CONTROLS AND MODIFICATION OF LARGE-SCALE CLIMATE–HYDROLOGY–ECOLOGY ASSOCIATIONS

by

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A thesis submitted to the University of Birmingham for the degree of DOCTOR OF PHILOSOPHY

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July 2014

ABSTRACT

The study aimed to disentangle the climate–hydrology–ecology chain of processes at large spatial and temporal scales. River ecology was considered in terms of some of the main controls of physical habitat (environmental flows, hydraulics, and water temperature). The research included four complementing studies investigating associations between: (1) climate (atmospheric circulation and regional climate) and river flows; (2) river flows and river hydraulics; (3) regional climate and river water temperature; (4) regional climate and environmental flows. The first three studies focused on current conditions, had a national (mainland UK, or England and Wales) geographical scope and a seasonal temporal scale, and used only near-natural sites. In each study, the main drivers were identified, as well as the rivers or regions most/least sensitive. UK-focussed findings were then put into the wider context of future climate- and human-induced river flow change at the pan-European scale: a novel method to assess ecological risk due to flow alteration was developed and applied to flow scenarios for the 2050s. The role of basin properties in modifying those associations was also assessed. Two key aspects emerged: (i) importance of seasonal patterns; and (ii) strong basin property patterns. The study addressed the lack of studies with extensive geographical coverage, high site density, and long periods of records. Spatial patterns could only be found for studies involving climate and flow (historical or future projections); for hydraulics and temperature, spatial patterns were related to basin properties. For all studies, a small set of basin properties were found to have a significant influence: elevation, permeability (except for hydraulics), size (hydraulics and temperature only).

δὶς ἐς τὸν αὐτὸν ποταμὸν οὐκ ἂν ἐμβαίης.

You could not step twice into the same river.

Heraclitus of Ephesus (Fragment 41 quoted by Plato in *Cratylus* 402a)

To Dr C.

From Mr C.

ACKNOWLEDGEMENTS

This thesis is dedicated to my parents and their ancestors, and to my children Tom and Loïs and their potential descendants.

My PhD was for the most part funded by the Natural Environment Research Council. I would like to thank my supervisors Prof David Hannah and Prof Mike Acreman, as well as my colleagues from the Centre for Ecology and Hydrology who supported me in this endeavour. In particular, I would like to thank Oliver Swain, whose extensive knowledge of computing and data management was a great help in the early days of my research.

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LIST OF ABBREVIATIONS

AC	Atmospheric Circulation
AIC	Akaike's Information Criterion
ANOVA	ANalysis Of VAriance
AT	Air Temperature
CA	Clustering Analysis
CEH	Centre for Ecology and Hydrology
CHESS	Climate Hydrology and Ecology research Support System
CP	Capital Works
CRU	Climate Research Unit
CSI	Catchment Spatial Information
EA	Environment Agency
ERFA	Ecological Risk due to Flow Alteration
EU	European Union
FEH	Flood Estimation Handbook
GES	Good Ecological Status
HSD	Honestly Significant Difference
IRN	Intelligent River Network
JULES	Joint UK Land Environment Simulator
LOCAR	LOwland CAtchment Research
LWR	Long Wave Radiation
ML	Multi-level
MMI	Multimodel Inference
MORECS	Meteorological Office Rainfall and Evaporation Calculation System
MSE	Mean Squared Error
NAO	North Atlantic Oscillation
NAOI	NAO Index
NRFA	National River Flow Archive
P	Precipitation
PE	Potential Evaporation
RC	Regional Climate
RI	Relative Importance
SCENES	water SCenarios for Europe and for NEighbouring States
SH	Specific Humidity
SMD	Soil Moisture Deficit
SWR	Short Wave Radiation
UKAWMN	UK Acid Water Monitoring Network
UKMO	UK Meteorological Office
WaterGAP	Water–Global Assessment and Prognosis
WFD	Water Framework Directive
WS	Wind Speed
WT	Water Temperature

1. INTRODUCTION

Assessing the impact of climate natural variability or change on freshwater ecology requires a better understanding of the complex chain of processes occurring between climate signals and ecological responses. In particular, unlike for the terrestrial environment, freshwater ecosystems have to contend with the extra layer of processes that is hydrology. ‘Ecology’ refers to river freshwater ecology (i.e. excluding lakes and estuaries).

Figure 1.1 is a schematic diagram of the study undertaken for this thesis. For greater clarity, not all components of the climate–hydrology–ecology chain of processes are included (for example, water chemistry and sediments would play a key role as well) nor all interactions and feedbacks. Associations that are investigated in this work are shown as solid arrows, while the dashed arrows indicate linkages that are only mentioned qualitatively and/or in references. River ecology is considered from the perspective of the main physical variables that control the river ecosystems: temperature, hydraulics (e.g. depth, velocity), environmental flows (‘e-flows’). Temperature and hydraulics are straightforward physical variables, i.e. they can be measured, while environmental flows are an intellectual construct referring to those components of the river flow regime that are necessary to a healthy river ecosystem (this is why it is shown in a dotted box). In addition, since river sites are physically connected to the upstream hydrological river network, basin properties may play a role at all stages in the chain of processes (represented by the surrounding dashed box on the diagram). This diagram, although simplified, demonstrates the complexity of the climate–hydrology–ecology process chain, with a mixture of direct and indirect linkages between the various components (e.g. direct climate–temperature association, but indirect for climate–hydraulics via river flows).

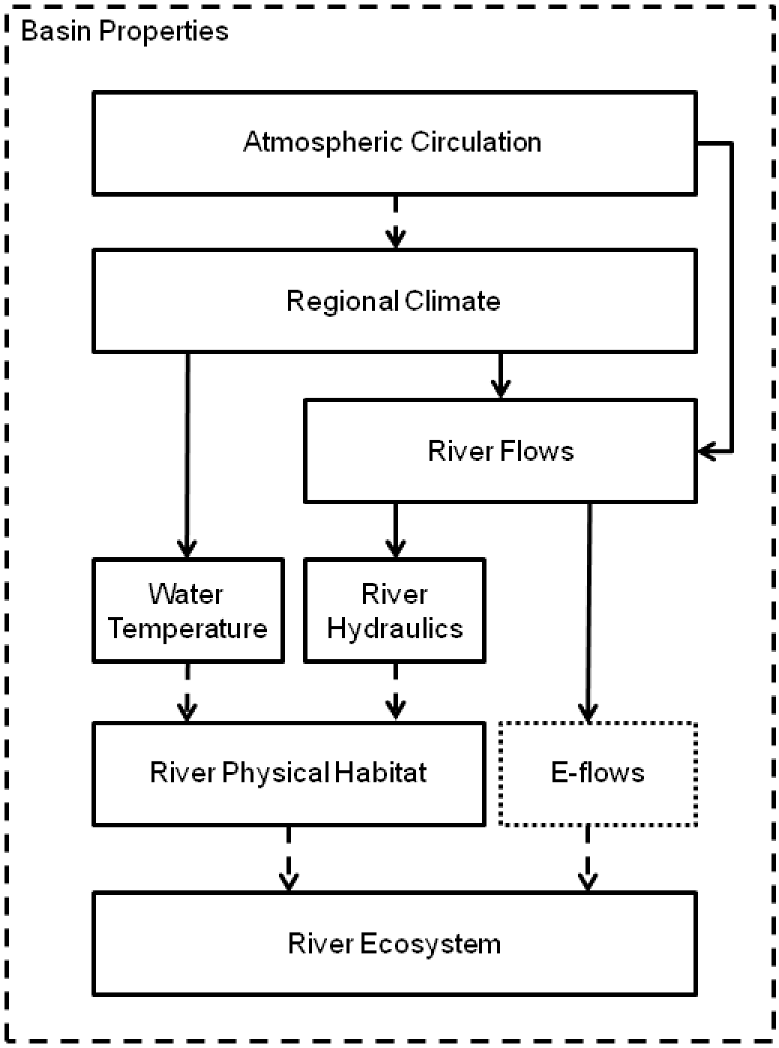

Figure 1.1: Schematic diagram of the study.

1.1 Research gaps and objectives

The literature review (Chapter 2) identifies that there is still limited knowledge of these linkages, especially at the larger (national, regional) spatial and temporal (seasonal) scales, with very few studies looking at the whole climate–hydrology–ecology chain. Basin properties are generally recognised as important but most often not investigated in detail. The overall aim of the thesis is therefore to disentangle the chain of processes presented in the study schematic diagram by achieving the following objectives:

1) To identify the main drivers of each linkage (solid arrows only)

2) To identify where and when rivers are least/most sensitive to changes in these processes, either arising from natural variability or future change
3) To assess the influence of basins as modifiers of the above associations

Beyond the scientific interest, there is a practical rationale for these objectives. Knowing which are the main drivers (objective 1), and mapping most/least sensitive regions or rivers within the study area (objective 2) are powerful decision support tool, allowing to prioritise resources (e.g. scientists monitoring only most relevant variables, practitioners targeting mitigation activities where and when most useful). Finally, relating those to basin properties (objective 3), as per regionalisation techniques, could be used as a high-level screening mechanism in the absence of environmental data, but with the increasingly wide availability of spatial information.

1.2 Thesis structure

Chapter 2 presents the literature review and further details the research gaps and objectives introduced here, while Chapter 3 presents the research design, data and methods used in this thesis. The first three result chapters (4–6) focus on current near-natural conditions (i.e. human influences are excluded as well as possible), national (UK) spatial scale and seasonal temporal scale where applicable: (1) Chapter 4; atmospheric circulation (AC)–river flows and regional climate (RC)–river flows associations; (2) Chapter 5; river flows and river hydraulics; (3) Chapter 6, RC and water temperature. In order to put findings from these chapters into a broader context and to gauge their transferability, Chapter 7 explores how future (c. 2050s) climate- and human-induced change would put river ecosystems at risk at the pan-European scale. The role of basin properties is investigated in each of the four result chapters.

Chapter 8 draws overall conclusions from the four result chapters and introduces potential future research avenues.

Parts of this thesis have been presented at workshops and conferences, and published in journals; in all cases, as first and corresponding author, C. Laizé led on the study design and write-up, performed all analyses, and managed the contributions from his co-authors as detailed below:

- Chapter 4: Journal of Hydrology paper (Laizé and Hannah, 2010; Appendix II); European Geosciences Union 2009 (poster presentation); British Hydrological Society (BHS) Symposium 2008 (oral presentation, conference paper); D. Hannah contributed comments on manuscripts and poster, and guidance as PhD supervisor.
- Chapter 6: HydroEco 2013, Rennes, France (oral presentation); American Geophysical Union (AGU) Fall Meeting 2012 (poster presentation); co-authors were C. Bruna Meredith (part of the data sourcing), M. Dunbar (statistical advice), and D. Hannah (comments on poster, PhD supervision).
- Chapter 7: River Research and Applications paper (Laizé *et al.*, 2014; Appendix III); AGU Fall Meeting 2011 (poster); BHS Third International Symposium 2010 (oral presentation, conference paper); co-authors were M. Acreman (method outline and advice during its development, additional paragraph, comments on manuscripts), C. Schneider and M. Florke (model runs), M. Dunbar (statistical advice), H. Houghton-Carr (project management), and D. Hannah (comments on manuscripts and poster, PhD supervision).

2. LITERATURE REVIEW AND RESEARCH OBJECTIVES

2.1 Overview

There are rather direct linkages between climate and terrestrial ecology to the point that vegetation maps were used in the past to map climate, many climate zones were named from their typical vegetation, and still nowadays paleoclimatology makes extensive use of vegetation to reconstruct past climate (Bonan, 2002). Yet, several studies illustrated the complexity of climate–terrestrial ecology associations. For example, Stenseth *et al.* (2002) investigated the effect of large-scale climate indices on sea fish and birds, and showed that disentangling the ecological consequences of climatic variation is not simple, and requires exploring the underlying causal mechanisms; Hallett *et al.* (2004) demonstrated that these large-scale climate indices can outperform regional-scale indices in predicting ecological processes related to sheep. In their literature review of the effects of global change on biodiversity, Oliver and Morecroft (2014) highlighted the complex interactions between climate and land use drivers.

Climate–freshwater ecology associations include extra layers of processes. Indeed, multiple factors determine the health of a river ecosystem (Norris and Thoms, 1999; Webb *et al.*, 2008; Moss, 2010; Acreman *et al.*, 2014b), e.g. light, water temperature, nutrients, discharge, channel structure, physical barriers to connectivity, species interactions and management practices (e.g. weed cutting, dredging, fish stocking). Many of the natural factors are interdependent (Vannote *et al.*, 1980; Rosenfeld *et al.*, 2007) and anthropogenic factors often co-vary (47% of 9,330 European river sites were found to be impacted by multiple pressures; Schinegger *et al.*, 2012). Ultimately, freshwater ecosystems are subjected to pressures produced by complex interactions between natural and human factors (Grantham *et al.*, 2010; Hart and Calhoun, 2010).

Heino *et al.* (2009) noted that there are many more published studies on climate change impact on terrestrial biodiversity than on freshwaters. There are also relatively few studies attempting to integrate climate–hydrology–ecology, and most often the geographical extent and/or site density are limited: single basin in Wales, UK (Bradley and Ormerod, 2001), c. 50 sites in southern England, UK (Durance and Ormerod, 2007); single site in France (Daufresne *et al.*, 2004); single mountainous basin in France (Hannah *et al.*, 2007); single basin in Canada (Wolfe *et al.*, 2008).

A schematic diagram of the climate–hydrology–ecology study undertaken for this thesis has been introduced in Chapter 1. The linkage between climate and river flow (i.e. discharge in m^3s^{-1}) belongs to the field of hydroclimatology, for which there are a number of commonly used approaches covering data requirements, methods, variables and metrics. Specific research gaps and objectives are covered in section 2.2.

All elements of a flow regime are important to river ecosystems, e.g. high, medium, and low flows, timing and frequency of extreme events (Tennant, 1976; Junk *et al.*, 1989; Poff *et al.*, 1997; Richter *et al.*, 1997), which is captured in the term 'environmental flows' (Acreman *et al.*, 2014a). However, apart from dilution effects, discharge has only an indirect effect on river ecosystems. Indeed river organisms respond to hydraulics, either directly (e.g. shear stress), or via the physical habitat (i.e. depth and veloctiy; Waters, 1976) created by the interaction between flow and channel morphology (Booker and Acreman, 2007*).* The relation between physical habitat and biota has been demonstrated, for example for trout abundance (Jowett, 1992), benthic community diversity (Gore *et al.*, 1998), spawning density of salmon (Gallagher and Gard, 1999). The importance of hydraulic habitat is ultimately demonstrated in the rapid emergence of ecohydraulics as a sub-field (Maddock *et al.*, 2013). This provides the rationale for investigating the river flows–hydraulics linkage, which is covered in details in section 2.3. Physical habitat is also conditioned by stream temperature, a key physical variable for many river processes (Hannah and Garner, 2015); the linkage between climate and temperature is reviewed in section 2.4.

Lastly, although discharge is an indirect driver for river ecosystems, analysing environmental flow alteration is a sensible and practical approach to assess impacts on river ecosystems (e.g. Richter *et al.*, 1996) especially when dealing with large-scale patterns, or in the absence of habitat or biological data. This is the approach taken to investigate future river ecosystems, and is reviewed in section 2.5.

2.2 Climate–river flows

Improving understanding of climatic forcing on river flow represents a major research challenge of practical relevance (Chorley, 1969; Kingston *et al.*, 2007; Kingston *et al.*, 2009) due to high socio-economic dependence on water resources (Vörösmarty, 2002; Montanari *et al.*, 2013) and sensitivity of riverine and riparian ecology to flow variability (Hannah *et al.*, 2007). Moreover, there is a pressing need to predict accurately future water stress and risk within the context of climate change (Bower *et al.*, 2004; Harding *et al.*, 2014). Over the last decade, increased research focus has been directed toward identifying and explaining large-scale hydroclimatological linkages as demonstrated through major international initiatives such as the UNESCO–International Hydrological Programme Flow Regimes from International Experimental and Network Data (Servat and Demuth, 2006) and the International Association of Hydrological Sciences–Prediction in Ungauged Basins (e.g. Theme 1 on basin inter-comparison and classification; Sivapalan *et al.*, 2003; Hrachowitz *et al.*, 2013).

The climate–river flow chain of causality can be conceptualised in simple terms with large-scale AC (e.g. North Atlantic Oscillation (NAO)) influencing RC (e.g. basin-scale precipitation and air temperature) that provides the 'input signal' to the river basin that is modified by basin properties and basin–RC feedbacks (Wilby *et al.*, 1997; Phillips and McGregor, 2002). Several hydroclimatological studies demonstrated that useful insight and/or forecasting skills may be gained from investigating AC–flow (e.g. Stahl and Demuth, 1999; Svensson and Prudhomme, 2005; Kingston *et al.*, 2007) and RC–flow relationships (e.g. Phillips *et al.*, 2003; Bower *et al.*, 2004).

Understanding the role of basin properties is paramount to evaluating climate change signals in river flow (that may be dampened or enhanced by basin properties). However, basin properties are often not, or insufficiently, considered in such climate–flow research. Basin typology is an important topic within hydroclimatological classification (Wagener *et al.*, 2007). The importance of basin physical characteristics for hydrology is well established (e.g. Horton, 1945; Strahler, 1957); basin properties are central to making predictions for ungauged basins (Burn and Boorman, 1992; Croke *et al.*, 2006; Yadav *et al.*, 2007). Basin physical properties play a pivotal role in the rainfall–runoff relationship at small spatial (e.g. basin) and temporal (e.g. daily) scales, with development of basin-modified rainfall–runoff transfer functions providing the basis for many regionalisation approaches, for example, continuous rainfall–runoff modelling (Young, 2006; Kay *et al.*, 2007). However, as spatial scale increases, it can be hypothesized that the impact of climate variability takes precedence over land-use controls (Blöschl *et al.*, 2007) and, by extension, basin physical properties more generally. By analogy, it may be hypothesised that over longer time scales (i.e. seasonal and beyond) the influence of basin properties on flows may also diminish relative to climate variability.

