' climate scenario, the regions of Northumbrian Water, Scottish Water, Severn Trent Water, Southern Water, and Wessex Water each exhibit drought severity of 0.0 Ml/d on average and at the 10th and 90th percentiles. The Dŵr Cymru region incurs the smallest non-zero drought severity and the smallest range across all probability levels, ranging from 2 601.9 Ml/d at the 10th percentile to 3 570.0 Ml/d at the 90th percentile, with a mean of 3 028.8 Ml/d. The United Utilities region incurs the highest drought severity with the greatest range: 51 429.9 Ml/d at the 10th percentile, 77 947.8 Ml/d at the 90th percentile, and 63 661.8 Ml/d on average.

With the exception of Scottish Water, all regions exhibit non-zero drought severity under scenarios of future climate. Most regions show similar trends in drought severity, this being comparatively inflated drought severity between the 2050s and the 2020s and between the 2080s and the 2050s; however, the Northumbrian Water region shows a decrease in drought severity at the 10% level between the 2020s and 2050s.

The droughts of greatest severity occur in the United Utilities region across all climate scenarios and probability levels. By the 2020s and 2050s, the greatest absolute changes in drought severity at the 10% level occurs in the United Utilities region, while, at the mean and 90% levels, it is the Thames Water region that exhibits greatest absolute change. By the 2080s, the greatest absolute changes in drought severity occur in the

Thames Water region at all probability levels. Excluding regions with drought severity of 0.0 Ml/d under the 'baseline' climate scenario, the greatest relative changes in drought severity at all probability levels occur in the Thames Water region.

Undertaker	Scenario	Severity (Ml/d)		
		P10	Mean	P90
Anglian Water	Baseline	25 018.2	31 860.6	39 906.9
	2020s	26 758.3	36 085.1	46 564.4
	2050s	32 232.3	46 390.5	62 034.4
	2080s	34 317.7	54 751.1	77 000.6
Dŵr Cymru	Baseline	2 601.9	3 028.8	3 570.0
	2020s	2 629.2	3 228.5	3 918.6
	2050s	2 648.3	3 352.7	4 089.0
	2080s	2 675.2	3 530.8	4 372.1
Northumbrian Water	Baseline	0.0	0.0	0.0
	2020s	2 237.7	2 634.9	2 966.3
	2050s	2 237.1	2 619.4	2 996.6
	2080s	2 250.0	2 699.5	3 182.3
Scottish Water	Baseline	0.0	0.0	0.0
	2020s	0.0	0.0	0.0
	2050s	0.0	0.0	0.0
	2080s	0.0	0.0	0.0
Severn Trent Water	Baseline	0.0	0.0	0.0
	2020s	5 807.6	7 712.8	11 853.2
	2050s	5 912.6	10 153.8	16 597.7
	2080s	6 012.6	11 116.0	19 225.1
South West Water	Baseline	3 180.4	4 932.2	6 766.8
	2020s	8 302.9	12 604.3	17 174.2
	2050s	14 141.6	19 963.7	25 837.6
	2080s	18 160.5	25 402.4	33 827.0
Southern Water	Baseline	0.0	0.0	0.0
	2020s	1 824.1	2 333.6	3 330.3
	2050s	1 859.8	2 648.1	4 262.8
	2080s	1 868.4	2 861.6	4 712.5
Thames Water	Baseline	13 776.0	27 079.4	39 752.6
	2020s	34 263.8	66 071.6	101 384.9
	2050s	68 358.8	118 789.3	171 794.8
	2080s	91 668.9	152 972.2	215 851.6
United Utilities	Baseline	51 429.9	63 661.8	77 947.8
	2020s	75 293.2	100 917.9	128 249.0
	2050s	107 677.8	144 236.6	183 272.9
	2080s	118 579.5	167 127.3	217 028.0
Wessex Water	Baseline	0.0	0.0	0.0
	2020s	1 155.0	1 641.3	2 328.3
	2050s	1 163.3	2 087.8	3 760.3
	2080s	1 179.4	2 682.0	5 042.7
Yorkshire Water	Baseline	39 927.6	49 030.6	58 681.8
	2020s	53 983.2	72 817.7	92 985.7
	2050s	77 910.1	106 780.2	138 767.1
	2080s	84 610.3	124 477.2	169 259.9

Table 5.5: Event severity by undertaker, climate scenario and percentile for the 'no transfers' strategy.

Table 5.6 shows drought event duration by undertaker, climate scenario and percentile for the ‘no transfers’ strategy, measured as the count of sequential months having maximum accumulated deficit greater than three months’ accumulated demand.

The Scottish Water region has drought duration of 0.0 months under all climate scenarios and across all probability levels.

Under the 1961-1990 ‘baseline’ climate scenario, the regions of Northumbrian Water, Scottish Water, Severn Trent Water, Southern Water, and Wessex Water each exhibit drought duration of 0.0 months on average and at the 10^{th} and 90^{th} percentiles.

The Dŵr Cymru region incurs the smallest non-zero drought duration and the smallest range across all probability levels, ranging from 2.0 months at the 10^{th} percentile to 7.0 months at the 90^{th} percentile, with a mean of 4.0 months. The Yorkshire Water region incurs the highest drought duration: 256.9 months (21.4 years) at the 10^{th} percentile, 284.0 months (23.7 years) at the 90^{th} percentile, and 311.5 months (26.0 years) on average. The Thames Water region displayed the greatest range in drought duration, specifically 53.3 months (4.4 years) at the 10% level and 268.0 months (22.3 years) at the 90% level.

With the exception of Scottish Water, all regions exhibit non-zero drought duration under scenarios of future climate. All regions show similar trends in drought duration, this being equal or comparatively inflated drought duration between the 2050s and the 2020s and between the 2080s and the 2050s.

The droughts of greatest duration occur in the Yorkshire Water region across all climate scenarios at the 10% level; however, the United Utilities and Yorkshire Water regions tie for maximum drought event duration in the 2050s and the 2080s at the mean and 90% levels, respectively. Drought events are longer in the United Utilities region than in the Yorkshire Water region at the 90% level in the 2020s and 2050s, whereas drought events are of greater duration in the Yorkshire Water region than in the United Utilities region on average in the 2020s. Across all climate scenarios and probability levels, the greatest absolute changes in drought duration occur in the Thames Water region, except in the 2080s, when, at the 90% level, the greatest absolute change occurs in the Wessex Water region. Excluding regions with drought duration of 0.0 Ml/d under the ‘baseline’ climate scenario, the greatest relative changes in drought duration at all probability levels occur in the Dŵr Cymru region.

Undertaker	Scenario	Duration (months)		
		P10	Mean	P90
Anglian Water	Baseline	223.5	251.0	287.3
	2020s	228.9	260.0	291.0
	2050s	245.0	277.0	305.1
	2080s	253.9	284.0	314.0
Dŵr Cymru	Baseline	2.0	4.0	7.0
	2020s	4.0	12.0	23.0
	2050s	11.0	26.0	44.0
	2080s	16.0	37.0	63.0
Northumbrian Water	Baseline	0.0	0.0	0.0
	2020s	2.0	3.0	8.0
	2050s	2.0	5.0	11.0
	2080s	2.0	8.0	18.0
Scottish Water	Baseline	0.0	0.0	0.0
	2020s	0.0	0.0	0.0
	2050s	0.0	0.0	0.0
	2080s	0.0	0.0	0.0
Severn Trent Water	Baseline	0.0	0.0	0.0
	2020s	2.0	6.0	14.5
	2050s	2.0	12.0	29.0
	2080s	3.0	20.0	45.0
South West Water	Baseline	170.1	240.0	304.1
	2020s	270.0	310.0	340.0
	2050s	306.0	329.0	342.0
	2080s	318.0	335.0	348.0
Southern Water	Baseline	0.0	0.0	0.0
	2020s	1.2	4.0	10.8
	2050s	2.0	7.0	18.0
	2080s	3.0	13.0	31.0
Thames Water	Baseline	53.3	171.0	268.0
	2020s	196.0	265.0	317.0
	2050s	277.3	307.0	338.0
	2080s	292.0	319.0	341.0
United Utilities	Baseline	246.9	275.0	302.1
	2020s	280.0	303.0	329.0
	2050s	300.0	321.0	341.0
	2080s	304.0	327.0	342.0
Wessex Water	Baseline	0.0	0.0	0.0
	2020s	4.0	15.0	29.0
	2050s	5.0	26.0	58.0
	2080s	5.0	46.0	113.3
Yorkshire Water	Baseline	256.9	284.0	311.5
	2020s	281.0	305.0	328.0
	2050s	304.0	321.0	340.0
	2080s	305.0	326.0	342.0

Table 5.6: Event duration by undertaker, climate scenario and percentile for the 'no transfers' strategy.

Table 5.7 shows drought event frequency by undertaker, climate scenario and percentile for the 'no transfers' strategy, measured as the count of sequential events having maximum accumulated deficit greater than three events' accumulated demand.

The Scottish Water region has drought frequency of zero events under all climate scenarios and across all probability levels.

Under the 1961-1990 'baseline' climate scenario, the regions of Northumbrian Water, Scottish Water, Severn Trent Water, Southern Water, and Wessex Water each exhibit drought frequency of zero events on average and at the 10th and 90th percentiles. In the Anglian Water, South West Water, Thames Water and Yorkshire Water regions, only a single drought event occurs at each probability level; however, in the Dŵr Cymru region, one event occurs at the 10% level, and on average, while three events occur at the 90% level.

The Anglian Water, South West Water, Thames Water, United Utilities and Yorkshire Water regions continue to exhibit only one event for each climate scenario and at each probability level. The Dŵr Cymru, Northumbrian Water, Severn Trent Water and Wessex Water regions exhibit similar trends to one another at all probability levels, namely a tendency towards greater drought frequency in the 2050s relative to the 2020s and in the 2080s relative to the 2050s.

The greatest absolute and relative changes in drought frequency occur in the Dŵr Cymru region.

Undertaker	Scenario	Frequency (Count)		
		P10	Mean	P90
Anglian Water	Baseline	1.0	1.0	1.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	1.0
	2080s	1.0	1.0	1.0
Dŵr Cymru	Baseline	1.0	1.0	3.0
	2020s	1.0	3.0	6.0
	2050s	4.0	7.0	12.0
	2080s	6.0	10.0	15.0
Northumbrian Water	Baseline	0.0	0.0	0.0
	2020s	1.0	1.0	2.0
	2050s	1.0	1.0	3.0
	2080s	1.0	2.0	5.0
Scottish Water	Baseline	0.0	0.0	0.0
	2020s	0.0	0.0	0.0
	2050s	0.0	0.0	0.0
	2080s	0.0	0.0	0.0
Severn Trent Water	Baseline	0.0	0.0	0.0
	2020s	1.0	1.0	1.5
	2050s	1.0	1.0	2.0
	2080s	1.0	2.0	4.0
South West Water	Baseline	1.0	1.0	1.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	1.0
	2080s	1.0	1.0	1.0
Southern Water	Baseline	0.0	0.0	0.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	2.0
	2080s	1.0	2.0	5.0
Thames Water	Baseline	1.0	1.0	1.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	1.0
	2080s	1.0	1.0	1.0
United Utilities	Baseline	1.0	1.0	1.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	1.0
	2080s	1.0	1.0	1.0
Wessex Water	Baseline	0.0	0.0	0.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	3.0
	2080s	1.0	2.0	4.0
Yorkshire Water	Baseline	1.0	1.0	1.0
	2020s	1.0	1.0	1.0
	2050s	1.0	1.0	1.0
	2080s	1.0	1.0	1.0

Table 5.7: Event frequency by undertaker, climate scenario and percentile for the 'no transfers' strategy.

Table 5.8 shows the relative change in drought event severity by undertaker and percentile between the 'with transfers' strategy and the 'no transfers' strategy for the 1961-1990 'baseline' climate scenario.

These results imply that drought severity is substantially less under the 'with transfers' strategy than under the 'no transfers' strategy in the Anglian Water region: the reduction in drought severity was 83.5% at the 10% level, 81.0% on average, and 79.3% at the 90% level.

Minor reductions in drought severity also occur in the Dŵr Cymru region at the 90% level: 0.1% at the 10% level, 0.3% on average, and 0.8% at the 90% level.

Drought severity is unchanged in the Severn Trent Water and Thames water regions at all probability levels.