A number of studies demonstrate the existence of linkages between long-term hydrological behaviour and basin properties. However, which properties and hydrological indicators are related, and the strength of these relationships vary depending on the geographical location and type of basins, and on the specific hydrological indicators being investigated. There are two main approaches used to investigate this issue. On the one hand, studies using a *physically-based modelling framework* show that the effects of seasonal climatic variability on long-term hydrology (e.g. annual water balance) is modulated by diverse sets of basin properties: soil, vegetation and topography (Woods, 2003), mature forest cover (Detenbeck *et al.*, 2005), and soil properties and topography (Yokoo *et al.*, 2008). Notably, the combination of physiographic and climate descriptors was found to have more influence on flows than either driver acting alone (Berger and Entekhabi, 2001; Hejazi and Moglen, 2008), and the importance of basin scale is confirmed (e.g. land-use change only noticeable at smaller scales; Hurkmans *et al.*, 2009). On the other hand, some studies focus on *statistical analysis of historical data*. For example, long-term river flow trends in Swiss basins were found to be correlated with mean basin elevation, glacier and rock coverage, and basin mean soil depth (Birsan *et al.*, 2005); whereas, in the USA, river flow trends were related to elevation and forest and wetland coverage (Johnston and Shmagin, 2008). The role of hydrogeological controls on stream flow sensitivity to climate variation was confirmed by Jefferson *et al.* (2008) using catchments with contrasting geological properties and drainage efficiencies (groundwater-dominated and quick runoff-dominated). Meanwhile, an international assessment using 1,508 basins, covering the whole range of sizes, found that land-use information can explain a small part of long-term river flows (Oudin *et al.*, 2008). Subsequently, Oudin *et al.* (2010) generated two distinct pools using c. 900 French basins based on hydrology and on basin properties: both pools overlapped for 60% of the basins, with the remaining 40% having regimes influenced by specific geologies. In contrast, for 459 Austrian basins, land use, soil types, and geology did not seem to exert a major control on runoff coefficients (Merz and Blöschl, 2009). In a UK context, while studies agree generally on the importance of understanding the influence of basin properties, in particular geology, often research has not proceeded much beyond characterisation of a broad northwest–southeast or lowland–upland divide that maps onto national-scale topographic and climatic gradients (Arnell *et al.*, 1990).

There have been relatively few UK studies of hydroclimatological associations (Table 2.1), and they have employed: (1) single sites or networks of basins with restricted geographical coverage and/or sparse density; and/or (2) river flow records impacted by anthropogenic influences. Kingston *et al.* (2006) identified both these research gaps as important because limited spatial scope leads to incomplete or contradictory evidence in integrating the full climate–flow process cascade, and using impacted basins introduces confounding effects that can mask climatic control on flows.

Table 2.1: Recent hydroclimatological studies of the UK or parts thereof.

Authors	Geographical Coverage	Number of UK Basins
Smith and Phillips (2013)	East Anglia (England)	11
Lavers *et al.* (2010)	UK	10
Sen (2009)	England & Wales	15
Kingston *et al.* (2006)	Northern North Atlantic incl. Scotland	12
Svensson and Prudhomme (2005)	UK	20
Bower *et al.* (2004)	UK	35
Wilby *et al.* (2004)	Thames basin (England)	1
Phillips *et al.* (2003)	UK	2
Wedgebrow *et al.* (2002)	England & Wales	14
Wilby (2001)	UK	12
Harris *et al.* (2000)	England & Wales	4
Shorthouse and Arnell (1999)	Western Europe incl. UK	n/a
Arnell *et al.* (1990)	UK	112

This section identified two important research objectives: to improve the understanding of climate–river flow association, and of the way it is influenced by basin properties. It also identified the following research gaps: (1) few UK studies of climate–river flow associations; (2) restricted geographical coverage and/or sparse site density; (3) river flow records impacted by anthropogenic influences; (4) basin properties only investigated very broadly. These gaps and objectives are addressed in Chapter 4.

2.3 River flows–river hydraulics

As seen in section 2.1, the discharge–habitat association provides a way to assess ecological impacts in a river (Cavendish and Duncan, 1986; Jowett, 1990; Beecher *et al.*, 1993). For example, one major ecological impact of drought is habitat loss due to decreasing depths and velocities (Dollar *et al.*, 2013). The hydraulic sensitivity to flow change of a site is consequently of major interest.

Bovee (1982) was the first to base a habitat–discharge model on these concepts. First, depth and velocity suitability for various species or life stages have been collated (e.g. field observation, experiments, expert knowledge). For example, Figure 2.1 gives the suitability curves for juvenile trout (0–7cm); a suitability of 1 depth- or velocity-wise means that any parts of the river with such depths or velocities are suitable as habitat (suitability curves for other species or life stages are different but generally have similar shapes). Regarding depth, it shows that a minimum depth is required but past a certain threshold depth, there is no evidence that organisms prefer higher depths; to summarise, if it is deep enough, all available habitat is suitable. Velocity is more complex; organisms need the water to flow fast enough to bring enough food to them but not so fast that they get exhausted swimming, or simply washed away. The peak of the suitability curve in Figure 2.1 corresponds to the energetic optimum (food intake *v* swimming). At a given cross-section, depth and velocity suitability indices are combined to give the proportion of the cross-section that is usable by juvenile trout (see examples for a few selected UK sites in Figure 2.2). The shapes of these curves are controlled by the site hydraulic characteristics.

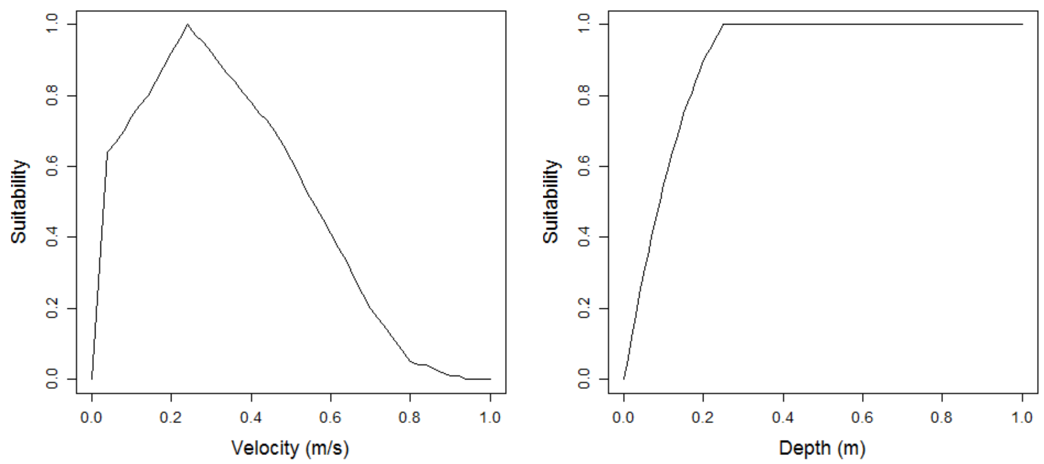

Figure 2.1: Velocity (left) and depth (right) suitability curves for juvenile trout (0–7cm).

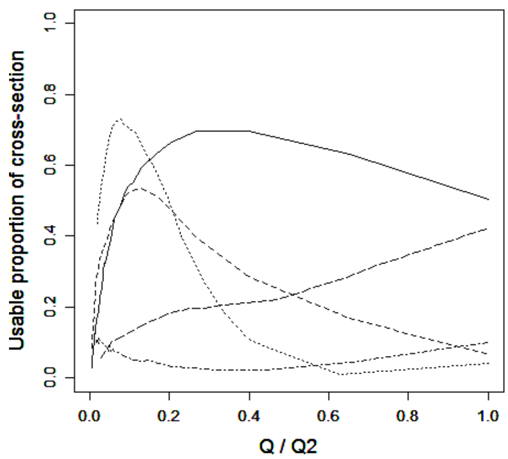

Figure 2.2: Proportion of cross-section usable by juvenile trout (0–7cm) as function of flow (standardised with bankfull flow Q_2) for UK selected sites.

One shortcoming of full physical habitat models is that they are site-specific and require extensive collection of field data including velocities, depths and water surface elevations at several different flows (Bovee, 1982). Habitat–discharge models based on simpler measurements of river channels have been developed worldwide, e.g. France (Lamouroux and

Capra, 2002), New Zealand (Lamouroux and Jowett, 2005). Hydraulic geometry (HG) is a simple characterisation of river hydraulics based on wetted width, mean water depth, and mean water velocity, which are power functions of flow in natural rivers (Leopold and Maddock, 1953)**.** The suitability curves are based on detailed hydraulic data (i.e. panel velocities and depths), which are aggregated by using HG, but it has been recognised that HG provides a very good approximation for less demanding data requirements (Jowett, 1998; Rosenfeld *et al.*, 2007).

The assumption that rivers within the same physiographic regions should have similar HG equations (Johnson and Fecko, 2008) forms the basis for channel design tools, e.g. regional curves in the USA (Keaton *et al.*, 2005), or for predictive models of HG equations (e.g. Booker, 2010)**,** while some authors argue that HG and basin physical characteristics are actually not as strongly associated as believed, with more local factors controlling HG (Ridenour, 2001). This makes the understanding of the influence of basin properties on HG an important topic (Keaton *et al.*, 2005).

There are few studies formally investigating the influence of physical factors on HG (Table 2.2); most of them focus on the USA or New Zealand, and tend to consider a limited number of physical factors. The only recent major UK study on HG (c. 1,000 sites in England and Wales; Booker and Dunbar, 2008), the focus of which was to develop a predictive model of HG equations rather than characterising UK hydraulic patterns, only explored basin properties based on literature, not on a formal analysis. In addition, studies often focus solely on the exponents of the HG equations while ignoring the multipliers (Dingman, 2007).

Table 2.2: Studies formally investigating the influence of physical factors on HG.

Reference	Geographical Scope	Number of Sites	Physical Factors
Booker (2010); W only	New Zealand	326	Basin size, climate, geology, topography, land cover
Rosenfeld *et al.* (2007)	New Zealand	73	Steepness
Keaton *et al.* (2005)	USA	41	Geology
Dodov and Foufoula-Georgiou (2004); W only	USA	85	Basin size
Malkinson and Wittenberg (2007)	Israel	1	Riparian vegetation
Wohl (2004)	USA, New Zealand, Nepal	10 rivers with multiple sites	Site topography
Merritt and Wohl (2003)	USA	22	Steepness, vegetation
Döll *et al.* (2002)	USA	17	Urban/rural land use
Jowett (1998)	New Zealand	73	Steepness
Huang and Warner (1995)	USA and UK	>500	Stability and sediment properties of banks
Miller and Onesti (1977)	USA	103 (single basin)	Basin drainage structure and shape
Park (1977)	Worldwide	211	Climate

This section identified two important research objectives: to improve knowledge of river hydraulic (HG) sensitivity to flow, and of the way it is influenced by basin properties. It also identified the following research gaps: (1) few UK studies; (2) limited number of sites and/or basins; and/or (3) limited number of physical properties investigated. These gaps and objectives are addressed in Chapter 5.

2.4 Climate–water temperature

River and stream water temperature (WT) is a key control of many river processes (e.g. ecology, biogeochemistry) and services (e.g. power plant cooling, recreational use); Webb *et al.* (2008). From the perspective of river ecology, its influence is both direct (e.g. organism growth rates (Imholt *et al.*, 2013), predator–prey interactions (Boscarino *et al.*, 2007), activity of poikilotherms, geographical distribution (Boisneau *et al.*, 2008)) and indirect (e.g. water quality (chemical kinetics), nutrient consumption, food availability (Hannah and Garner, 2015)).

Consequently, the effect of climate change and variability on stream temperature is a major scientific and practical concern. River thermal sensitivity to climate change and variability is controlled by complex drivers that need to be unravelled in order to better understand patterns of spatio-temporal variability and the relative importance of different controls to inform water and land management, specially climate change mitigation and adaptations strategies. There is a growing body of river temperature research but there is still limited understanding of large-scale spatial and temporal variability in climate–WT associations, and of the influence of basin properties as modifiers of these relationships (Garner *et al.*, 2013).

River thermal regimes are complex because they involve many interacting drivers. Caissie (2006) identified atmospheric conditions as the most important group of influencing factors, with basin physical properties (e.g. topography, geology) as also important; while streambed exchanges (e.g. groundwater input) and stream discharge were considered secondary influences.

The main climate variables (Figure 2.3) which constitute the atmospheric conditions group, can be identified by analysing the theoretical heat budget for a stream reach without tributary, which may be expressed as with Equation 2.1 (adapted from Webb and Zhang, 1997):

$$Q_n = Q_r + Q_h + Q_e + Q_b + Q_f + Q_a \qquad \text{Equation 2.1}$$

where Q_n is the total net heat exchange, Q_r the heat flux due to net radiation, Q_h the heat flux due to sensible transfer between air and water (sensible heat), Q_e the heat flux due to evaporation and condensation (latent heat), Q_b the heat flux due to bed conduction, Q_f the heat flux due to friction at the bed and banks, and Q_a the heat flux due to advective transfer by precipitation and groundwater.

The different components of Equation 2.1 correspond to different processes, some not related to climatic conditions. Q_r corresponds to the net radiative energy fluxes, i.e. the heat received minus the heat emitted by the river. Of the heat flux received by the river, the processes associated with climate are short wave radiation (SWR, direct sunlight) and long wave radiation (LWR), which is radiation bouncing back on clouds and re-emitted towards the ground. Q_h corresponds to energy exchanges between air and water (at the surface) leading to a long-term equilibrium between air temperature (AT) and WT; this causes water cooling or heating depending on circumstances. Q_e is mostly evaporation i.e. cooling of water. Q_b and Q_f do not relate directly to climate processes, and can be assumed to be negligible anyway (Hannah *et al.*, 2008). Q_a corresponds to advective heat exchanges, i.e. due to a volume of water at a different temperature coming into the river system, cooling or heating the river depending on circumstances. The climatic component of this is precipitation (P), which is thought to have a limited contribution (Caissie, 2006). It is worth emphasising that these processes are very different in their form (radiative heat flux for SWR and LWR, convective for AT, evaporative for SH, advective for P).

These variables are not independent; Figure 2.3 features a schematic representation of the interactions between these variables. Short and long wave radiations heat up water but also the air, then air and water exchanged heat to reach equilibrium. Additionally, wind plays a significant role in cooling water by increasing evaporation (i.e. by removing moisture at the water surface) and in modifying the air–water exchanges by increasing mixing; the physical equations underpinning the role of wind can be found in Caissie *et al.* (2007).

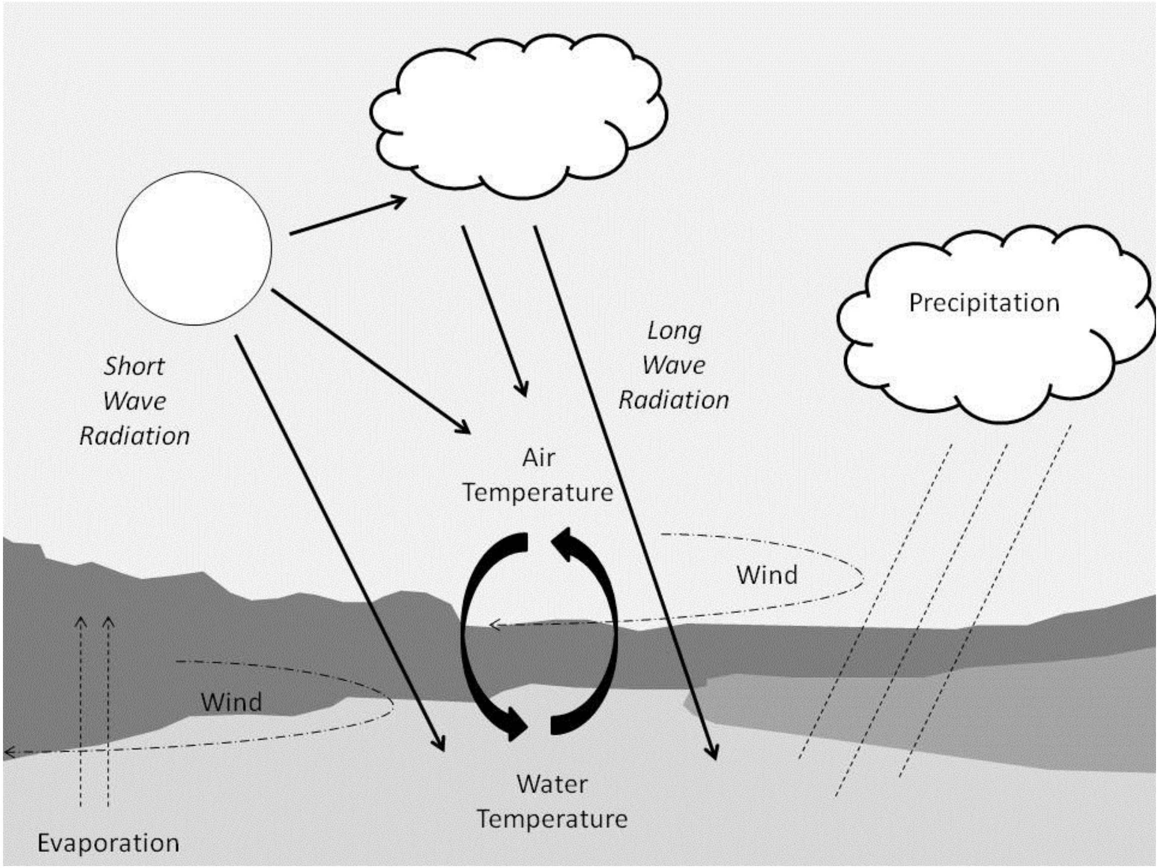

Figure 2.3: Multiple interdependent climate controls of water temperature [adapted from Caissie (2006) and Hannah *et al.* (2008)].

UK-focused studies (Table 2.3) tend to be either specific to a few monitoring sites, to have a limited geographical extent, and/or to consider few climate drivers. One major difficulty is to pair WT and climate monitoring sites, as monitoring is rarely coordinated, then to identify time series with long enough common periods of record. For example, Garner *et al.* (2013) could only match water temperature monitoring sites with climate and hydrological monitoring sites for 38 temperature sites out of c. 3,000 sites. This study is one the very few to consider explicitly the role of a limited number of basin properties.

In most of these studies, given the limited number of sites, analyses are done on a site by site basis, which limits the extent to which broad pattern can be inferred (statistical results for a given site are only valid for that site, and, if sites are fully pooled, ignoring the inherent data structure can lead to spurious results). In contrast, a study like Garner *et al.* (2013) groups sites together using classification techniques in order to capture the national patterns. However, doing so causes a loss of data (data-points of all sites within a class are aggregated, e.g. with class summary statistics) where data are already relatively scarce, and it is not necessarily possible to apply results at class level back to the individual site ("ecological fallacy"). An alternative method should be investigated.

Table 2.3: Climate–water temperature studies carried out in the UK.

Reference	Number of Sites	Number of Basins	Location	Number of Climatic Variables	Length of Study Period
Wilby *et al.* (2014)	36	2	central England	1	2 years
Garner *et al.* (2013)	38	-	England & Wales	1	
Broadmeadow *et al.* (2011)	10	2	south England	3	3 years
Brown *et al.* (2010)	6	1	north England	2	2 years
Hrachowitz *et al.* (2010)	25	1	northeast Scotland	0	2 years
Hannah *et al.* (2008)	2	1	northeast Scotland	7*	2 years
Malcolm *et al.* (2004)	6	1	northeast Scotland	1	3 years
Hannah *et al.* (2004)	1	1	northeast Scotland	9*	6 months
Webb *et al.* (2003)	4	1	southwest England	1	5 years
Langan *et al.* (2001)	1	1	northeast Scotland	1	30 years
Evans *et al.* (1998)	1	1	west England	9*	17 days
Webb and Zhang (1999)	2	2	South England	5	2 seasons
Crisp (1997)	5	1	northwest Wales	1	3 years
Webb and Zhang (1997)	11	1	southwest England	4	2 seasons

* includes different measurements of related climatic variables

The research objectives identified in this section are to improve the understanding (i) of large-scale spatial and temporal variability in climate–WT associations, and (ii) of the influence of basin properties as modifiers of these relationships. This section identified the following research gaps: (1) climate–WT studies in the UK only using a limited number of WT sites and climate explanatory variables, and/or limited geographical extent; (2) limited knowledge of role of basin properties as modifiers of climate–WT associations; (3) need for alternative analysis method to optimise data usefulness. Research gaps and objectives are addressed in Chapter 6.

2.5 Future environmental flows

Discharge is a key habitat variable, which changes dynamically in space and over time (Bunn and Arthington, 2002; Monk *et al.*, 2008a). In addition to natural variations, river discharge may be influenced heavily by anthropogenic activities, such as water abstraction, storage in reservoirs and effluent returns, all associated with public supply, agriculture and industry. Several authors have suggested that many elements of the river flow regime, such as magnitude, variability and timing can influence freshwater ecosystems (Junk *et al.*, 1989; Richter *et al.*, 1996; Poff *et al.*, 1997; Biggs *et al.*, 2005; Arthington *et al.*, 2006; Kennen *et al.*, 2007; Monk *et al.*, 2008b). For example, the loss of wet–dry cycles and the stabilisation of water levels reduce the growth and survival of native aquatic macrophytes and favour invasive macrophytes (Bunn and Arthington, 2002). Further examples of the ecological impact of flow regime changes have been collated by Richter *et al.* (1998), while Bunn and Arthington (2002), Lytle and Poff (2004), Bragg *et al.* (2005) and Poff and Zimmerman (2010) provide comprehensive reviews of the literature.

Most flow–ecology studies have been based on the 'natural flow paradigm' (Poff *et al.*, 1997), which uses the unaltered flow regime as the baseline reference condition and assumes any departure from 'natural' will lead to ecological change. Change can be interpreted in terms of impacts on living organisms (see references above) and/or more generally in terms of loss of ecosystem functions or services. For example, a change in flow regime causing a decrease in fish population also has an impact on fish-related ecosystem services that is food provision and recreation (Okruszko *et al.*, 2011). The functional relationship between flow alteration and ecological impact can take many forms (Arthington *et al.*, 2006), but is normally a linear (or curvilinear) response, or a threshold response/step function (Poff *et al.*, 2010). For the latter, there are clear threshold responses (e.g. overbank flows needed to support riparian vegetation or to provide fish access to floodplain), but, for the former, critical points may need to be defined by expert judgement (Biggs and Rogers, 2003; Arthington *et al.*, 2004; Richter *et al.*, 2006). Many ecosystems have a high capacity to absorb disturbances without significant alteration, consequently some ecosystem functions and services may be restored by re-introducing certain flow regime elements, whereas for other functions, the ecosystem may be pushed beyond its resilience limits and may change to a new irreversible state. The resilience of ecosystems was conceptualised by Holling (1973) and has been subsequently applied widely (for a recent example relevant to rivers see Robson and Mitchell, 2010).

The Millennium Ecosystem Assessment (2005) shows that many water-dependent ecosystems are being degraded or lost, with freshwater systems suffering due to withdrawal of water for human needs and fragmentation/loss of connectivity due to regulatory structures (Nilsson *et al.*, 2005). River discharge is anticipated to change in the future and it is estimated currently that habitats associated with 65% of ‘continental discharge’ are at risk worldwide (Vörösmarty *et al.*, 2010). Similarly, Schinegger *et al.* (2012) found that of 9,330 European river sites, 41% had altered hydrology and 35% altered morphology. In this context, there is a pressing need to better quantify broad scale future risks to European river ecosystems due to flow regime alterations.

There are few studies in the scientific literature addressing future ecologically relevant flow regimes and most focus on a limited number of sites and/or a limited geographical extent, and are often qualitative rather than quantitative. As highlighted in Heino *et al.* (2009), there are many more papers on the impact of climate change on terrestrial biodiversity than on freshwater, and results about the latter tend to be for a small number of organisms, ecosystems, or regions. For example, the impact of climate change on macro-invertebrates in two UK rivers was investigated by Wright *et al.* (2004) while Graham and Harrod (2009) focused on fish in Britain and Ireland. More comprehensive analyses of climate impact on all aspects of freshwater ecosystems have been published with varying geographical extents: local (Johnson *et al.*, 2009); UK-wide (Clarke, 2009; Wilby *et al.*, 2010); regional (northern regions; Heino *et al.*, 2009). Döll and Zhang (2010) undertook a worldwide study of future ecologically relevant flows, using a broad-scale gridded model with a cell resolution of 30' x 30' (about 55 x 55 km^2 at the equator, which is equivalent to 3,025 km^2) and flow statistics that were a broad summary of the flow regimes (e.g. long-term annual averages).

The research objectives identified in this section are (i) to assess river ecological risk due to future flow alteration at the broad pan-European scale; and (ii) to identify which parts of Europe or which types of basins are most/least at risk. There are a number of research gaps: (1) there are few studies on impact of climate change on freshwater ecosystems; (2) studies have limited number of sites, limited geographical extent, and/or coarse resolution; (3) they are often descriptive rather than quantitative; (4) they tend to consider only climate-induced change, not combined climate and socio-economic pressures; (5) they tend not to consider all ecologically-relevant aspects of the flow regime. Research gaps and objectives are addressed in Chapter 7.

3. RESEARCH DESIGN, DATA AND METHODS

3.1 Research design

The research design breaks down the conceptual diagram presented in the introduction (Figure 1.1) into four independent but complementing studies, which investigate a specific step in the climate–hydrology–ecology chain of processes (solid arrows on diagram); Table 3.1 gives a summary of these studies.

Table 3.1: Overview of the research design.

Association	Geographical Extent	Time Scale	Period	Number of Sites
Climate (AC and RC)–river flows	Mainland UK	Seasonal	1975–2005	104
River flows–river hydraulics	England and Wales	Not applicable	1993–2006	>2,500
Climate (RC)–water temperature	Mainland UK	Seasonal	1984–2007	35
Climate (RC)–environmental flows	Greater Europe (including UK)	Monthly	2040–2069	>30,000

The first three studies (Chapters 4–6) focus on current conditions. As much as practically feasible, they are using data free of artificial influences, and their geographical scope is national (mainland UK, or England and Wales). Geographical extent, site density, and period of records have been maximised given monitoring situation and data availability in the UK. For the climate–river flows and the climate–WT studies, the research focuses on longer time steps because in highly variable systems, some associations are only identifiable at longer time steps. It also allows resolving issues with data collected at different time steps and temporal auto-correlation. In addition, longer time steps are more relevant to river ecosystems, as they usually respond to longer term signals (e.g some hydroecological models use half-year time steps; Laizé *et al.*, 2012). This partly reflects data availability (biological monitoring has often a frequency of one sample per season or per half-year), partly the fact that ecosystems are resilient and can cope with much variability (Holling, 1973; Robson and Mitchell, 2010).

The fourth study (Chapter 7) focuses on future conditions. It considers both climate and human impacts on environmental flows, and expands the geographical scope to greater Europe to provide a broader spatial context and to allow for cross-scale comparison. European rivers are modelled as c. 30,000 cells, corresponding to c. 700 major basins.

3.2 Data

3.2.1 Climate

3.2.1.1 Precipitation

Monthly basin average precipitation data (unit: mm) for the gauging sites used in Chapter 4 were derived from UK Meteorological Office (UKMO) raingauge network measurements interpolated at basin-scale using the Voronoy methodology (British Standards Institution, 1996).

3.2.1.2 Meteorological Office Rainfall and Evaporation Calculation System (MORECS)

Two variables from MORECS (Hough and Jones, 1997) were used in Chapter 4: (1) monthly estimates of Potential Evaporation (PE) from a free-water surface as given by the Penman–Monteith equation; (2) Soil Moisture Deficit (SMD) i.e. amount of water needed to raise soil moisture content to field capacity, estimated as the difference between modelled actual evaporation and modelled rainfall; both units: mm. The MORECS data are available as 40-km grids across the UK.

3.2.1.3 North Atlantic Oscillation Index (NAOI)

Monthly values of the NAOI were retrieved from the Climate Research Unit (CRU, University of East Anglia, UK; http://www.cru.uea.ac.uk/cru/data/nao/; accessed February 2008). This NAOI version is calculated from the difference in surface pressures between Gibraltar and Iceland (Jones *et al.*, 1997).

3.2.1.4 Climate Hydrology and Ecology research Support System (CHESS)

The CHESS dataset features six climate variables (Table 3.2). CHESS is the forcing dataset for the Joint UK Land Environment Simulator model (JULES; Best *et al.*, 2011). CHESS is a UK-wide 1-km grid dataset derived by downscaling the UKMO MORECS 40-km grids (Hough and Jones, 1997) except for precipitation, which is based on raingauge data (Keller *et al.*, 2006). For each 1-km cell, modelled daily time series of all variables are available for the period 1971–2007. The processes linked to AT, LWR, P, and SWR are given in the stream heat budget overview in section 2.4. Specific humidity (SH) gives a measure of evaporation (i.e. the more humidity, the less evaporation). Wind speed (WS) is self-explanatory. These variables are used in Chapter 6.

Table 3.2: CHESS data.

Climate Variable	Abbreviation	Units	Explanation
Air temperature	AT	^{o}K	
Long wave radiation	LWR	$W\ m^{-2}$	Downward energy bounced back by clouds
Specific humidity	SH	$kg\ kg^{-1}$	
Precipitation	P	$kg\ m^{-2}d^{-1}$	Unit equivalent to $mm\ d^{-1}$
Short wave radiation	SWR	$W\ m^{-2}$	Downward direct energy (i.e. sunlight)
Wind speed	WS	$m\ s^{-1}$	

3.2.2 Hydrology

3.2.2.1 Observed river flows

Gauged river flows are used in Chapter 4. In the UK, hydrometric data collected by the principal measuring authorities—Environment Agency (EA) in England and Wales, Scottish Environment Protection Agency in Scotland, and the Rivers Agency in Northern Ireland—are stored in the National River Flow Archive (NRFA). This database includes more than 1,300 gauging sites and a total of more than 45,000 station-years of daily mean river flow records (unit: m^3s^{-1}). The NRFA has identified a subset of 132 reference basins covering the country ('benchmark catchments'), which are considered of high scientific value because of their near-natural river flow regimes (Bradford and Marsh, 2003). Hence, these benchmark catchments provide a useful resource for assessment of climate–hydrology associations without the confounding factor of major direct (e.g. water abstraction) or indirect (e.g. land-use change) human modification of flows. Benchmark status is granted to basins for which the gauging station has: (1) good hydrometric performance across the range of flows and (2) little or no disturbance of the flow regime by abstractions, discharges or other flow regulation. Since there are very few pristine basins in the UK, the NRFA defines near-natural basins as those with hydrometric records 'undisturbed' at low flows (i.e. the observed Q_{95} flow, which is the flow equalled or exceeded 95% of the time, is within 10% of the naturalised Q_{95}).

3.2.2.2 Modelled river flows

Modelled monthly flow (unit: m^3s^{-1}) time series for pan-European rivers were used to investigate future conditions. The data were generated with the global hydrological model WaterGAP (Water–Global Assessment and Prognosis), and are described in Chapter 7 within the context of the full study.

3.2.3 River hydraulics

Detailed hydraulic measurements were retrieved from the EA. This dataset consists of the detailed gauging information recorded while doing spot flow measurement at cross-sections for various operational reasons, as opposed to continuous flow monitoring at established gauging stations. The raw dataset includes 4,445 sites totalling 42,591 measurements over the 1993–2006 period (with most gaugings within 1996–2006). The number of records per site ranges from one to 215, with 30 on average. A vast majority of gauging used standard hand-held current meters. Standard gauging techniques were applied (i.e. cross-sections split into panels for which velocities are measured vertically at different depths). For each gauging, the detailed panel data include average velocity over a set period, depth of measurement, distance from the bank, etc. Flows are not held in this database but were calculated using standard velocity–area equations. Similarly, any site-averaged hydraulic variables used in this thesis were calculated as part of the data processing. Regarding naturalness, there were no recent or authoritative metadata available to objectively filter out impacted sites so that all data were assumed to be reasonably natural. However, qualitative information about historical channel modifications was used in the analysis. See Chapter 5 for details.

3.2.4 River water temperature

The WT data used in Chapter 6 were collated from various completed or on-going projects, involving or ran by the Centre for Ecology and Hydrology (CEH), UK. The temporal resolution of the individual datasets therefore varies, as well as the way data are or were collected. As often the case, water temperature is not the main focus of these projects: fish for the rivers Frome (Welton *et al.*, 1999), Great Ouse, and Tadnoll (Edwards *et al.*, 2009) studies; impact of forestry on water quality for the Plynlimon catchment project (Neal *et al.*, 2010); acidification monitoring for the UK Acid Water Monitoring Network (UKAWMN) project (Evans *et al.*, 2008); hydrological and biogeochemical processes for the LOwland CAtchment Research (LOCAR) project (Wheater *et al.*, 2006). These datasets totalled individually 41 sites. Given the specifications of the original projects, temperature data can be considered free of artificial influences.

3.2.5 Physical properties

Basin and site physical basin properties used in Chapters 4 to 6 came from threes sources:

- UK Flood Estimation Handbook (FEH), the UK industry standard for flood regionalisation studies, which includes 19 basin descriptors (Bayliss, 1999); a selection of descriptors were used therein, which are listed with detailed definitions in Appendix I, Table 1.
- NRFA Catchment Spatial Information dataset (CSI); developed by Laizé (2004) and expanded by Laizé (2008), the CSI dataset provides for any gauged site on the NRFA database: basin elevation distribution (based on CEH 50-m grid Integrated Hydrological Digital Terrain Model), bedrock and superficial deposit permeability (based on 1:625,000 Hydrogeological map from the British Geological Survey), and land use (broad categories based on CEH Land Cover Map 2000); used in Chapter 4, where more details are given.
- CEH Intelligent River Network (IRN; Dawson *et al.*, 2002); the IRN is a geographical information system (GIS) application designed for automated site and basin information extraction for UK rivers; variables include altitude of site, distance from source, slope, Strahler and Shreve indices, and total length of upstream rivers; used in Chapter 5.

Chapter 7 used the basin properties built within the WaterGAP model, i.e. elevation, land cover, geology; more detailed are given in the relevant section.

It is noteworthy that many physical properties are correlated, whether by design (as some FEH descriptors), or due to their occurrence in the UK (e.g. permeable basins mostly in lowland areas). In each chapter, all properties were tested for their significant influences. Then, properties identified as having a significant influence were checked for redundancy (using property definitions, correlation matrices, and/or pair plots), and eventually dropped or grouped ("meta-properties") as part of result interpretation. Knowledge gained in each preceding chapter informed the next, In particular, in Chapter 4, land cover was found not to bring much additional insight, so was not used in Chapters 5 and 6. However, it was investigated in Chapter 7 given the a priori different European context.

3.3 Methods

This section introduces existing methods or statistical techniques that have been used in this thesis. Specific details of their implementation for a given study are detailed in the corresponding chapter. Ecological Risk due to Flow Alteration (ERFA) is a new method, which was developed as a core component of Chapter 7 and is presented there.

3.3.1 Seasonal variables

Seasonal time series were computed for several variables from the corresponding daily time series in Chapters 4 and 6. Common season definitions were applied: December–February (winter), March–May (spring), June–August (summer), and September–November (autumn). For winter, the seasonal data for year y are based on data from December of year y-1 to February of year y (e.g. for 1976, December 1975, January and February 1976).

3.3.2 Classification

Classification, also called clustering analysis (CA), was used in Chapter 4. Aggregating basin information at regional scales is typically the first step in analysing hydroclimatological associations (Stahl and Demuth, 1999), which are often characterised by strong regional patterns (Shorthouse and Arnell, 1999). Previous published studies commonly group basins with similar flow regimes using CA then calculate composite flow series for identified classes (e.g. Kingston *et al*., 2006).

CA belongs to the field of multivariate statistics, which includes other techniques like ordination. Multivariate statistics aim at identifying patterns in the data but not deriving inferences. CA specifically aims at identifying clusters (or classes) of similar data-points. A detailed description of the clustering statistics can be found in Gordon (1999).

First, a matrix is built with the descriptive variables of interest on one side (e.g. flow metrics, physical characteristics), and the observations (e.g. at sites, on different days) on the other side). Then distances between the entries in the descriptive variable space are calculated. Different measures of distance are possible but this thesis used Euclidean distances. The resulting matrix is called the dissimilarity matrix (the farther entries are in the variable space, the more dissimilar they are) and is the input to the CA algorithm.

As it is common practice with CA, different hierarchical and non-hierarchical clustering techniques are applied because different CA algorithms generally identify different classes. Statistical usage recommends to retain the technique producing classes of fairly equal size (a class with few members being most likely an artefact due to outlier data) and that can be broadly interpreted physically, within the context of the study (Gordon, 1999). In this thesis, hierarchical clustering was performed using seven methods: single, average and complete linkages, median, centroid, McQuitty, and Ward. Dendrograms and scree plots (agglomeration schedules) were inspected to assess clustering algorithms' performance, and to decide how many clusters should be retained. These are two complementing types of plots showing how different would be a CA using n clusters from one using $n+1$ clusters.