Undertaker	Scenario	Change in severity		
		P10	Mean	P90
Anglian Water	Baseline	-83.5%	-81.0%	-79.3%
Dŵr Cymru	Baseline	-0.1%	-0.3%	-0.8%
Severn Trent Water	Baseline	0.0%	0.0%	0.0%
Thames Water	Baseline	0.0%	0.0%	0.0%

Table 5.8: Relative change in drought event severity by undertaker and percentile between the 'with transfers' strategy and the 'no transfers' strategy for the 1961-1990 'baseline' climate scenario.

Table 5.9 shows the relative change in drought event duration by undertaker and percentile between the ‘with transfers’ strategy and the ‘no transfers’ strategy for the 1961-1990 ‘baseline’ climate scenario.

These results imply that drought duration is substantially less under the ‘with transfers’ strategy than under the ‘no transfers’ strategy in the Anglian Water region: the reduction at the 10% and 90% levels is 93.0% and 36.2%, respectively. The average reduction is 63.7%. A minor reduction in drought duration of 5.7% also occurs in the Dŵr Cymru region at the 90% level. All other differences are zero (i.e. no change in drought duration).

Undertaker	Scenario	Change in duration		
		P10	Mean	P90
Anglian Water	Baseline	-93.0%	-63.7%	-36.2%
Dŵr Cymru	Baseline	0.0%	0.0%	5.7%
Severn Trent Water	Baseline	0.0%	0.0%	0.0%
Thames Water	Baseline	0.0%	0.0%	0.0%

Table 5.9: Relative change in drought event duration by undertaker and percentile between the ‘with transfers’ strategy and the ‘no transfers’ strategy for the 1961-1990 ‘baseline’ climate scenario.

Table 5.10 shows the relative change in drought event frequency by undertaker and percentile between the 'with transfers' strategy and the 'no transfers' strategy for the 1961-1990 'baseline' climate scenario.

These results imply that drought frequency is unchanged under the 'with transfers' strategy in comparison with the 'no transfers' strategy, at all probability levels.

Undertaker	Scenario	Change in frequency		
		P10	Mean	P90
Anglian Water	Baseline	0.0	0.0	0.0
Dŵr Cymru	Baseline	0.0	0.0	0.0
Severn Trent Water	Baseline	0.0	0.0	0.0
Thames Water	Baseline	0.0	0.0	0.0

Table 5.10: Absolute change in drought event frequency by undertaker and percentile between the 'with transfers' strategy and the 'no transfers' strategy for the 1961-1990 'baseline' climate scenario.

Table 5.11 shows the relative change in drought event severity by undertaker, climate scenario and percentile between the ‘with transfers’ strategy and the ‘no transfers’ strategy for three climate scenarios: 2010-2039 (the ‘2020s’); 2040-2069 (the ‘2050s’), and; 2070-2099 (the ‘2080s’).

The ‘with transfers’ strategy assumes changes in the water supply infrastructure system only from 2040 onward; therefore, no differences are observed between the ‘no transfers’ strategy and the ‘with transfers’ strategy in the 2020s.

The severity of drought events in the Anglian Water region is lesser under the ‘with transfers’ strategy than the ‘no transfers’ strategy in the 2050s and 2080s. In the case of the former, the reduction in drought severity is 69.1% at the 10% level and 47.7% at the 90% level. The mean reduction is 55.8%. In the case of the latter, the reduction in drought severity is 63.3% at the 10% level and 36.6% at the 90% level. The mean reduction is 46.8%.

For the most part, no differences in drought severity emerge in the Dŵr Cymru region between the ‘with transfers’ strategy than the ‘no transfers’ strategy: only a small reduction of 0.1% is evident in the 2050s at the 90% level.

Small increases in drought severity occur in the Severn Trent Water region by the 2050s in comparison to those arising under the ‘no transfers’ strategy: 0.4% at the 10% level, 0.7% on average, and 2.4% at the 90% level. Conversely, small decreases in drought severity of occur in the 2080s: 0.6% at the 10% level, 0.9% on average, and 0.8% at the 90% level.

In the Thames Water region, similar decreases in drought severity occur in the 2050s and 2080s. In the case of the former, these are 4.6% at the 10% level, 3.8% on average, and 3.1% at the 90% level. In the case of the latter, these are 4.7% at the 10% level, 3.6% on average, and 3.1% at the 90% level.

Undertaker	**Scenario**	**Change in severity**		
		P10	**Mean**	**P90**
Anglian Water	2050s	-69.1%	-55.8%	-47.7%
	2080s	-63.3%	-46.8%	-36.6%
Dŵr Cymru	2050s	0.0%	0.0%	-0.1%
	2080s	0.0%	0.0%	0.0%
Severn Trent Water	2050s	0.4%	0.7%	2.4%
	2080s	-0.6%	-0.9%	-0.8%
Thames Water	2050s	-4.6%	-3.8%	-3.1%
	2080s	-4.7%	-3.6%	-3.1%

Table 5.11: Relative change in event severity by undertaker, climate scenario and percentile for the ‘with transfers’ strategy.

Table 5.12 shows the relative change in drought event duration by undertaker, climate scenario and percentile between the ‘with transfers’ strategy and the ‘no transfers’ strategy for the 2020s, the 2050s, and the 2080s.

These results imply that the duration of drought events in the Anglian Water region is lesser under the ‘with transfers’ strategy than the ‘no transfers’ strategy in the 2050s and 2080s. In the case of the former, the reduction in drought duration is 33.9% at the 10% level and 4.0% at the 90% level. The mean reduction is 15.2%. In the case of the latter, the reduction in drought duration is 22.8% at the 10% level and 2.9% at the 90% level. The mean reduction is 9.2%.

Increases in drought duration emerge in the Dŵr Cymru region between the ‘with transfers’ strategy than the ‘no transfers’ strategy in both the 2050s and 2080s. In the case of the former, the increase in drought duration is 7.3% at the 10% level and 2.3% at the 90% level. The mean increase is 3.8%. In the case of the latter, the increase in drought duration is 6.3% at the 10% level and 1.6% at the 90% level. The mean increase is 5.4%.

Under the ‘with transfers’ strategy, a 50% increase in drought duration occurs in the Severn Trent Water region at the 10% level by the 2050s. Conversely, a small decrease in drought duration of 4.4% occurs in the 2080s at the 90% level.