Dendograms are hierarchical trees with a single cluster on top (with all entries), branching down, with each individual entries in their own "cluster" at the bottom; the closer are the *n* and *n+1* clusters on the tree, the less different they are. They are most useful to assess if clusters are evenly sized. Scree plots are curves with the cumulative difference on one axis and the number of clusters on the other. They usually feature an inflexion point indicating the the optimal number of clusters. Resulting clusters were mapped to check if they had broad physical meaning. Ward's minimal variance method (Ward, 1963) was found to yield the most physically meaningful and evenly-sized classes, which is consistent with previous hydrological regionalisation studies by Bower *et al.* (2004) and Hannah *et al.* (2005). This method starts with singleton clusters, and at each stage, identifies and merges the pair of clusters that causes the minimum increase in total within-cluster variance after merging.

A limitation of hierarchical clustering algorithms is that once a basin is assigned to a class, it cannot be re-assigned to another class (i.e. clusters cannot be refined once constituted), thus leading to potentially sub-optimal solutions. One approach to deal with this limitation is to perform non-hierarchical clustering (*k*-means) to re-assign across cluster membership, using the hierarchical cluster centres as the starting point. Using *k*-means has constraints as it cannot handle missing data, i.e. either some data in-filling is required beforehand, or part of the data cannot be used. In this study, *k*-means was tested, but the refinement achieved using this two-stage clustering procedure was very limited, so that hierarchical clustering only was ultimately retained.

3.3.3 Modelling techniques

3.3.3.1 Linear regression

Explanatory modelling was used as the tool to investigate and characterise associations between variables of interest. The basis for modelling was linear regression either because associations were linear (eventually after a simple variable transformation, e.g. natural logarithms in non-linear power laws in Chapter 5), or because, following common modelling usage, the research initial focus was to assess the linear portion of the associations. Details on linear regression can be found in statistical textbooks, for example, Sokal and Rohlf (1995). Single (i.e. one predictor) or multiple (i.e. several predictors) linear regression was used depending on circumstances. Linear regression was either applied on its own (e.g. Chapters 4), or combined with more complex statistical techniques (e.g. Chapters 5 and 6), which are described below.

3.3.3.2 Multi-level modelling

The multi-level (ML) modelling framework was used with linear regression to analyse multiple-site datasets by pooling all sites together while taking into account the data structure. In Chapters 5 and 6, the respective datasets of both studies did present a structure (e.g. data-points at given site, sites on given river and/or within given catchment), which supported the use of ML. It is noteworthy that ML modelling is not restricted to linear regression, but since it was the only type used in this thesis, it is presented within that context.

When analysing multiple-site datasets, there are two common alternatives: performing one regression per site, or one regression on all sites pooled together. On the one hand, site-specific regressions (i) can make results highly uncertain for sites with few data-points; (ii) are more prone to Type II errors (i.e. identifying significant relationships spuriously; with a threshold *p* value of 0.05, fitting regressions for 100 sites would give on average five Type II errors). Drawing out general patterns (e.g. variation between sites, effect of site characteristics) can therefore be difficult. On the other hand, full pooling of sites ignores the clustering of samples within sites, which may hide important differences between sites and may cause problems with statistical inference (e.g. violation of the assumption of independence between samples, sites with large or small numbers of samples equally influencing the model outcome).

ML modelling allows for the pooling of data from different sites while taking into account the data hierarchical structure. For example, a common ML structure is with two levels: individual observations (level 1) nested within monitoring sites (level 2). A ML model has two components, which correspond to generic patterns (i.e. similar to a regression on fully-pooled data) and to level-specific patterns. This is illustrated with a simple two-level (observations within sites) model of water temperature as a function of air temperature (data from Chapter 6) in Figure 3.1. The generic patterns, which are described by the explanatory variables as in a standard regression, are called the ‘fixed component’ or ‘fixed effects’ of the model; in Figure 3.1, this is the regression line (solid black) for all sites (grey and black crosses) together. The unexplained variation between levels (i.e. site-specific patterns here) is termed the ‘random component’ or ‘random effects’. The random component captures the fact that levels may respond differently to a given predictor (example of one site as black crosses and dash line in Figure 3.1). In practice, a ML model outputs both fixed component coefficients, which are the same for all levels and random component coefficients, which vary from one level to another. Not all explanatory variables from the fixed component are included in the random component, but if a variable is in the random component, it is required to be in the fixed component as well.

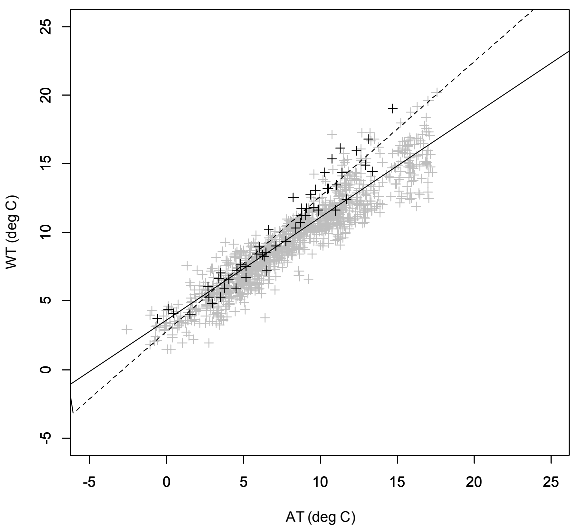

Figure 3.1: Illustration of generic response (fixed component; all sites as grey and black crossses, fitted regression as solid line) *v* site-specific response (random component; example of one site only displayed as black crosses, fitted regression as dash line); example based on air (AT) and water (WT) temperature data from Chapter 6.

3.3.4 Model selection

3.3.4.1 Information criterion

Two different model selection techniques were applied. Both used the Akaike's Information Criterion (AIC; Akaike, 1974). AIC comes from the field of information theory, and is calculated in Equation 3.1 as follows:

$$AIC = 2k - 2\ln(L) \qquad \text{Equation 3.1}$$

Where k is the number of predictors in the model, and L the maximised likelihood function of the model.

AIC selects models offering the best compromise between goodness of fit and predictor parsimony. When comparing a set of models, the better models are the ones with the smaller AIC (including negative values). AIC corrected for small-size datasets ('AICc') was used in Chapter 6 according to statistical usage (i.e. small sample size and/or large number of variables; Burnham and Anderson, 2002).

3.3.4.2 Stepwise

The multiple linear regressions presented in Chapter 4 were selected using the stepwise regression technique based on AIC. This selection technique retains one model, i.e. the one with the lowest AIC. Note that this may lead to the inclusion of variables that have, on their own, a high *p* value. There are two variants of stepwise: backward elimination and forward selection. With backward stepwise, the starting model includes all candidate variables. One variable is deleted, the AIC of the new model calculated. If the AIC improves, that variable is dropped. This process is repeated until there is no further improvement of the AIC. With forward stepwise, the starting model has only one variable. One variable is added, the AIC of the new model calculated, and the variable retained if there is any improvement. Similarly, the process is repeated until there is no further improvement of the AIC. Forward and backward stepwise techniques were both applied and selected identical models.

3.3.4.3 Multimodel inference

Multimodel inference (MMI) is a model selection technique that considers sets of models and model outputs. With MMI, model selection yields sets of good models rather a single best one. Using a traditional model selection technique, like stepwise regression, the model with the best (i.e. the lowest) AIC would be selected. This presents two issues: (1) due to the algorithms underlying these types of selection techniques, some model formulations may end up not being tested thus causing a sub-optimal selection; (2) given models with similar AIC values have similarly good performance, it is not statistically correct to keep the lowest AIC model only as the best model and discard the others. MMI addresses these issues by selecting sets of good models. In practice, all possible combinations of the predictors in the full model are fitted and the resulting models are ranked based on their AIC. Then, following recommended statistical usage, all models within four points of the lowest AIC are selected

(Zuur *et al.*, 2009). MMI was used with ML models in Chapter 6; Grueber *et al.* (2011) cover the above points in details and give a very good example of such an application of MMI in a natural sciences context.

3.3.5 Model performance

Model performance was assessed by using plots of observed versus modelled values (such as in Chapter 6), and/or the Mean Squared Error (MSE) defined as the mean of the squared differences between observed and modelled variables (such as in Chapter 5).

3.3.6 Testing association between variables

3.3.6.1 Kendall test

The Kendall *tau* (Kendall, 1938) is a rank-based correlation test used in Chapters 4 and 7. It was chosen because it is the most appropriate for hydrological and climatological datasets, which do not conform to assumptions underlying other correlation tests (e.g. normal distribution). Kendall was preferred to Spearman, another common rank-based test, because the former allows easier interpretations of results, and provides the basis for other tests commonly used in climatology and hydrology (e.g. Mann–Kendall test for trend).

3.3.6.2 Analysis of variance

Univariate ANalysis Of VAriance (ANOVA; Sokal and Rohlf, 1995) was used to assess if a given variable y is significantly related to a given basin property x. It is the same technique that compares two nested models when doing model selection, but, in this case, formally testing two hypotheses: H_0: y = a (y equal to its mean, y and x not related); H_1: y = a + bx (linear relationship between y and x). Consequently, a basin property is considered having significant influence on a variable of interest when the p value of the ANOVA test (F test) is below or equal to 0.05. The variable y can be categorical (such as the flow classes in Chapter

4) or continuous (such as the site-specific coefficients in Chapter 6). In the former case, the interpretation of the test is: H_0, basin property means are the same across all classes; H_1, basin property means differ for at least one class.

3.3.6.3 Tukey's Honestly Significant Difference

Used with classes, ANOVA only tests if classes are all similar or not. Multiple comparison procedures are then applied to determine which classes differ. These procedures are designed to compare many pairs of classes at once, thereby avoiding Type II errors, which would happen if testing each pair independently. Tukey's Honestly Significant Difference (HSD; Tukey, 1949) test was used; pairs of classes, for which Tukey's HSD test p value ≤ 0.05 are considered significantly different (Chapters 4, 5, and 7).

4. CLIMATE AND RIVER FLOWS

4.1 Introduction

This chapter addresses the research gaps and objectives identified in section 2.2. It aims at better understanding climatic forcing on river flow and the role of basin properties at dampening or enhancing across the UK for calendar seasons by: (1) characterising spatial patterns in winter, spring, summer and autumn flows; (2) identifying regions for which AC and RC drivers exert strongest control on seasonal flows; and (3) identifying basin properties which have a significant influence on seasonal flows. Research gaps were: (i) few UK studies of hydroclimatological associations; (ii) restricted geographical coverage and/or sparse site density; (iii) river flow records impacted by anthropogenic influences; (iv) basin property influence investigated at very broad level only. They are addressed by using a denser and more extensive network than previous work (Table 2.1) with a total 104 gauged basins covering mainland Great Britain and having near-natural flow records, and a wider selection of basin properties.

4.2 Data

4.2.1 River flows

Gauged daily mean flows were retrieved from the NRFA for all benchmark catchments on the British mainland (excluding Northern Ireland) with records for 1975–2005, i.e. a subset of 104 out of 132 benchmark catchments (see 3.2.2.1 and Figure 4.1). This time span was chosen for analysis because it offered the optimum trade-off between maximising geographical coverage and number of basins against minimising amount of missing data. Seasonal flow averages (unit: m^3s^{-1}) were computed from the daily flow data. To permit ready comparison of basins with different river flow magnitudes, seasonal flows were standardised by subtracting the overall mean and dividing by the standard deviation to give *z*-scores (mean = 0; standard deviation = 1; dimensionless) prior to analysis.

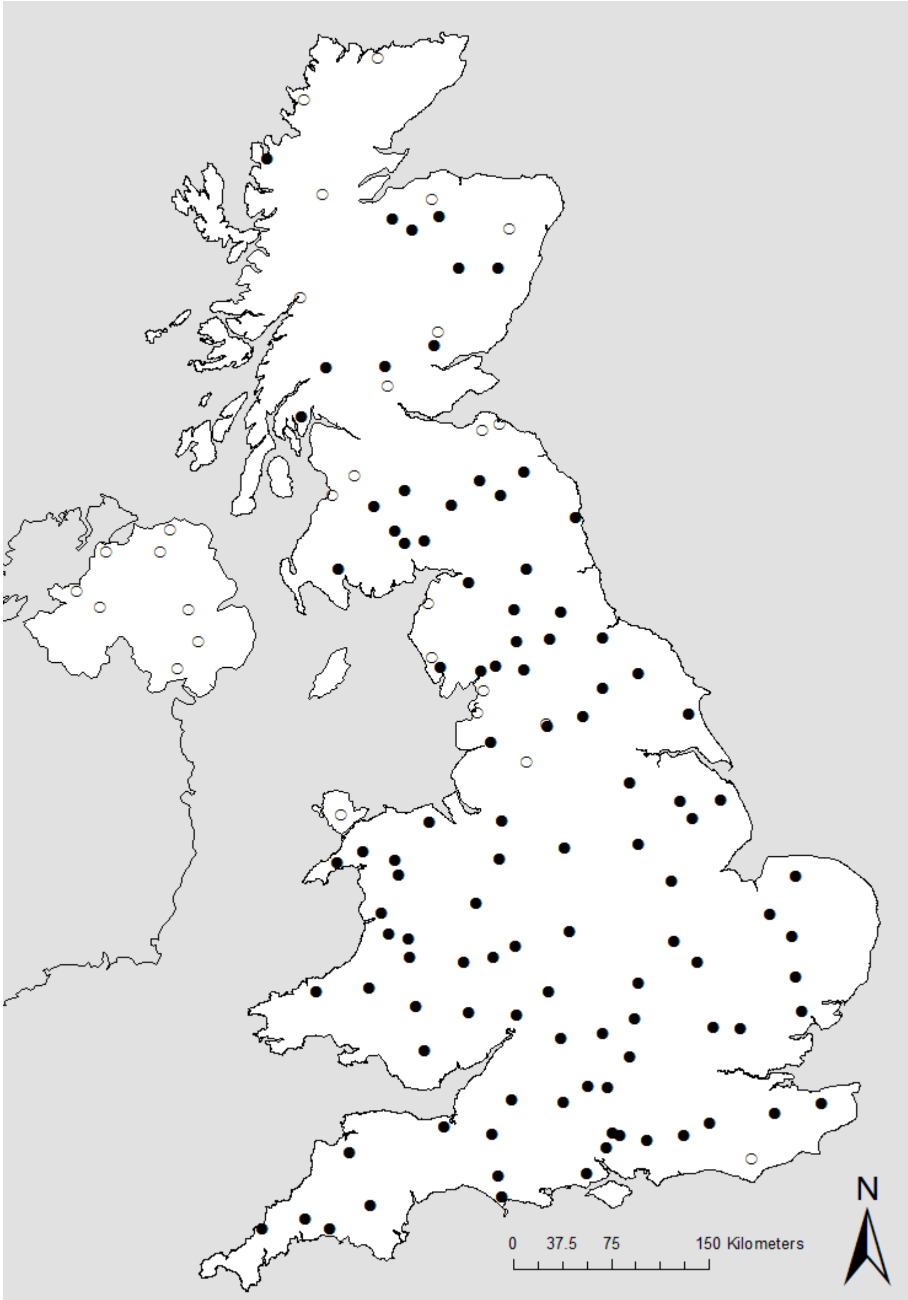

Figure 4.1: Distribution of 132 near-natural basins across the UK ('benchmark catchments'); solid dots indicate the subset of 104 basins with records in the 1975–2005 period used in this study.

4.2.2 Regional climate

The variables selected to characterise basin climate over the same period as flow records were observed precipitation (rainfall; see 3.2.1.1), modelled PE and SMD from MORECS (see 3.2.1.2); all units: mm. Precipitation gives a measure of water input, PE of potential water losses, and SMD an indication of the antecedent moisture conditions. In a GIS, the basin boundaries were overlaid on the MORECS 40-km grid to calculate mean PE and SMD for each of the 104 basins. Most basins were contained wholly within a single MORECS grid cell. For basins overlapping more than one MORECS grid cells, a weighted average value was calculated based on the proportion of contributing cells. Similarly to river flows, seasonal averages of basin precipitation, PE, and SMD were standardised by *z*-scores (dimensionless).

4.2.3 Atmospheric circulation

The NAO is one of the major large-scale climate controls in Europe (Hurrell, 1995) and exerts a strong influence on hydroclimatological variables (Wilby *et al.*, 1997; Kingston *et al.*, 2007). It is acknowledged that there are other circulation patterns that may be important for UK climate (e.g. Scandinavian and East Atlantic patterns) and other atmospheric classifications (e.g. Lamb Weather Types and Grosswetterlagen; Fleig *et al.*, 2011) but it was beyond the scope of this thesis to investigate all of these potential climate drivers. Monthly values of the NAOI were retrieved from CRU (see 3.2.1.3), from which the winter NAOI (i.e. average December–February) was calculated. Given that previous work demonstrated that the influence of the NAO on hydrological systems is strongest in winter (Wilby, 2001; Phillips *et al.*, 2003), only the winter NAOI was used in this study.

4.2.4 Basin physical properties

A selection of basin properties were analysed, which can be considered static at the time scale of this study (physiography, land cover, geology, etc.) as opposed to dynamic properties (average rainfall, wetness, etc). Two sources were used (see 3.2.5): (1) FEH descriptors (full list with definitions in Appendix I, Table 1); (2) NRFA CSI.

4.3 Method

Often hydroclimatological associations are characterised by strong regional patterns (Shorthouse and Arnell, 1999); therefore, aggregation of basin information at the regional scale is a typical first step in such analyses (e.g. Stahl and Demuth, 1999). In previous research, a common approach has been to statistically group basins with similar flow regimes and to calculate composite flow time-series for the emergent classes (e.g. Kingston *et al.*, 2006; Monk *et al.*, 2008b). In this study, for each season independently, basins were grouped according to similarity of their flow regimes, thus giving four distinct sets of classes, then composite time-series of flows and climatic data (precipitation PE, SMD) were derived for which AC– and RC–seasonal flow relationships are investigated. Composite time series were calculated for each class in a season as the mean flow, precipitation, PE, and SMD for all basins included in that class.

4.3.1 Classification of seasonal flows

Building on previous hydrological regime classification studies (Hannah *et al.*, 2000; Bower *et al.*, 2004; Hannah *et al.*, 2005), for each season independently, basins were grouped based on similarity of standardised flow indices as identified with CA using Ward's hierarchical clustering (see 3.3.2).

4.3.2 Assessing seasonal flow associations with regional climate and atmospheric circulation

RC–flow relationships were investigated through univariate and multiple linear regression analyses. Results from univariate linear regressions (R^2) are presented only if they are significant at the 5% level (i.e. *T* test, p value ≤ 0.05). For multiple linear regressions, the best model were identified using both backward and forward stepwise selection (see 3.3.4.2), which gave the same results.

AC–flow relationships were investigated using the Kendall *tau* test (see 3.3.6.1). Since the study used winter NAOI to describe AC, this part of the analysis investigated AC–flow relationships that were lagged for spring, summer and autumn, but not lagged for winter.

4.3.3 Assessing seasonal flow associations with basin properties

ANOVA (see 3.3.6.2) was used to assess if different seasonal flow classes have different distributions of basin properties (significance at the 5% level). If it was the case, Tukey's HSD test (see 3.3.6.3) was then applied to assess which pairs of classes are significantly different (at the 5% level).

4.4 Results

4.4.1 Mapping of seasonal flow classes

For each season, the 104 basins were classified as mapped in Figures 4.2 to 4.5. The number of flow classes varies between eight (winter), seven (spring and summer) and six (autumn). For ease of reference, classes are named based on geographical regions (Table 4.1).

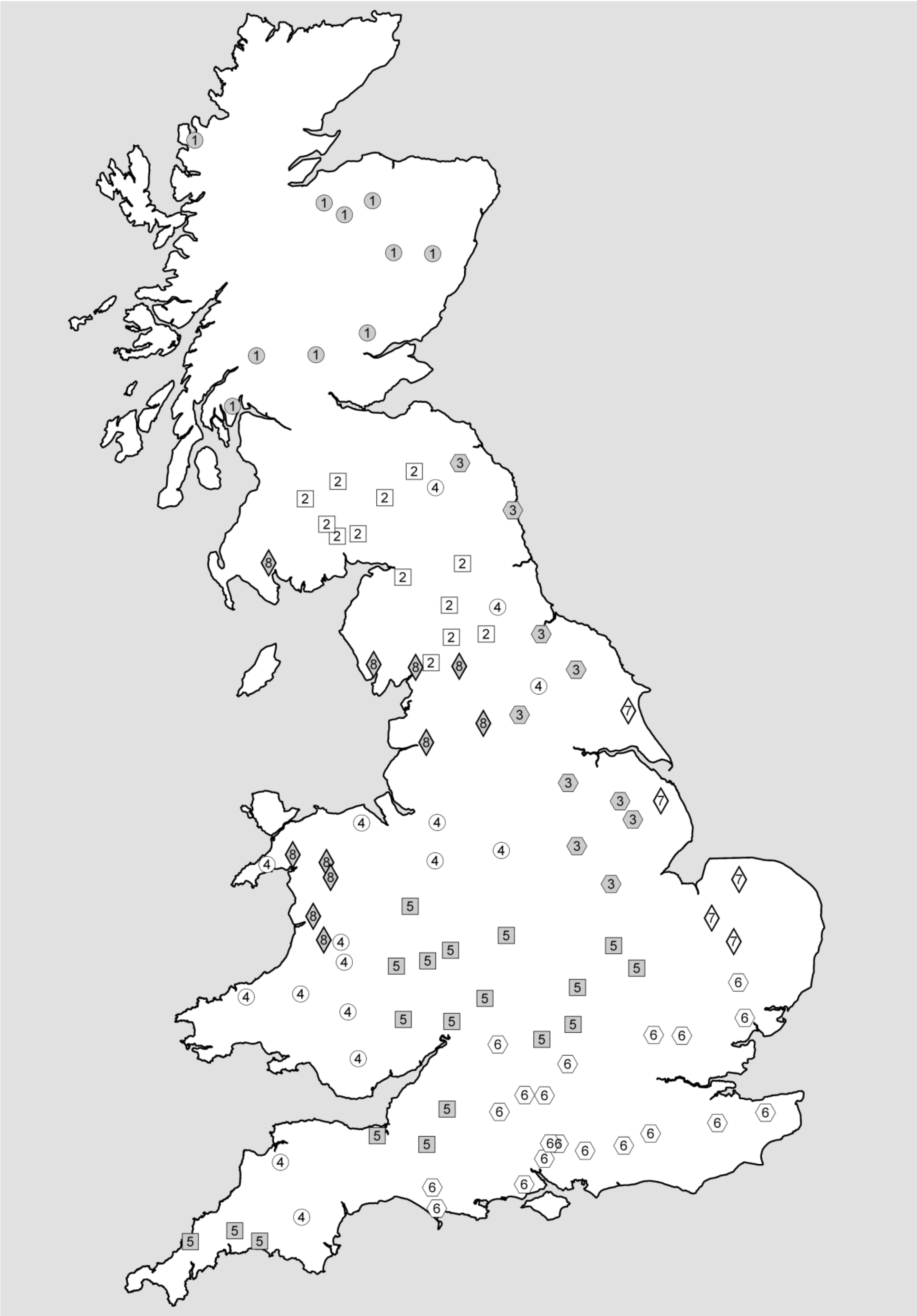

Figure 4.2: Distribution of winter river flow classes for 1975–2005.

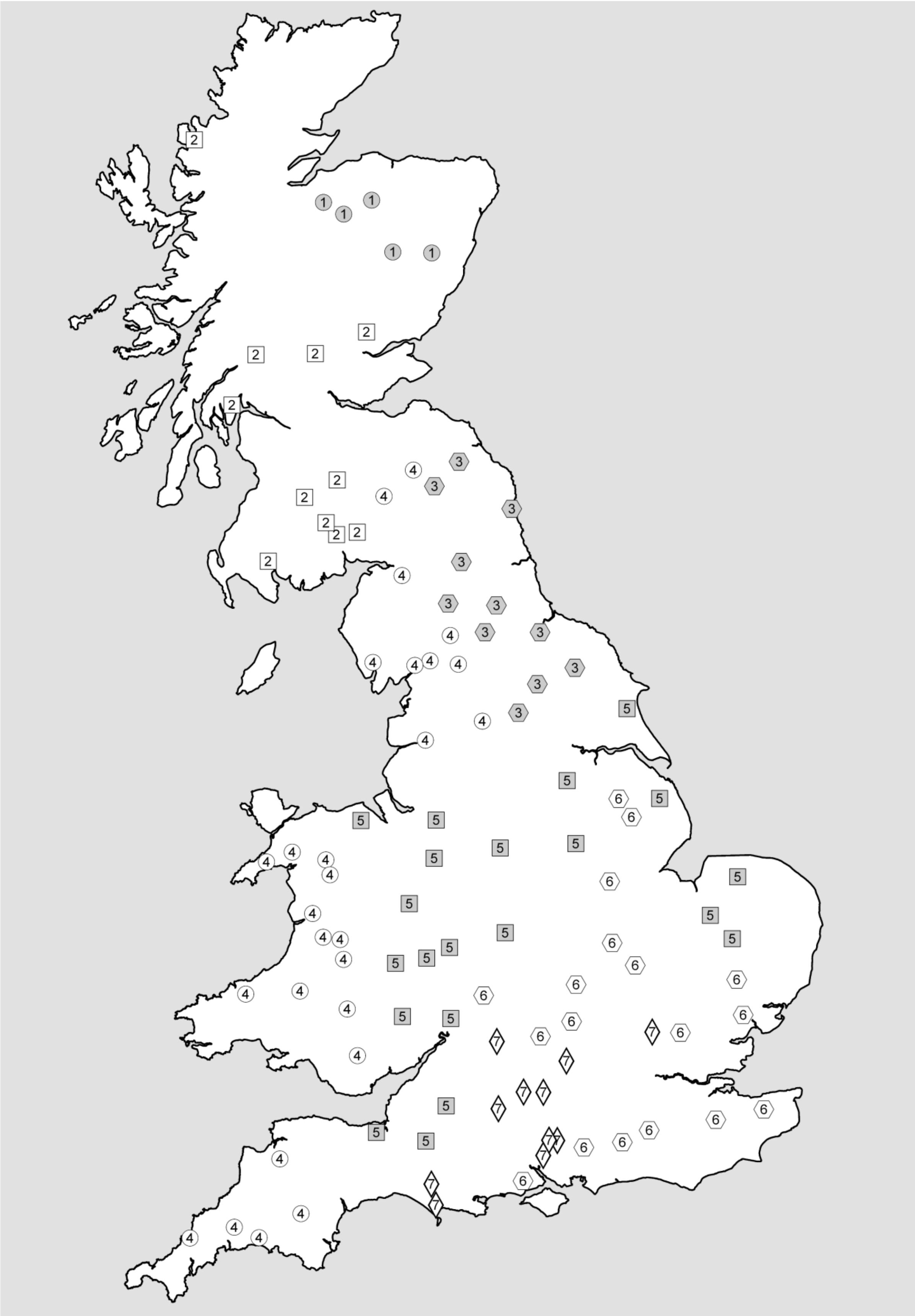

Figure 4.3: Distribution of spring river flow classes for 1975–2005.

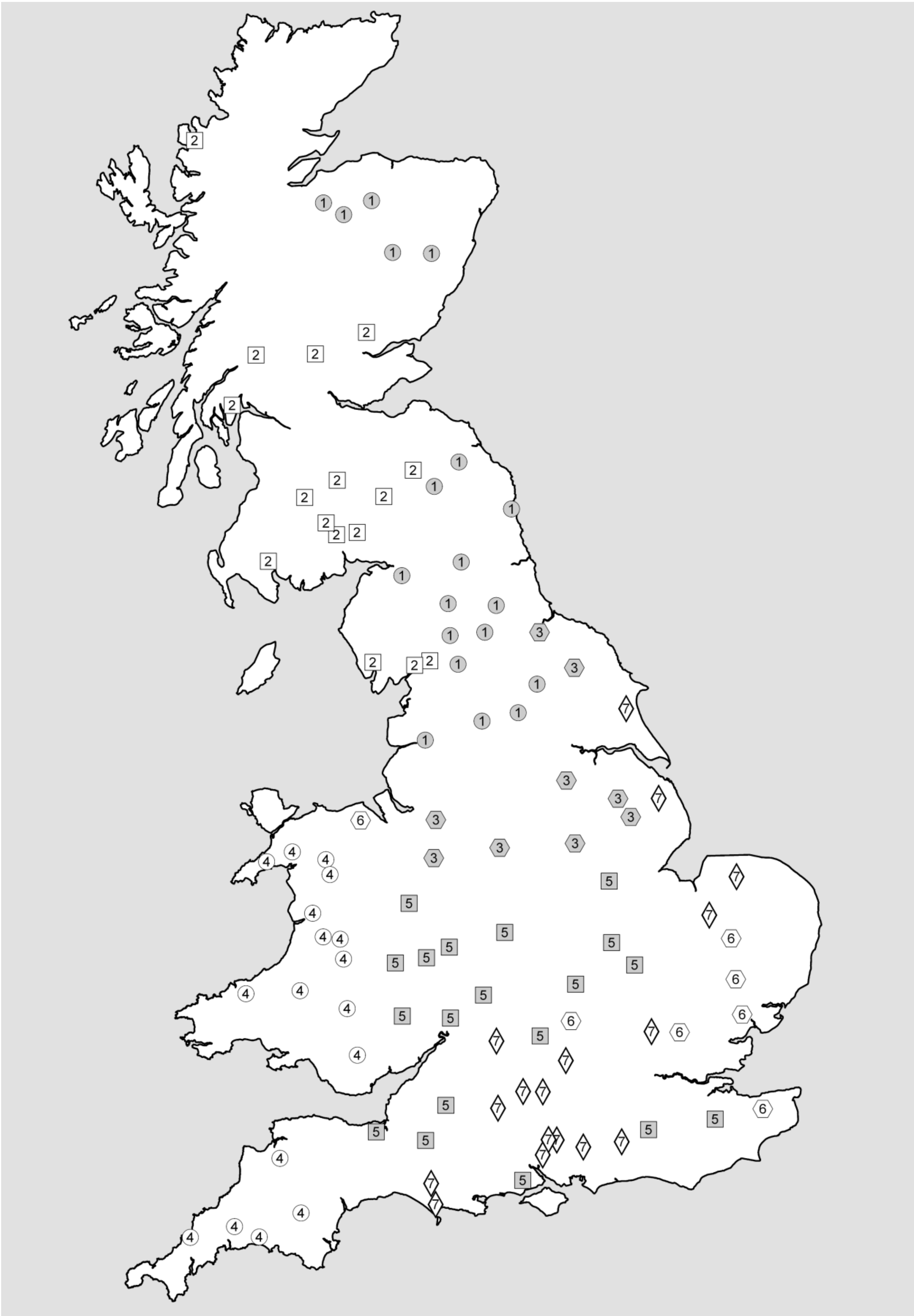

Figure 4.4: Distribution of summer river flow classes for 1975–2005.

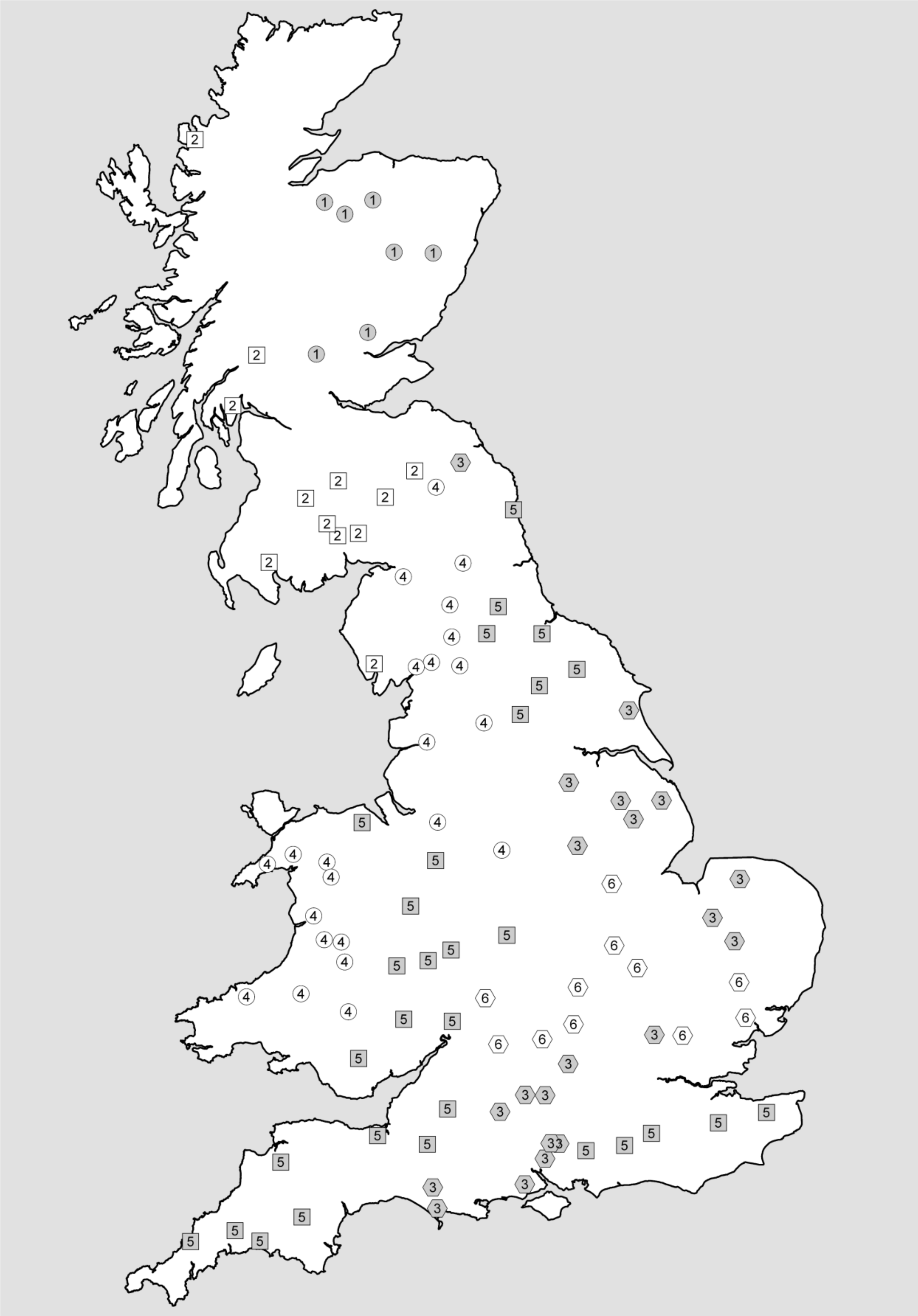

Figure 4.5: Distribution of autumn river flow classes for 1975–2005.

Table 4.1: Geographical location of seasonal flow classes.

Class Number	Class Name			
	Winter	Spring	Summer	Autumn
1	northern Scotland	northern Scotland	northern Scotland & northern England	northern Scotland
2	southern Scotland & northern England	western Scotland	western Scotland & northwest England	southern Scotland
3	northeast England	northeast England	central & northeast England	eastern & southern England
4	western England & Wales	western England & Wales	southwest England & Wales	northwest England & Wales
5	central & southwest England	central & eastern England	central England	central, northeast & southern England
6	southern & southeast England	central & southeast England	southeast England	central & eastern England
7	eastern England	southern England	eastern & southern England	-
8	northern Wales	-	-	-

4.4.2 Characterisation of seasonal flows

Composite time series of standardised flows were derived for each season by calculating the mean across all basins within each class. The classification differentiates clearly between basins with contrasting inter-annual patterns of seasonal flows on the basis of drier and wetter phases regarding timing, duration, and magnitude. To illustrate the latter point, winter and summer, which give the most distinct results in the subsequent analysis, are discussed below (Figures 4.6 and 4.7, respectively); similar comments could be made for the spring and autumn plots, although their specific patterns are slightly different (see Appendix I, Figures 1 and 2).

Regarding timing and duration of flow patterns, for winter, in the late 1970s, northern Scotland (class 1), southern Scotland and northern England (class 2), and southern and southeast England (class 6) are drier while northeast England (class 3) and eastern England (class 7) are wetter than average; the remaining classes have intermediate patterns for that period. Notably, classes 1 and 6 are very distinct from class 2 with the latter having a longer dry spell (extending to the early 1980s) but some much wetter years than the former (e.g. 1994 and 1995). For summer, while northern Scotland and northern England (class 1) and southeast England (class 6) exhibit a late 80s to mid-90s continuous dry spell, western Scotland and northwest England (class 2) has a later dry spell onset (starting in 1994 and ending in 1997) after an initial period of limited variation around the average. The remaining classes show a similar a dry period to classes 1 and 6 but interrupted by a number of wetter years.