In the Thames Water region, decreases in drought duration of 3.4% and 2.4% occur in the 2050s at the 10% and 90% probability levels, respectively, with an average decrease of 2.0%. Decreases of 2.8% and 0.6% occur in the 2080s at the 10% and 90% probability levels, respectively, and the average decrease in drought duration for this climate scenario was 1.6%.

Undertaker	Scenario	Change in duration		
		P10	Mean	P90
Anglian Water	2050s	-33.9%	-15.2%	-4.0%
	2080s	-22.8%	-9.2%	-2.9%
Dŵr Cymru	2050s	7.3%	3.8%	2.3%
	2080s	6.3%	5.4%	1.6%
Severn Trent Water	2050s	50.0%	0.0%	0.0%
	2080s	0.0%	0.0%	-4.4%
Thames Water	2050s	-3.4%	-2.0%	-2.4%
	2080s	-2.8%	-1.6%	-0.6%

Table 5.12: Relative change in event duration by undertaker, climate scenario and percentile for the 'with transfers' strategy.

Table 5.13 shows the absolute change in drought event frequency by undertaker, climate scenario and percentile between the 'with transfers' strategy and the 'no transfers' strategy for the 2020s, the 2050s, and the 2080s.

The change in drought event frequency under the 'with transfers' strategy in comparison with the 'no transfers' strategy is 0.0 events at all probability levels in the Anglian Water, Severn Trent Water and Thames Water regions.

In the Dŵr Cymru region, an increase in drought event frequency of 1.0 event occurs on average in the 2050s and at the 90% level in the 2080s. No other differences in drought event frequency are evident in this region.

Undertaker	**Scenario**	**Change in frequency**		
		P10	**Mean**	**P90**
Anglian Water	2050s	0.0	0.0	0.0
	2080s	0.0	0.0	0.0
Dŵr Cymru	2050s	0.0	1.0	0.0
	2080s	0.0	0.0	1.0
Severn Trent Water	2050s	0.0	0.0	0.0
	2080s	0.0	0.0	0.0
Thames Water	2050s	0.0	0.0	0.0
	2080s	0.0	0.0	0.0

Table 5.13: Absolute change in event frequency by undertaker, climate scenario and percentile for the 'with transfers' strategy.

5.6 Discussion

5.6.1 Current findings

This study is an assessment of the impact of climate change on the severity, duration and frequency of drought events arising from accumulated deficits in the quantity of water available to meet demand. It uses a nationally consistent representation of the water supply infrastructure system that facilitates exploration of alternative infrastructure strategies, and uses probabilistic projections of hydrological variables to sample the uncertainties inherent in climate projection.

In a simplified representation of the water supply infrastructure of the UK that aggregates water resource zones and water sources operated by the same operator and precludes transfers between regions, six of the eleven regions modelled exhibited droughts under the 1961-1990 'baseline' climate scenario at the 10% probability level, on average, and at the 90% probability level.

Under three scenarios of future climate representative of the periods 2010-2039 ('the 2020s'), 2040-2069 ('the 2050s') and 2070-2099 ('the 2080s'), with the exception of the Scottish Water region, all regions exhibited substantial increases in drought severity and duration that, with very few exceptions, increased between the 2020s and the 2050s and between the 2050s and the 2080s. In most cases, drought frequency remained unchanged between climate scenarios; however, the regions having smaller increases in drought severity, and, to some extent, drought duration showed increases in drought frequency.

The assumption of a strategy of connectivity between the regions of Dŵr Cymru, Severn Trent Water, Anglian Water and Thames Water substantially reduced drought severity and duration in the Anglian Water region, and, to a lesser extent, the Thames Water region, under the 1961-1990 'baseline' climate, the 2050s and the 2080s.

5.6.2 Model of watershed areas

The model of watershed areas developed for this model captures the ‘natural’ watershed areas of water bodies in Scotland listed in the Register of British Dams (Building Research Establishment, 1994) and water bodies in England and Wales listed in the Register of Large Raised Reservoirs (Environment Agency, Personal Communication).

Published records of this parameter for comparison are sparse and estimated by inconsistent means (e.g. Gustard *et al.*, 1987); however, spot-checking of available records suggests that the model performs acceptably well for reservoirs for which the ‘natural’ watershed area approximately equals the ‘total’ watershed area. This group of reservoirs includes Kielder Water, for which the watershed area estimated by the model of watershed areas is 243.3 km^2 and the area published by Gustard *et al.* (1987) is 237.0 km^2: a difference of less than 2.7% from the published value. In cases where reservoirs have substantial difference between the ‘natural’ watershed area and the ‘total’ watershed area, such as Haweswater, the model of watershed areas is only effective at approximating the ‘natural’ areas. This leads to misestimating of watershed areas and thus reservoir inflows in these cases, possibly leading to an ultimate misestimating of infrastructure system failure.

The impact of this is lessened in this study by the small number of reservoirs affected by this phenomenon and the small extent to which it occurs in most cases (Gustard *et al.*, 1987) and by the aggregation of reservoirs by undertaker. For example, although such reservoirs may be of local importance individually, whereby underestimation of their watersheds would have significant impact on modelled performance of the local water supply infrastructure system, this effect is mitigated when storage and inflows are aggregated over multiple water resource zones.

5.6.3 Model of water infrastructure

The model of water infrastructure simulates the allocation of water in simplified representations of the major regional water supply infrastructure systems of Great Britain under multiple climate scenarios and infrastructure strategies. In all cases, the performance of the system is assessed under conditions of the demand for water services reported for the period 2010-2011, and the water available for use by source type over the same reporting period is assumed a proxy for deployable output (e.g. Ofwat, 2011).

Under the 1961-1990 'baseline' climate scenario, the model evolved droughts (defined as accumulated deficits in water allocated exceeding three months' demand) in the regions of Anglian Water, Dŵr Cymru, South West Water, Thames Water and Yorkshire Water. The most severe and long lasting of these occurred in the north of England, but regions in the south and east also appeared vulnerable. Joint inspection of drought event severity, duration and frequency indicates that, in 90% of simulations, these regions entered drought within 10 years of the 30-year simulation, and did not recover sufficiently during the remainder of the simulation to overcome accumulated deficits and exit the drought state. Only the infrastructure system of the Dŵr Cymru region demonstrated recovery, exhibiting not only a small number of drought events, but that these events were relatively short (fewer than ten months in duration under 90% of simulations), and of relatively low severity (around four months' accumulated demand). This behaviour relates to the margin between water available for use and demand, which, in this model, is static except for reservoir storage. In practice, individual sources, including a wide variety of source types, would have more variable water available for use than presented here, allowing for margins that are more variable. In addition, demand is generally not static, varying throughout the year in response to consumer behaviour and population. In general, however, systemic failure within 10 years is perhaps reasonable for water supply networks in the UK, which are managed on a five-year basis to avoid such outcomes. This model does not include adaptation measures on this timescale, resulting in failure.