With respect to flow pattern magnitude, for winter, northeast England (class 3) and northern Wales (class 8) feature the same sequence of drier/wetter years during 2000–2005 but the former shows limited departure from the average compared to the latter. For summer, southwest England and Wales (class 4) varies within a wider range of flows over 1975–2005 than central England (class 5), particularly from the 1990s onward.

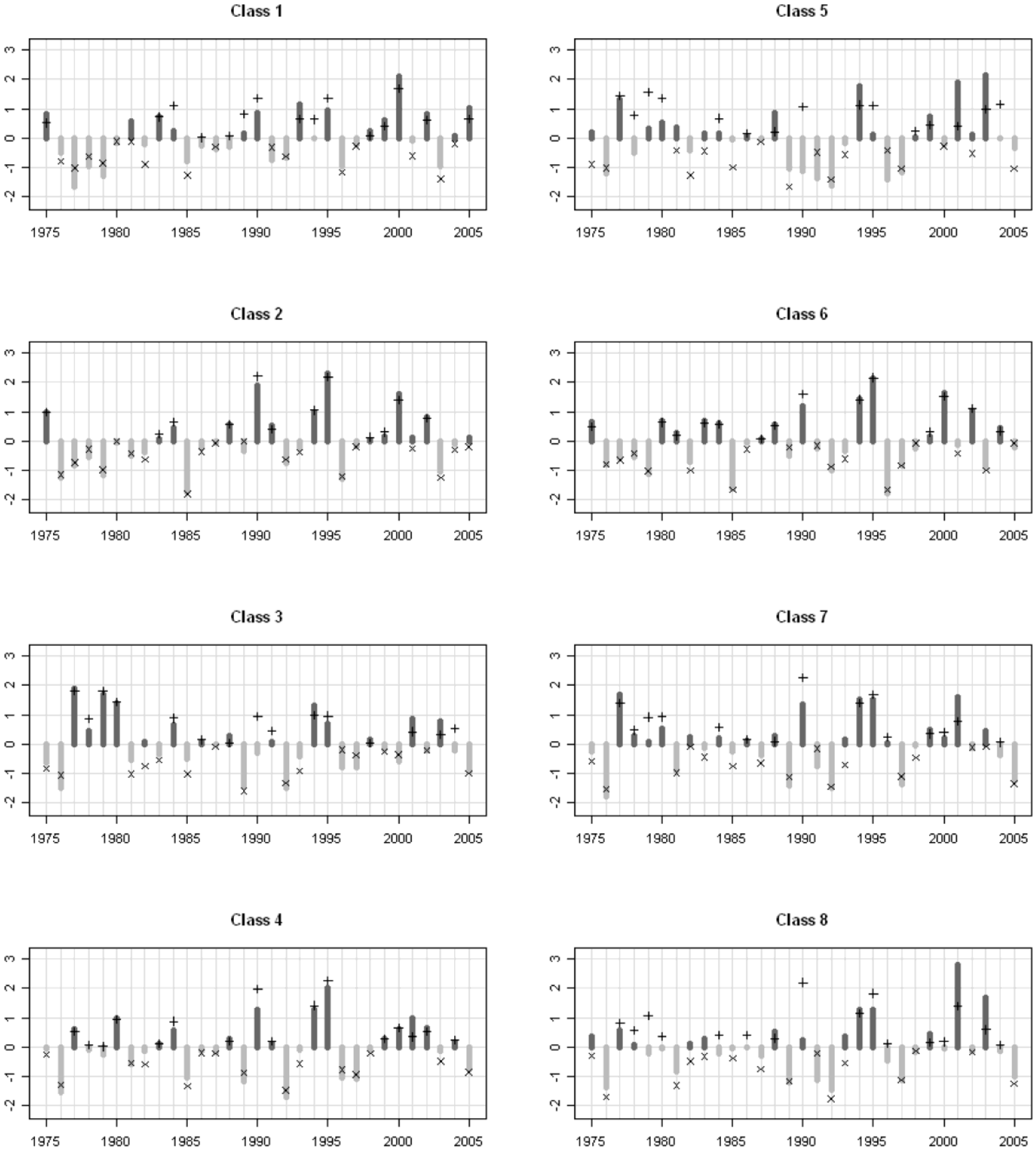

Figure 4.6: Winter composite river flow (dark and light grey bars denote positive (i.e. wetter) and negative (i.e. drier) *z*-scores, respectively) and rainfall (+ and x symbols denote positive and negative *z*-scores, respectively) by class for 1975–2005.

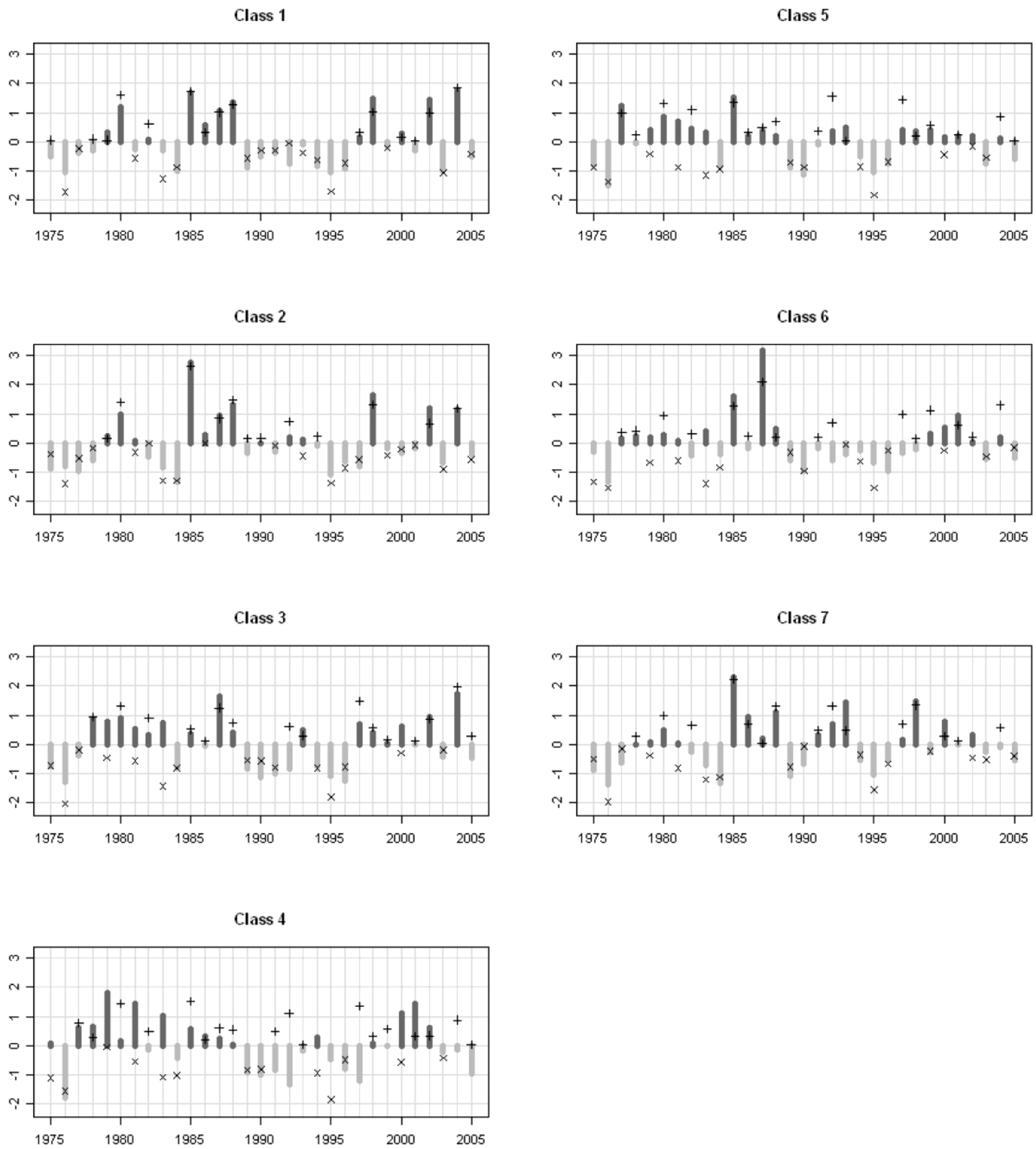

Figure 4.7: Summer composite river flow (dark and light grey bars denote positive (i.e. wetter) and negative (i.e. drier) z-scores, respectively) and rainfall (+ and x symbols denote positive and negative z-scores, respectively) by class for 1975–2005.

4.4.3 Sensitivity of seasonal flows to regional climate

Multiple linear regression was used to model the composite seasonal flows for each class as a function of rainfall, PE, and SMD to identify classes most and least sensitive to the regional climatic drivers (Table 4.2). Significant ($p \leq 0.05$) univariate regression results are also given for comparison with those of multiple regression and to identify the nature and relative strength of relationships for the three climate predictors. In winter, spring and autumn, rainfall alone provides most of the model fit with PE and SMD improving prediction very slightly. Contrastingly, in summer, rainfall is the main predictor for just three of the seven classes.

4.4.4 Sensitivity of seasonal flows to atmospheric circulation

Correlation of winter NAOI against the four sets of composite seasonal flows was performed using the Kendall test; only winter and summer seasons featured classes with significant correlations (i.e. $p \leq 0.10$; Table 4.3). In winter, four contiguous classes show positive correlations; they cover the northwest part of the British mainland (see Figure 4.2). In summer, two classes (northeast and central England) show lagged negative correlations with the winter NAOI.

Table 4.2: Linear regression of seasonal flow against regional climate variables (Rain, PE, SMD). [Univariate R^2 given if p value ≤ 0.05. Multiple regression model featured if better than univariate. Best fit highlighted in bold.]

Season	Class Number	Univariate			Multiple	
		Rain	PE	SMD	Predictors	Fit
winter	1	0.74	0.42	0.13	Rain, PE	**0.77**
	2	**0.96**	0.32	-	-	-
	3	0.79	0.23	0.31	Rain, PE, SMD	**0.86**
	4	0.91	-	0.36	Rain, PE	**0.92**
	5	0.81	-	0.50	Rain, SMD	**0.83**
	6	0.54	-	0.42	Rain, SMD	**0.59**
	7	0.33	-	0.35	Rain, SMD	**0.47**
	8	**0.97**	0.30	0.13	-	-
spring	1	0.52	-	-	Rain, SMD	**0.59**
	2	0.90	-	-	Rain, SMD	**0.93**
	3	**0.83**	0.14	0.44	-	-
	4	0.87	-	0.28	Rain, SMD	**0.91**
	5	0.72	0.18	0.40	Rain, SMD	**0.75**
	6	0.82	0.26	0.54	Rain, PE, SMD	**0.86**
	7	0.23	-	-	Rain, SMD	**0.29**
summer	1	0.83	0.42	0.70	Rain, SMD	**0.85**
	2	0.87	0.28	0.50	Rain, SMD	**0.88**
	3	0.51	0.52	**0.70**	-	-
	4	0.73	0.44	0.65	Rain, PE	**0.78**
	5	0.52	0.65	0.79	PE, SMD	**0.81**
	6	0.41	0.37	**0.72**	-	-
	7	-	0.31	0.24	Rain, PE	**0.46**
autumn	1	0.81	-	0.40	Rain, PE, SMD	**0.87**
	2	**0.88**	0.14	-	-	-
	3	0.56	0.14	0.49	Rain, PE	**0.60**
	4	0.90	-	0.32	Rain, PE	**0.92**
	5	0.81	-	0.58	Rain, SMD	**0.84**
	6	**0.66**	0.13	0.55	-	-

Table 4.3: Kendall correlation (*tau*) of winter NAOI and seasonal flow index (*p* value ≤ 0.10).

Season	Flow Class	Region	Kendall *tau*
winter	1	north Scotland	0.54
	2	south Scotland–north England	0.48
	4	west–central	0.21
	8	west	0.45
summer	1	northeast	-0.23
	5	central	-0.23

4.4.5 Associations between seasonal flows and basin properties

Table 4.4 gives a sample of the ANOVA and Tukey's HSD analyses of the FEH descriptors for winter and spring flows; the full results for FEH, land use, elevation, and geology properties for all seasons can be found in Appendix I, Table 2 (a–f). Firstly, ANOVA was used to filter out properties that do not differentiate between flow classes (with corresponding cell in Table 4.4 kept blank). Secondly, Tukey's HSD test was applied to those remaining properties in order to identify flow classes significantly different (significance at 5% level). In Table 4.4, classes not significantly different are grouped on the same line. Groups can overlap because basin property means may only differ by a small amount between classes; hence extreme classes are significantly different from each other while being similar to middle-range classes.

4.4.5.1 FEH descriptors

Several FEH descriptors were excluded from the analysis because they either characterise basin climate or they do not characterise basin physiography. One climate descriptor, SAAR6190 (i.e. 1961–1990 average rainfall), was retained as it was found useful to interpret results (see 4.5.2). ALTBAR (basin mean altitude) was removed to avoid data redundancy since other elevation attributes are included in this analysis (see 4.4.5.3 Elevation).

Table 4.4: Grouping of seasonal flow classes with similar basin properties; for each property, each line represents one group of flow classes for which their average values of that property are not statistically different (ANOVA and Tukey's HSD); 'grouping mean' is the average property value for all classes in each group; this is a sample only, see full results in Appendix I, Table 2.

Property	Season			
	Winter		Spring	
	Flow Class Group	Group Mean	Flow Class Group	Group Mean
FEH				
AREA	1 2 4 7 8	364.85		
	2 3 4 5 6 7 8	179.89		
ASPBAR	1 2 3 4 5 6 7	133.51		
	2 3 4 5 6 7 8	150.26		
ASPVAR	1 2 4 5 6 7 8	0.17	1 2 4 5 6 7	0.17
	3 7	0.25	3 5 6 7	0.22
BFIHOST	1 2 3 4 5 8	0.45	1 2 3 4 6	0.42
	6 7	0.75	5	0.64
			7	0.86
DPLBAR			1 2 3 4 5	22.31
			2 3 4 5 6 7	17.19
DPSBAR	1 8	186.22	1 2 4	164.40
	2 4 8	139.03	3 5 6 7	66.95
	3 5 6 7	55.20		
	2 4 5	106.92		
LDP			1 2 3 4 5	42.30
			2 3 4 5 6 7	32.34
SAAR6190	1 2 4	1431.10	1 3 5 6 7	882.02
	3 5 6 7	752.39	2 4	1709.99
	1 8	1780.10		
SPRHOST	1 2 3 4 8	42.35	1 2 3 4 6	43.60
	3 4 5	35.83	5	26.11
	6 7	20.20	7	13.87

A number of FEH properties do not show any clear pattern between groups. AREA (basin area in km^2) was expected to have little impact as the classification was based on standardised flows, thus removing the scale effect of basin size in terms of magnitude (size could still affect the timing especially in slow responding basins). This is verified for spring and summer but not for winter and autumn. This result is probably due to one outlier basin being greater than 4,500 km^2 while all the others range from ~3 km^2 to 1,500 km^2; for example, in autumn, the large basin falls into class 1. ASPBAR is the mean of the dominant aspect of slopes in a basin (decimal degree; 0 = North, 90 = East, etc). ASPBAR does not appear to differentiate groups except in winter for which flow classes 1 and 8 are different. This could be linked to orographic enhancement of rainfall, occurring mainly in winter and highly directional (Svensson and Jakob, 2002); classes 1 and 8 are in mountainous areas on the northwest windward side of the country, where orographic enhancement would occur. ASPVAR represents the invariability of slope directions; a value near 0 indicates considerable variability while near 1 means the basin tends to face one particular direction. The analysis shows only one class per season (or none for autumn) significantly differs, albeit only by a small amount, from the other classes. DPLBAR is the mean drainage path length, i.e. the mean of distances between each river network node and the basin outlet; it characterises basin size and morphology. The autumn groups match the autumn AREA ones and are likely due to the same outlier basin. Similar conclusions are drawn for LDP (longest drainage path to the outlet) as it characterises size principally.

The above being said, however, some FEH properties exhibit clear between-group contrasts. DPSBAR is the mean drainage path slope (mean of all inter-nodal slopes) and separates with two non-overlapping groups for spring. BFIHOST is an index of base flow as proportion of total flow derived from soil types. Non-overlapping groups are evident for all seasons and distinguish between responsive (low BFIHOST) and unresponsive (high BFIHOST) basins (Figure 4.8). SPRHOST is standard percentage runoff derived using the same soil types. It is generally negatively correlated to BIFHOST thus yields similar groups, although there is some group overlap and this variable may be deemed redundant given inclusion of BFIHOST.

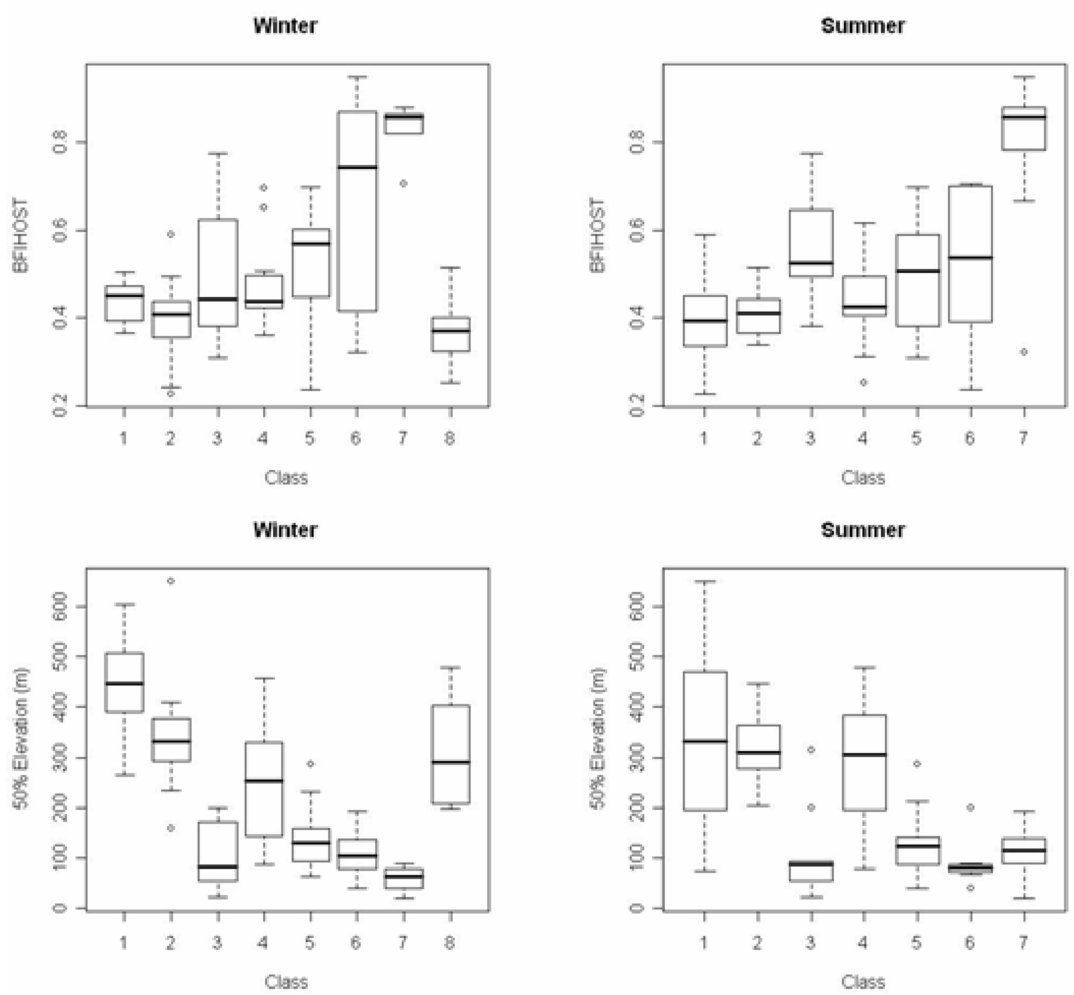

Figure 4.8: Boxplots of BFIHOST and median basin elevation by class for winter and summer.

4.4.5.2 Land use

Benchmark basins were selected due to their near-natural conditions (see 4.2.1); hence, they do not span the full spectrum of land use found in the UK. Land use types thus not properly sampled are: (1) 'inland bare ground' and 'inland water', which are present in only a few basins up to 5 and 8%, respectively; (2) 'bog', 'montane', and 'built-up area', which present a variation on the problem with most basins having none and a handful having a high percentage of these land use types (e.g. 101 basins contain 0–12% of 'built-up area' and three

20–65%). Although Table 4.4 shows no or few significantly different groups, it is difficult to state whether this is due to land use types having little influence or to the sampling.

The remaining land use types (‘woodland’, ‘arable’, ‘grassland’ and ‘heath’) are however well sampled by the benchmark subset. While ‘woodland’ shows almost no significantly different groups, ‘arable’ differentiates clearly basins with limited (e.g. winter, classes 1, 2, 4, and 8) or extensive arable land (e.g. autumn, classes 3 and 7); ’grassland’ and ‘heath’ also differentiate basin types although there is more overlap between types for some seasons (e.g. winter) than for others (e.g. autumn).

4.4.5.3 Elevation

The elevation statistics analysed are the minimum, 10th, 50th (median) and 90th percentiles, and maximum basin height. These data provide a good summary of basin hypsometric form. With the exception of minimum elevation, all statistics identify clearly two basin types: upland (> 200 m) and lowland (≤ 200 m). As an illustration, Figure 4.8 shows boxplots of the median elevation distribution within each region for winter and summer. Across seasons, the upland–lowland split is consistent, corresponding to upland basins in the west–northwest and lowland basins in east–southeast. On closer inspection, upland basins may be partitioned further, for example, in winter, classes 1, 4, and 8 are significantly different.

4.4.5.4 Geology

Bedrock permeability yield significant differences between classes with ‘impermeable’, i.e. fast responding, (autumn classes 1, 2, 4, 5 and 6) differentiated from ‘highly permeable’, i.e. slow responding, basins (autumn class 3). The ‘moderate permeability’ category does not provide as clear a separation as other geological categories. Superficial deposits show either no significant difference or yield overlapping groups, thus indicating less utility differencing seasonal flow classes.

4.5 Discussion

4.5.1 Hydroclimatological associations

This study has identified distinct seasonal flow classes across 104 UK gauged basins. The mapping of these flow classes shows two important features: (1) basin classification membership is not static between seasons with some basins remaining within the same classes across the seasons but other basins changing classes; and (2) while for some seasons (e.g. winter) classes tend to be contiguous, for other seasons classes are more spatially complex and include basins located far apart (e.g. summer classes 6 and 7; Figure 4.4). Since climate is the first-order control on river flows and basin properties a second-order modifier of the 'climate signal' (Bower *et al.*, 2004), the shifting spatial structure of classes may be explained by the strength of the climate signal *versus* basin modifiers varying between seasons. In winter, the stronger climate signal (for example, west–east rainfall gradient) may define the classes and account for more contiguous regions, while, in summer, basin properties, such as geology, may modify the weaker climate input to a greater extent and/or play a significant role in determining lagged response to antecedent inputs (generating spatially patchier hydrological response related to varied basin characteristics).

The winter NAO influences river flows by controlling moisture and heat advection over the UK (Kingston *et al.*, 2007). It is generally well accepted that a higher NAOI enhances westerly air flows across the UK that lead to higher than average precipitation and temperature, and, in turn, to higher river flows (*vice versa* for a lower NAOI). This study demonstrates that RC variables have stronger association with seasonal flows than AC (characterised by the NAOI). The best RC predictors vary depending on the season with rainfall being dominant in winter and its influence decreasing in summer. Although RC associations are stronger than AC and AC associations are strongest in winter, results do not confirm the assertion of Phillips *et al.* (2003) that river flows may be more sensitive to AC control than RC due to the former representing a wider range of climatic controls than single RC descriptors.

It may be hypothesised that classes for which RC–flow associations are strongest, that is the most responsive basins, may show the strongest correlation to AC (Wedgebrow *et al.*, 2002). In winter, this assertion is upheld for classes 2, 4, and 8 (see Tables 4.2 and 4.3). However, northeast England (class 3) and central and southwest England (class 5) yield better RC–flow fits than northern Scotland (class 1) but do not show significant correlation with NAOI. Classes 3, 5, 6 and 7 have SMD as a significant predictor unlike classes 1, 2, 4, and 8, for which rainfall is the main predictor. In summer, significant AC–flow correlation does not seem to match the strength of RC–flow associations. Location is likely to play role as NAO influence generally declines along north–south and east–west lines, hence more easterly locations or those in the lee of the Welsh mountains showing weaker correlations than more northerly ones. Yet, for the classes that have lower, or no significant, correlation to AC, SMD is generally a significant predictor. SMD represents basin storage, which may be more important in controlling summer response than in winter when precipitation inputs are higher.

Investigating the winter NAOI–summer flow association is of potential practical significance as it may characterise a lagged relationship (with 6-month lead). Only two summer classes (northern Scotland and northern England, class 1, and central England, class 5; see Figure 4.9) show significant correlation of winter NAOI–summer flow, although these classes contain a large number of basins and provide an extensive coverage of the mainland UK. These result improve on similar studies (Wilby, 2001; Svensson and Prudhomme, 2005) that identified comparable hydroclimatological associations but based on much coarser divisions of the UK and much fewer gauged basins.

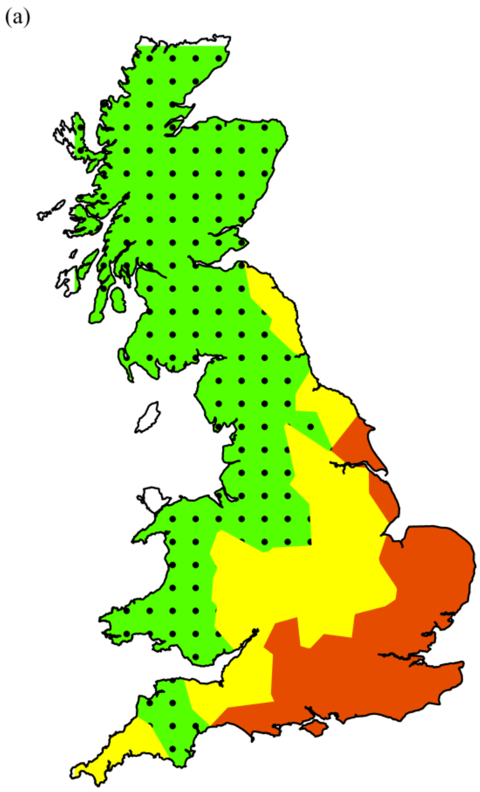

Figure 4.9: Basin types (green, upland impermeable; yellow, lowland impermeable; red, lowland permeable) and corresponding significant NAOI–flow correlation (dotted areas): (a) winter, positive correlation; (b) summer, negative correlation.

4.5.2 Influence of basin properties

Time and space scale issues (Blöschl *et al.*, 2007) can cause basin properties to exert very limited control over flows (Merz and Blöschl, 2009; Hurkmans *et al.*, 2009) but this study demonstrated that the following basin properties were found to be significantly different between seasonal flow classes and, hence, they may be deemed as modifiers of climate–flow associations: DPSBAR, BFIHOST, SPRHOST, land use categories 'arable', 'grassland' and 'heath', elevation, bedrock permeability. These properties are consistent with types previously found of importance: elevation/topography (Woods, 2003; Birsan *et al.*, 2005; Johnston and Shmagin, 2008; Yokoo *et al.*, 2008); land cover (Woods, 2003; Birsan *et al.*, 2005; Detenbeck *et al.*, 2005; Johnston and Shmagin, 2008; Oudin *et al.*, 2008); soil/geological properties (Woods, 2003; Birsan *et al.*, 2005; Jefferson *et al.*, 2008; Yokoo *et al.*, 2008). However, some of these properties are redundant as they either capture similar or opposite characteristics, or co-vary.

For example, BFIHOST and bedrock permeability characterise potential for basin water storage, that is permeable (high BFI) or impermeable (low BFI) basins. SPRHOST is negatively correlated to BFIHOST, so was not considered herein.

Certain properties co-vary in the UK context. DPSBAR (indicator of overall steepness) and elevation indicators identify similar groups with higher basins being steeper. Elevation and land-use appear to be linked with upland basins having a mixture of 'grassland', 'heath', or 'montane' whereas lowland basins are primarily 'arable'. This partitioning reflects the fact that arable lands are located typically on flat low-lying areas for practical reasons. Although each of these properties may contribute individually to the climate–flow modification, overall basin characteristics may be simplified as upland (elevation > 200m) and lowland (< 200m).

The combination of elevation and permeability properties yields potentially four 'basin types' (see Figure 4.8), although only three occur in the benchmark subset: upland impermeable, lowland impermeable, and lowland permeable (permeable geology is mostly found in UK lowlands).

These basin types were compared to the strength of the RC–flow associations (Sections 4.4.3 and 4.5.1; Table 4.2). Table 4.5 summarises which seasonal flow classes belong to which of the three basin types and the best-fit (as given by R^2) RC–flow association. For all seasons, the lowland permeable type has lower R^2 than the impermeable types, and upland impermeable tends to get higher R^2 than lowland impermeable, although there is some overlap. Therefore, a clear pattern is emergent: the higher and more impermeable the basins, the better the RC–flow fit. This pattern is consistent with groundwater-dominated river systems having specific hydrological characteristics (Sear *et al.*, 1999) with complex non-linear relations to climate signals (Holman *et al.*, 2009).

Table 4.5: Basin types and corresponding best RC–flow fits.

Season	Class Grouping	Basin Type	Range of R^2
winter	1 2 4 8	upland impermeable	0.77–0.97
	3 5	lowland impermeable	0.83 & 0.86
	6 7	lowland permeable	0.43 & 0.59
spring	1 2 3 4	upland impermeable	0.93–0.83
	6	lowland impermeable	0.86
	5 7	lowland permeable	0.29 & 0.75
summer	1 2 4	upland impermeable	0.78–0.88
	3 5 6	lowland impermeable	0.70–0.81
	7	lowland permeable	0.46
autumn	1 2 4	upland impermeable	0.87–0.92
	5 6	lowland impermeable	0.66 & 0.84
	3	lowland permeable	0.60

In order to interpret this pattern, it can be first hypothesised that the cause of the upland/lowland partition is the very good correlation between elevation and precipitation because higher areas tend to be located in the west, where more moisture is delivered by westerly weather systems from the Atlantic. This is corroborated by the SAAR6190 descriptor, which yields almost the same groups as elevation (Table 4.4). Basins located at higher elevations tend to get more rainfall hence they are subjected to more direct climatic forcing. In addition, properties that influence basin responsiveness co-vary with elevation, that is higher basins tend to be steeper with impermeable geology. For these basins, both primary (i.e. climate, rainfall) and secondary controls contribute to strengthen the RC–flow association, and it can be difficult to dissociate them clearly.

Secondly, the permeable/impermeable partition of lowland basins could be interpreted as follows. In contrast to uplands, lowland basins receive less rainfall and thus the influence of secondary controls (like permeability) may be hypothesised to have proportionally greater influence than primary (climate) controls. Permeable basins have lower R^2 for RC–flow associations, consistent with a greater buffering of the climate inputs than impermeable basins. The present selection of benchmark basins has no upland permeable type that would allow for assessment of permeability effects independently from elevation. However, it is notable that some lowland impermeable basins yield higher R^2 than upland impermeable basins; this may suggest an amount of interaction between properties not simply captured at the scale of this study.

As mentioned in section 4.5.1, considering the winter NAOI–flow association, Wedgebrow *et al.* (2002) showed for a limited number of UK basins that higher AC–flow correlations are found typically for basins with stronger RC–flow associations and this was matched against basin responsiveness only (i.e. the more responsive, the better RC–flow and AC–flow fits). In this study, only winter and summer seasons gave significant correlations (see Table 4.3). For winter, positive correlations (no lag) are found for classes 1, 2, 4, and 8 (upland impermeable) so that this is consistent with the findings at the RC scale. These results were confirmed by Burt and Howden (2013) who found a strong positive relationship between flows and NAO in upland UK areas for all seasons except summer. For summer, negative correlations (lagged) were found for classes 1 (upland impermeable) and 5 (lowland impermeable). This lagged negative association indicates stronger westerlies (positive NAOI) in winter are associated with lower river flows in summer. Similarly, Kettlewell *et al.* (2003) found a negative correlation between winter NAOI and summer rainfall, with strongest correlation for eastern Scotland; they found some of the driest recent summers have followed strong westerly positive NAO winters. The physical mechanisms for this relationship are unclear; however, it is possible that the cause may relate to memory within the climate system, potentially the North Atlantic Ocean.

4.6 Conclusions

By using records for a network of 104 near-natural gauged river basins distributed across mainland UK, in conjunction with regional climate, atmospheric circulation and basin properties data, this study has refined the understanding of seasonal hydroclimatological associations. Firstly, the characterisation of spatial patterns of seasonal flow regimes has shown inter-seasonal variability, which extends beyond the simple northwest uplands–southeast lowlands divide that is commonly assumed, in particular: (1) membership of flow classes is not static between seasons; (2) spatial structure of classes can be contiguous for some seasons but patchy for others. Secondly, AC (as represented by NAOI) and RC controls on seasonal flows were quantified for each flow class, with differences in best predictors and strength of both AC and RC associations between flow regions. The need for a regional approach to unpick complex AC–RC–flow links seems clear based on findings presented herein. Overall, RC variables were found to have stronger association with seasonal flows than NAOI. The best RC predictors vary with season; rainfall is dominant in winter but its influence decreases in summer when SMD becomes more important. Only winter and summer showed significant NAOI–flow correlations (at 10% level). It is noteworthy that the NAOI is not necessarily a perfect descriptor of the NAO. Thirdly, physical basin properties relating to elevation and permeability modify climate–flow associations at larger spatial (flow classes) and temporal (3-month averages) scales. Thus, composition of seasonal flow classes reflects not only climatic input but also the physical nature of the basins. It was found that a given property may be of influence for one season but not for another, and that many properties have only limited influence on modifying climate inputs. However, considerable collinearity in basin properties across the UK might make systematic identification of individual basin property effects on seasonal flows difficult.

For both winter and summer seasons, it may be concluded generally that the higher elevation and the more impermeable a basin is, the stronger is the RC–flow association. For the UK, this pattern of climate–flow association corresponds to a northwest–southeast gradient of exposure to prevailing westerly weather systems and basin type (Figure 4.9). Regarding NAOI–flow associations, regions of significant winter correlations match regions of stronger RC–flow association; summer correlations show an eastern shift. While disaggregating climate versus basin controls is difficult, these results indicate climate is a first order driver and basin properties are important modifiers of the climate–flow associations.

From a wider perspective, this study links to some of the basin typology issues raised in the hydrological community (Blöschl *et al.*, 2007; Wagener *et al.*, 2007; Sawicz *et al.*, 2011; Ali *et al.*, 2012; Koplin *et al.*, 2012; Berghuijs *et al.*, 2014; Chiverton *et al.*, 2014), in particular with regards to how best to represent characteristics of form and hydroclimatological conditions, and how this representation change with spatial and temporal scale. A recent study by Szolgayova *et al.* (2014), who found a strong positive correlation between long range dependence in European river flows and catchment area, suggests that possible future research could focus on basin size and alternative flow indices. Firstly, basin size was not used explicitly due to the data aggregation part of the classification process, but basin size could be investigated in relation to basin property influence, i.e. to pinpoint at what scale a given property does exert influence. Secondly, the seasonal flow indices used therein (i.e. 3-month averages) only capture a facet of the hydrological regime. Alternative indices could focus on: (1) longer or lagged seasons to capture better slow-responding basins, for which a massive rainfall input occurring toward the end of one season could only manifest in flows of the following season; (2) indices capturing other facets of the hydrograph (e.g. high/low flows) as different basin properties might be identified as significant modifiers; this would also link to hydroecological studies based on full description of the hydrograph, e.g. hydrological alteration-type approaches (Richter *et al.*, 1996; Laizé *et al.*, 2014; also see Chapter 7).