With the exception of Scottish Water, all regions experience drought events that, broadly, increase in severity and duration between the ‘baseline’ climate and the 2020s, the 2020s and the 2050s, and the 2050s and the 2080s. Regions already exhibiting unrecoverable system failure under the ‘baseline’ climate (e.g. Anglian Water, South West Water, Thames Water and Yorkshire Water) experience increases drought event severity and duration without incurring concomitant increases in drought event frequency. Other regions (e.g. Dŵr Cymru, Northumbrian Water, Severn Trent Water, Southern Water and Wessex Water) also show increases in drought severity and duration without necessarily incurring a frequency of one event that implies unrecoverable system failure.

The assumption of a series of water transfers from Dŵr Cymru to Severn Trent Water, from Severn Trent Water to Anglian Water and Thames Water, and from Anglian Water to Thames Water is effective at reducing drought severity and duration, but not frequency, in the Anglian Water region. It also reduces severity and duration to a lesser extent in the Severn Trent and Thames Water regions, and marginally decreases severity in the Dŵr Cymru region under the ‘baseline’ climate scenario (via improved reservoir spill retention) at the cost of exacerbating drought duration and frequency in the 2050s and 2080s.

The relative lack of change in response to enabling water transfers apparent in the Thames Water region relates to availability of resource in each sub-network and the prioritisation of resource allocation within the algorithms used. As explained in §5.4.2, the model is ‘locally greedy’, a practical impact being that, if there is no surplus water available for use in Dŵr Cymru, for example, the model will not export water from Dŵr Cymru – even if the transfer would benefit recipient regions more than it would cost Dŵr Cymru. As a result, although drought impacts affecting Thames Water were perhaps of greater magnitude that those affecting Dŵr Cymru, Severn Trent Water and

Anglian Water, none of these regions had exportable resource of sufficient quantity to offset those drought impacts.

A particular limitation of this analysis is the choice not to export the magnitudes of the transfers themselves at each time-step, which would provide direct evidence of the behaviours discussed herein; however, the model could be modified to output these data.

5.6.4 Demand

The assumption of constant demand, as used in this study, may seem contentious in the context of studies such as Walsh *et al.* (2016) and Borgomeo *et al.* (2014), which present the importance of demand in evaluating future water resource; however, the use of constant demand decouples strategy from scenario, enabling independent assessment of their impacts on system performance. For example, the use of a transient demand or population-demand model along with a strategy of connectivity between water resources sub-networks where none existed previously conflates the assumptions of both models, and makes it difficult to disentangle the impacts of changes in demand from changes in infrastructure.

The next step in this analysis is to run the model of water infrastructure repeatedly for different strategies of adaptation (e.g. ‘BAU’, ‘Water Grid’) and scenarios of constant demand of different magnitude, establishing system performance under each combination of strategy and scenario. The output can then be analysed and interpreted in terms of what constitutes acceptable performance, and a demand for which acceptable performance occurs for each strategy-scenario pair stated. This is then the capacity of the system under the conditions of that strategy-scenario pairing.

For example, suppose the model is re-run under the ‘BAU’ strategy for demands equivalent to 120, 130, 140 and 150 litres per capita per day (l/h/d), and ‘acceptable’ performance is defined as the performance of the system under the baseline climate and a demand of 150 l/h/d. If it is found that system performance is less than 'acceptable' in the 2020s at 150 l/h/d, in the 2050s for demand equal to or greater than 140 l/h/d and in the 2080s for demand equal to or greater than 150 l/h/d, but at least acceptable for all other pairings, the capacity of the system under the BAU strategy can be stated as 140 l/h/d in the 2020s, 130 l/h/d in the 2050s, and 120 l/h/d in the 2080s.

The feasibility of achieving these demands can then be discussed separately.

5.6.5 Further extensions

The modelling framework developed in the execution of this research and described in this thesis is very flexible and extensible. It allows for any number of water supply infrastructure components with any connectivity, provided they comply with the requirements of a flow network (e.g. Sedgewick, 2002), and allows for the use of time-varying values for any parameter within the model description.

This enables a wide range of behaviours, such as environmental controls (e.g. via substitution of q_{95} in Equation 29 and/or Equation 32 with different values), additional desalination plants (either by increasing the capacity of an existing desalination plant edge, or adding a new such edge with a non-zero capacity), operational constraints on demand (by reducing the capacity of the edge representing demand), or increased demand (by increasing the capacity of the edge representing demand).

By modifying the definition of the graph underpinning the model in these ways, any number of strategies and scenarios can be simulated.

Furthermore, the implementation of the model could be modified to export the full range of variable values assigned within the model at each time-step, including the magnitudes of any inter-basin water transfers.

5.7 Conclusions

In the context of the aims and objectives of this thesis, this study has quantified the impact of climate change on the performance of the public water supply infrastructure system of the UK in both the absence and presence of a water grid. In doing so, it has developed a modelling framework in response to the findings of §2, and implemented that modelling framework such that it is representative of the public water supply infrastructure system of the UK, supported by the data developed in §4 and from other sources (e.g. Ofwat, 2011).

The results suggest that, in the absence of intervention, water supply infrastructure networks in the north, east and south of England are unable to sustain the demand for water observed in 2010-2011 for periods of 10 years or more under a range of climate scenarios, including one representative of the 1961-1990 'baseline' climate. Regions in Wales, Scotland and the west and southwest of England are comparatively more resilient under the 'baseline' climate, but are, in most cases, equally vulnerable to drought events under climate conditions representative of the 2020s, 2050s and 2080s.

Intervention in the form of a Water Grid transferring water from Wales and the Midlands to the southeast of England is effective at reducing overall deficit; however, the magnitudes of accumulated deficits are so great and projected drought durations so long that such transfers are insufficient to mitigate droughts in the south and east of England.

Integral to this analysis was the construction of a model of reservoir watershed areas that estimated areas for over 90% of reservoirs by volume across Great Britain. The few reservoirs with total area unequal to their natural watershed area had a limited impact on this model in the context of its application.

The principal improvement required of this study is further validation of parameter values and performance under the 1961-1990 'baseline' climate scenario;

however, data available to support such an activity are generally sparse, incomplete, inconsistent and not directly relevant, hence their limited use in this study. In addition, there are a number of technical improvements possible to the model, such as the integration of effluent re-use as a source of water and the modelling of deployable output of individual sources rather than aggregation or the use of water available for use as a proxy; however, the implementation of either action would require a model of increased complexity.

6 Discussion and conclusions

6.1 Aims and objectives

With reference to §1.3, in its quantification of the performance of the water supply infrastructure system of the UK in the presence and absence of a 'water grid', the study described in §5, supported by the detail presented in the other study chapters comprising this thesis, demonstrates accomplishment of aim A1.

With respect to aim A2, the analyses of changes in DSI3 and DSI6 in §3 constitute quantification of the impact of climate change on indicators of meteorological and hydrological drought, respectively, the analyses of changes in ADF and Q95 in §4 constitute quantification of the impact of climate change on indicators of hydrological and water resources drought, and the analyses of the performance of the water supply infrastructure system in §5 constitute quantification of the impact of climate change on indicators of water resources drought. All of the above analyses occurred in the context of the methodology described in §2.5, which was designed in response to a critique of prevailing data and methods presented in §2.

In consideration of the objectives of this thesis, §2 reviewed relevant existing climate, hydrological and water resources data and methodologies, and identified research gaps relating to encapsulation of uncertainties associated with climate change projection via the use of probabilistic projections and the need for a consistent national-scale representation and simulation model of climate variables, hydrology, and water resources processes and infrastructure. This completed objective O1. Design of the framework presented in §2.5 completed objective O2, and implementation of that framework in §3, §4 and §5 completed objective O3. Finally, the study presented in §5 completed objective O4.

There are a number of limitations to the success of this study in meeting its aims and objectives; these are discussed in §6.3 and §6.4.

6.2 Principal findings

Firstly, the review presented in §2 identified a number of opportunities for research. The majority of studies analysing the impact of climate change on the water resources of the UK use 'ensembles of opportunity' comprising either GCM or RCM model outputs. This has given rise to significant uncertainty in the direction and magnitude of changes in metrics of water resource availability that could be largely addressed using probabilistic climate projections such as those comprising UKCP09. Furthermore, the organisational structure of the water industry in the UK has led to a disaggregated view of water resource infrastructure with no overall strategic modelling capability easily available using prevailing methodologies; however, limitations associated with the available data on existing infrastructure and its operation constrain the options available. This is broadly consistent with the findings of Cave (2009), for example.

Secondly, the study of precipitation presented in §3 suggest the UK may experience progressively fewer drought events of shorter duration but increased severity relative to the 1961-1990 baseline climate, throughout the 21st Century. Shorter events, associated with a three-month deficit in precipitation and meteorological drought, show slight tendency to be less frequent in future, while longer events, associated with a six-month deficit in precipitation and hydrological drought, show slight tendency to be more frequent in future. This general trend is consistent with changes in rainfall exhibited in outputs from UKCP09 (e.g. Jenkins *et al.*, 2009) and the gist of, for example, Burke and Brown (2010) and Rahiz and New (2013). Despite catering specifically for monthly spatial coherence, the results of this study did not show a more consistent spatial trend in changes than other large-scale studies, possibly due to spatial aggregation and the choice of drought metrics used.

Thirdly, the study of average river flows and low flows presented in §4 suggests that river flow is very likely to decrease on aggregate across the UK throughout the 21st

Century, driven primarily by suppressed summer flows in England and Wales and offset fractionally by elevated winter flows in Scotland and Wales. This occurs concomitantly with broad decreases in Q95, particularly in autumn, and perhaps associated with elevated evapotranspiration in summer. The magnitudes and directions of changes in average daily flow and Q95 shared similarities with studies such as Sanderson *et al.* (2012), von Christierson *et al.* (2012) and Rance *et al.* (2012), despite using substantially different climate model outputs and climate variables to drive hydrological simulation.

Finally, the study of water available to meet demand presented in §5 suggests that the UK may experience substantial increases in water resources drought severity and duration over the 21st Century, not wholly mitigable in the east and south of England via inter-basin transfers from Wales and the Midlands. Although failure to meet demand within a 25-year forecast period is often a feature exhibited by the 'do nothing' scenarios of water undertakers during water resources planning exercises (e.g. Thames Water, 2011), the results of this study likely exaggerate the specific impacts of this phenomenon due to simplifications in the representation of the water resource infrastructure system necessitated by poor data availability and limited treatment of uncertainty. Furthermore, until comparable studies quantifying system performance across undertakers' boundaries come to fruition, it is difficult to place the results of this study in a context outside that of the water undertakers' planning literature; however, studies such as Walsh *et al.* (2016) espouse the importance of including demand-side measures in adaptation strategies, and it would be relatively straightforward to implement such scenarios via the modelling framework presented in this thesis for comparison.

The outcomes of the studies of changes in metrics of water resource described in §3, §4 and §5 tell a broadly similar story: that the quantity of water available for use via the public water supply infrastructure system of the UK is likely to decrease over the course of the 21st Century.

Comparison between the analyses of §4 and those of §3 suggests broad consistency between the two studies in terms of the direction and spatial distribution of changes in river flow and precipitation. This is particularly so in the association of elevated drought severity with reduced low flows and non-winter average flows in the south and east of England, and reduced drought duration in Wales and Scotland (particularly for events associated with a six-month precipitation deficit), associated with sizeable increases in mean flow in autumn and winter, and low flow in winter. These findings are consistent with increasing evapotranspiration but decreasing precipitation in the southeast and increased winter precipitation in upland areas, respectively.

These signals are also present in the results of §5, despite confoundment via the inclusion of additional dependencies on water resource infrastructure and demand. In particular, signals around changes in Q95 and minimum base flow relative to the 1961-1990 baseline are of great importance in this model. Areas having marginal excess deployable output but a high dependence on groundwater abstraction, such as Thames Water and Anglian Water, show exacerbated water stress attributable to inability to extract as Q95 and base flow deteriorate throughout the 21st Century.

In all cases, further investigation and analysis is needed to quantify the exact nature of the statistical relationships between the results of §3, §4 and §5.

6.3 Successes

In accomplishing its aims and objectives, this study has achieved a number of successes. Principally, the modelling framework developed and implemented throughout this thesis demonstrates a clear alternative to existing models of the water supply infrastructure system of the UK, which, although detailed and informed by local knowledge, are proprietary and opaque. They are furthermore cumbersome to harness in a framework facilitating national-scale assessment and probabilistic projection of climate change impacts. The framework used herein largely addresses these concerns, in two ways.

Firstly, the framework is transparent in its use of data and its formulation; it is both very flexible and powerful in its capacity to describe water supply infrastructure systems of varying complexity, and; it is implementable for descriptions of physical infrastructure ranging from the very simple to the very detailed, and is relatively lightweight. Furthermore, the rules used for determining water allocated to meet demand within the model of water supply infrastructure are simple and transparent in comparison to those used in undertakers' models (e.g. Ofwat, 2010), but sufficiently flexible to capture gross system behaviours on a variety of spatiotemporal scales. The overall simplicity of the design lends itself to comparatively short and concurrently executable model run-times, relative to prevailing alternatives, and enables computationally tractable use of probabilistic climate change projections and thus a more complete treatment of uncertainty due to natural variability and modelling uncertainty via UKCP09 (e.g. Murphy *et al.*, 2009). In this regard, the capabilities of the framework greatly exceed the uses to which it has been put in this study.

For example, given sufficient time, a much more comprehensive and spatially rich implementation of the framework could be run using the data already collated as part of this PhD research project. This could include disaggregation of sources of water by river basin, and the association of different basins with an appropriate hydrological model from the ensemble available, which would introduce more subtle variation in the quantity of water available for use. In addition, ensembles of demand could be integrated as an additional time-varying dimension, extending the use of the modelling framework beyond assessment of impacts under conditions already reported and into the realm of future infrastructure capacity assessment.

Secondly, the framework is explicit in its use of probabilistic climate change projections to inform the quantity of water available for use. In using large sample sizes from across the whole distribution of projection outputs, this is a more complete treatment of the uncertainties attributable to climate change than studies using 'ensembles of opportunity' alone, encapsulating uncertainties arising natural climate variability and modelling. This approach has been argued for by Harris *et al.* (2014), among others, and a leap forward in quantifying uncertainties inherent in climate change projection relative to methodologies prevalent among undertakers' models (e.g. Environment Agency *et al.*, 2012) and other national-scale assessments of water resource made for the UK (e.g. Rance *et al.*, 2012). It is conceptually very similar to the approach presented by Borgomeo et al. (2014), but uses more general formulations of climate variables, hydrological processes and water resources simulation, with a focus on the whole of the UK rather than the Thames catchment alone; however, Borgomeo *et al.* (2014) has extended the analysis by applying the 'Level of Service' criteria for water service performance popular among water undertakers of the UK.

6.4 Limitations

The methodology employed herein is not without its drawbacks and limitations, however.

Firstly, instantiations of the framework are still not computationally inexpensive, in that they can take several months to compute, even in a concurrent computing architecture such as that used in this study. This was particularly so in the synthesis of climate and hydrological variables supporting the framework, but also in the execution of water resources models containing multiple inter-regional connections. The computational cost of the latter certainly prevented a more thorough exploration of the impacts of demand on the performance of the water supply infrastructure system, and sensitivity analysis around the parameterisation of the model of water supply infrastructure. This is perhaps partly mitigable by re-implementing computationally intensive algorithms or data structures within the model source code, which focused on transparency rather than performance, but could also be addressed through re-implementation of the computation environment used. Many of the model runs required to build the framework and generate water resources model outputs were executed on a single dual-core laptop computer: execution time could be cut dramatically by wrapping the model in a modern containerised environment supporting concurrent execution. While not a direct limitation of the science used, this is quite relevant to the deployment of technologies such as probabilistic climate projections in the context of water resources simulation: the size and complexity of water resources simulation models are typically such that limited computational resources, and, correspondingly, a limited number of model runs, are often focused on exploring cost and business factors rather than exploring sensitivity to climate drivers and demand drivers. A lighter, more efficient model means more model runs, which (potentially) means more understanding of risk and uncertainty.

Secondly, and in relation, this study uses UKCP09 to present a more complete treatment of uncertainties arising from climate projections, but ostensibly neglects uncertainties arising from other components of the framework. It is unreasonable to assume that uncertainties arising from climate change projections consistently dominate the uncertainty spectrum of the overall analysis (e.g. Sellami *et al.*, 2016); however, to include a complete treatment of all uncertainties arising is almost impossible: model uncertainty and parameter value uncertainty is introduced at almost every stage of the framework, from precipitation sampling through to reservoir storage estimation, and it is likely that there are many 'unknown unknowns' (e.g. Fung *et al.*, 2011). The problem of estimating such uncertainty is long-standing; studies such as that of Ajami *et al.* (2008) go further in assessing hydrological model uncertainty, for example. To develop a similar approach for the UK would require the use of multiple alternative hydrological model formulations, run with ensembles of parameter values, vastly inflating the computational cost of analysis. This cost could be offset by replacing computationally expensive components of the framework, such as the sampling methods used by the model of climate variables, for more direct, less expensive methods (e.g. Patton, 2012).

Thirdly, while UKCP09 is the most comprehensive projection of climate change available for the UK, it is not without its limitations. Not only are the GCMs underlying the analysis absent some key processes and subject to a wider set of known uncertainties than are encapsulated in the modelling framework, but the structure of UKCP09 as a whole is constrained by design choices related to the application of change factors and the transformation of values (e.g. Jones *et al.*, 2009a; Borgomeo *et al.*, 2014). Furthermore, UKCP09 was designed and its outputs computed prior to the shift to RCPs (e.g. van Vuuren *et al.*, 2011). While perhaps suboptimal, this does not need to be of paramount concern, as the SRES scenarios used by UKCP09 map relatively cleanly to pairings of RCPs and SSPs for evaluation in the new context (e.g. van Vuuren and Carter, 2014). It is partly the use of UKCP09 as a source of climate projection information that elevates this methodology above, for example, Rance *et al.* (2012) in this regard: substituting this component for another, less comprehensive, projection of future climate solely for reasons of its design being outdated would undermine this key strength of the methodology disproportionately.

Fourthly, the paucity of data relating to water resources in the UK hampered detailed configuration, calibration and validation of the models used throughout this study, particularly those related to the water supply infrastructure system. A traditional validation might compare correlated observations of input variables from a period with a known response from the water supply infrastructure system with modelled system performance in response to the same sequences of input variable values. This could include taking observations of river flows, reservoir inflows and groundwater levels from a time of exacerbated water shortage, running these through a model, and comparing modelled drought severity, duration and frequency with observed drought severity, duration and frequency. This is not necessarily tractable and/or reliable in the context of the UK water industry, for, although observations of climate and hydrological variables are relatively available, they are of variable coverage and reliability, and, more importantly, measurements of the performance of the public water supply and even records of infrastructure location and specification are very limited in comparison.

Fifthly, public water supply comprises only a fraction of the wider uses of water in the UK. While critical to the wellbeing of the population, other uses, such as cooling for power generation, agriculture and industry all abstract from the water environment, and thereby compete with, and increase stress upon, the public water supply infrastructure. While studies such as Byers *et al.* (2015), Byers *et al.* (2016), Wade *et al.*(2012) and Watts *et al.* (2015) look at the impacts of climate change on water users outside of the public water supply, there is some inconsistency in the methods used, particularly from the perspectives of climate model outputs and hydrological simulation.

6.5 Opportunities for further research

The completion of this research has given rise to a number of further questions answerable by further research:

Question 1 **What is the uncertainty arising from climate variable synthesis?**

In generating synthetic time-series of climate variables, this study uses single formulations of precipitation amount and occurrence and evapotranspiration. Neither process enables quantification of uncertainty arising from model structure and/or parameter values. A more complete evaluation of such uncertainty requires sampling from the output of multiple formulations, combined with multiple sets of parameter values.

Question 2 **What is the uncertainty arising from hydrological simulation?**

This study uses a single hydrological model, and calibrates a single set of parameter values. As with Question 1, more complete evaluation of hydrological model uncertainty requires sampling from the output of multiple hydrological models, having differing formulation and/or structure, combined with multiple sets of parameter values.

Question 3 **What is the uncertainty arising from water resources simulation?**

This study uses a single model of water resources, with a single set of parameter values. As with Question 1, more complete evaluation of water resource model uncertainty requires sampling from the output of multiple water resources models, having differing formulation and/or structure, combined with multiple sets of parameter values.

Question 4 **What are the impacts of operational practises?**

The water resources model used in this study is limited in its description of the physical system by data availability: detailed descriptions of physical infrastructure, operating parameters and yields are not available with consistency across the UK. The omission of operating characteristics is particularly challenging, as these are highly variable and sensitive to local characteristics and socioeconomic drivers; however, their inclusion often has material positive impacts on the performance of the water resource system that is not explored in this study (e.g.Adeloye *et al.*, 2016).

Question 5 **What is the 'capacity' of the system?**

As described in §5.6.4, can the 'capacity' of the system be estimated reliably from the model formulation used in this study?

Question 6 **What historical droughts can the model framework reproduce?**

The capacity of the implementation of the model framework used in this study to reproduce historical droughts from meteorological, hydrological and water resources perspectives has not yet been ascertained. This may form an end-to-end 'calibration' of sorts for the framework as a whole, which may be important in using it (and other frameworks like it) in practical planning exercises. This is an extremely complex and difficult challenge, not only because information on the environment, the physical infrastructure and its operation is sparse, confounded and/or incomplete, but also because obtaining unbiased indicators of droughts affecting water resources in particular is made difficult because of what appear to be political reasons and reasons of commercial sensitivity.

6.6 Conclusions

This thesis has reviewed prevailing data and methods for modelling the impacts of climate change on the performance of the water supply infrastructure system of the UK, developed and prototyped a suitable methodology for the modelling of inter-basin transfers in the UK under climate change, and addressed the limitations of existing data and methods in the context of this application. By succeeding in the endeavour, this study represents a significant step forward in terms of implementing a risk-based approach to strategic water resources management in the UK.

In developing a new modelling framework, this study outputted analyses of the impact of climate change on indicators of meteorological, hydrological and water resources drought, the principal outcomes of which analyses suggest that the UK is likely to experience progressively fewer drought events of shorter duration and increased severity, resulting in substantial reductions in river flows and the time available to abstract from sources of water for the purposes of water supply. This leads to substantial increases in water resources drought severity and duration over the 21st Century, not wholly mitigable in the east and south of England via inter-basin transfers from Wales and the Midlands.

A number of limitations exist in this analysis, including a paucity of available relevant data pertaining to hydrological processes and water supply infrastructure, and inclusion in the framework of the uncertainties arising from hydrological and water resources modelling. These limitations could be addressed, to some extent, by further research; however, data availability is unlikely to improve in the UK.

In an international context, the specific outcomes of this research, being UK-centric, are of limited direct applicability; however, the novel approach taken in modelling climate variables and hydrological processes has been recognised via publication (Byers *et al.*, 2015; Byers *et al.*, 2016).

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Appendix A The Drought Severity Index (DSI)

After Phillips and McGregor (1998), The Drought Severity Index (DSI) is a measure of drought severity and duration with a retrospective component. Unlike alternative indexes, such as the Palmer index (Palmer, 1965), the DSI is computable from sparse data, requiring only observations of monthly rainfall as input.

From Blenkinsop and Fowler (2007), the n-monthly DSI (i.e. DSIn) is calculated as follows:

1. For each observation of monthly precipitation, compute the anomaly from the site 1961-1990 mean (Standard Average Annual Rainfall; SAAR)
2. If the anomaly is less than zero, and the preceding n-month anomaly is also less than its mean, a drought event is initiated, and DSI is assigned a value proportional to the anomaly at the current time-step
3. If the n-month mean total is exceeded, the drought event terminates, and DSI is assigned a value of zero
4. Finally, values of DSI are standardised by the site SAAR

In this study, the severity of an event is defined as the maximum value of DSI occurring during a drought event, while the duration of an event is defined as the number of months for which a drought event is active.