5. RIVER FLOW AND RIVER HYDRAULICS

5.1 Introduction

This chapter addresses the research gaps and objectives identified in section 2.3 by assessing river hydraulic sensitivity to flow variability for an extensive set of cross-sections in England and Wales (UK), and its relation to a wide selection of basin and site properties. The literature review established the validity of using HG to investigate river flows–river hydraulics associations within an ecological context (physical habitat). HG assumes that, and describes how, river channels adjust dynamically to the flow regime, given local bed and bank conditions (Knighton, 1975; Rhodes, 1987; Wohl, 2004). HG concepts were first formalised by Leopold and Maddock (1953), who showed that wetted width, mean water depth, and mean water velocity in a natural river channel can be modelled as simple power functions of flow (Equations 5.1 to 5.3). This applies both for a fixed channel cross-section at different flows ('at-a-station'), and for different cross-sections along a river channel at a fixed flow percentile e.g. median flows ('downstream'). A number of refined or expanded versions of the equations can be found in the literature (Singh, 2003; Lee and Julien, 2006; Afzalimehr *et al.*, 2009) but, due to the data available, this study uses Leopold and Maddock's original formulas, and considers at-a-station HG only.

$$W = \mathrm{a}Q^{\mathrm{b}} \qquad \text{Equation 5.1}$$

$$D = \mathrm{c}Q^{\mathrm{f}} \qquad \text{Equation 5.2}$$

$$V = \mathrm{k}Q^{\mathrm{m}} \qquad \text{Equation 5.3}$$

Where W is the wetted width (m), D the mean depth (m), V the mean velocity (m^2s^{-1}), Q the discharge (m^3s^{-1}), and a, c, k, b, f, and m are numerical constants. To maintain continuity in the above equation, the sum of b, f, and m and the product of a, c, and k must equal 1. Indeed, for a given discharge Q, the river can be approximated as a channel with a rectangular section (W x D) and mean velocity V, so that:

$$Q = W \times D \times V \qquad \text{Equation 5.4}$$

Then:

$$Q = \mathrm{a}Q^{\mathrm{b}} \times \mathrm{c}Q^{\mathrm{f}} \times \mathrm{k}Q^{\mathrm{m}} \qquad \text{Equation 5.5}$$

Therefore:

$$Q = \mathrm{ack}Q^{\mathrm{b+f+m}} \qquad \text{Equation 5.6}$$

Departure from these mass balance constraints can happen for a variety of reasons: measurement errors during gauging, model fitting errors, and/or channels not behaving in a natural way from a hydraulic perspective, for example, due to engineering works or re-sectioning.

5.2 Data

The original hydraulic data collected by the EA consist of the detailed measurements recorded when gauging flows as per standard gauging practice: distance from bank, depth, and velocity at each measurement point of each panel dividing the cross-section where each gauging occurred (see 3.2.3). The number of measurements per panel is one (at 0.6 x depth), two (at 0.2 and 0.8 x depth), or three (at 0.2, 0.6, and 0.8 x depth) depending on depth. After being thoroughly quality-controlled (e.g. to remove duplicate records), the raw data was used to calculate mean depth, total width, mean velocity and discharge for each gauging. A subset of 2,583 sites was used (see below for details). Since no metadata was available to assess any degree of human influence on the records, historical channel modification information was obtained from a database of location and type of flood defence works carried out between 1930 and 1980 (Brookes *et al.*, 1983) hereafter referred to as capital works (CP).

Basin physical properties were obtained from the FEH descriptors and from the IRN, while site properties were derived from the IRN only (see 3.2.5). Deriving site information from the FEH and IRN datasets requires matching sites onto their respective modelled drainage network in bespoke GIS applications. Those networks may differ, and it is sometimes difficult to find a suitable consistent match. As a result, physical properties were obtained for: FEH, 1,772 sites; IRN, 1,674 sites; both, 1,579 sites.

5.3 Derivation of HG coefficients

Because of the underlying hypothesis that sites with similar characteristics and basin properties may have similar HG equations, there was a justification to using ML modelling. Three ML models (*W*, *D*, *V*) with two levels, i.e. observations (level 1) within sites (level 2), and including both intercept and flow in the random component were fitted. In parallel, individual regressions (i.e. one per site) were also fitted. First, spurious gauging (e.g. negative flows or wetted widths) were removed, and only sites with at least three gaugings were retained, because ML would have had convergence issues otherwise. Models were consequently fitted on 2,954 sites totalling 39,124 records. Plots of observed *v* modelled *W*, *D*, *V* (Figure 5.1) and MSEs (Table 5.1) confirmed that the ML approach gave better predictions for all three HG variables.

Quality control consisted of removing sites with negative b–f–m exponents and of screening the HG coefficients for conformance with the mass balance (b–f–m sum and a–c–k product equal to 1; see above). An error of 10% was allowed for each coefficient so that acceptable b–f–m sums would be within 10% of the theoretical value (additive errors), while a–c–k products would be within 30% (multiplicative errors). Sites with b–f–m sum within 0.9–1.1

were consequently retained. Then inspecting the distribution of the a–c–k products showed that they were within the 30% error range but centred on approximately 0.8 rather than 1. Such an offset, the meaning of which is that a, c, and k tend to be underestimated, could be due to the way data were recorded (e.g. where depths or widths are measured from). Given that the primary focus of this study is on hydraulic sensitivity (i.e. exponents b, f, and m), and that the multipliers a, c, and k are essentially a scaling factor, it was considered appropriate to simply use the b–f–m sum criterion; this was supported by testing several additional a–c–k ranges with no notable improvement to model fit.

This resulted in 2,583 sites with HG coefficients. The MSEs for this final set (third column in Table 5.1) were improved as a result. Inspection of the physical descriptors showed that the sites are representative of the main UK river types, except for the higher altitude streams: the highest site is c. 400 m and the highest mean basin elevation is c. 650 m, thus missing the 400–1200 m elevation range. The location map of the selected sites shows an overall good geographical coverage of the study area with the exception of northern Wales (Figure 5.2).

Table 5.1: MSEs for HG models.

MSE	Regression per Site	ML	ML after b–f–m Check
W	0.141	0.048	0.045
D	0.116	0.067	0.059
V	0.136	0.099	0.093

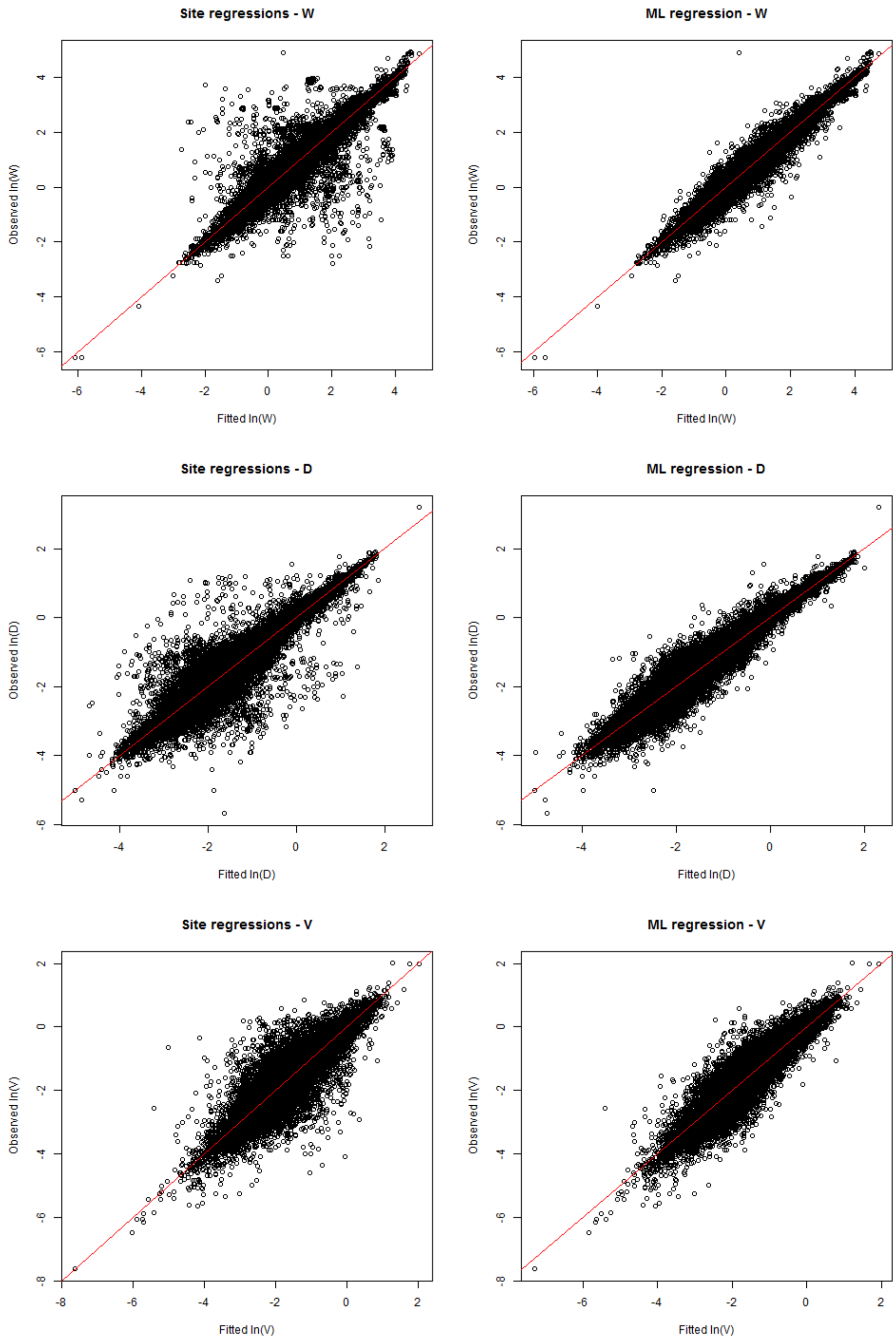

Figure 5.1: Plots of predicted *v* observed HG variables fitted with one regression per site (left) and with one ML model for all sites together (right).

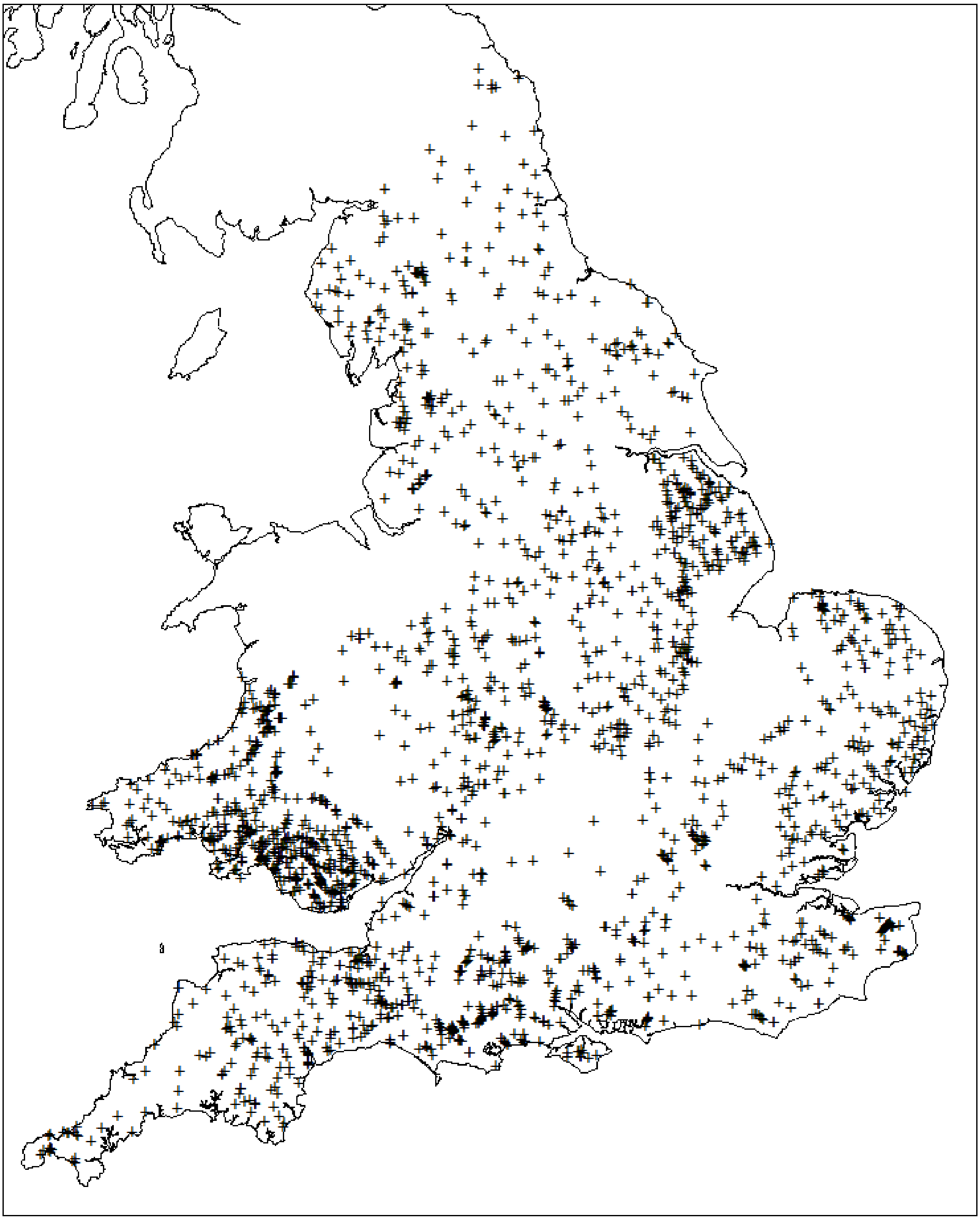

Figure 5.2: Location map of study sites (black crosses).

5.4 Investigating artificial influences

As explained above, sites behaving in a natural way from a hydraulic perspective should satisfy the mass balance constraint. The sites were filtered against the b–f–m sum criterion, and the hydraulic dataset, only including sites on river stretches without any physical structures such as weirs (Booker and Dunbar, 2008), can be reasonably assumed to be hydraulically natural, but given the long history of river modification in England and Wales (several centuries; Brookes *et al.*, 1983), it was considered necessary to verify this assumption. The CP data was the only one that could be obtained for a majority of the HG sites, and they showed that about 50% of the sites are on channels that have been modified. However, the CP data are qualitative only, aggregated per river stretch (actual works could be quite far from a given HG site), and covering the 1930s to the 1980s (HG data were recorded from 1993 to 2006). The CP data were used in a test run of the analysis of the HG–physical properties associations (see below) but did not yield conclusive patterns (making either no difference, or causing very inconsistent patterns), possibly because they capture as much physical basin types as any possible artificial influence (modified sites tend to be in lowland and larger basins, where urban areas and flood defences are more frequent). As a consequence, the CP data were not conclusive in invalidating the assumption that the study sites can be considered natural from the perspective of hydraulics.

5.5 HG exponent typology

As explained in section 5.1, the HG coefficients are related via the mass balance constraint (b–f–m sum and a–c–k product equal to one) so should not only be investigated on their own, but also together. Park (1977) and Rhodes (1978) suggested the use of ternary diagrams as a way to analyse the simultaneous variation of HG exponents: Figure 5.3 is such a diagram showing the location of the 2,583 study sites in the b–f–m space. The diagram does not show obvious clusters of sites. CA was applied to the dataset and confirmed there was no pattern. Instead, sites were classified according to key exponent threshold proposed by Rhodes (1978, 1987).

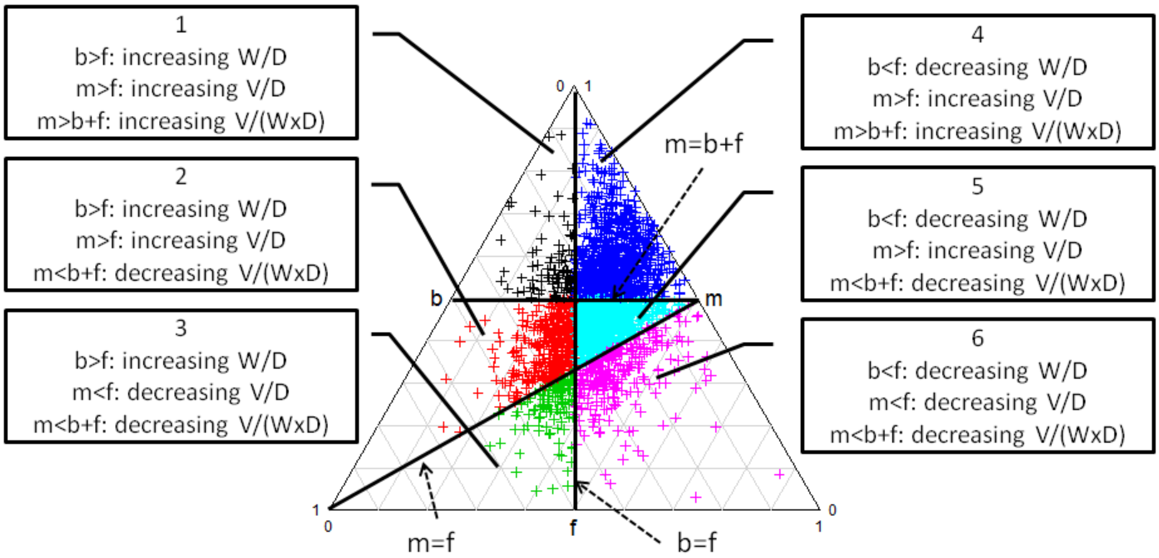

Figure 5.3: Ternary diagram of study sites (+) classified according to exponent thresholds (lines); classes numbered 1 to 6.

The vertical line (b = f) separates sites on the basis of the width to depth ratio: sites on left side of the line (classes 1–3), width increases faster than depth as discharge increases, so channels become relatively wider and shallower, while they get narrower and deeper for sites on right side of the line (classes 4–6). In addition to channel shape, this relates to sediment transport. The horizontal line (m = b + f) relates to the velocity to wetted area ratio: the velocity of sites on top of the line (classes 1 and 4) increases faster than their area. Conversely for sites bottom of the line (classes 2, 3, 5, and 6). The oblique line (m = f) corresponds to the velocity to depth ratio, and distinguishes between channels with velocity increasing faster than depth (classes 1, 2, 4, and 5) and those with depth increasing faster than velocity (classes 3 and 6). This relates variations on shear stress and channel competence (i.e. maximum particle size that can be transported). These classes were mapped to check for geographical patterns.

5.6 Analyses of physical property influence

Two distinct analyses were performed, which focused on the associations (i) between physical properties and HG classes, and (ii) between physical properties and HG coefficients.

The HG class analysis (see 5.7.2) consisted of univariate ANOVA to assess if different HG classes have different distributions of physical properties (comparing a model with basin property means similar for all classes against a model with means differing for at least one class; see 3.3.6.2), and, if so, followed by Tukey's HSD test (see 3.3.6.3) to assess which pairs of classes are significantly different. Both steps used a 5% significance level.

The HG coefficient analysis (see 5.7.3) had two stages. Firstly, univariate ANOVA was applied to each coefficient (i.e. exponents b, f, m, and multipliers a, c, k) against each property in turn. For example, taking exponent b and the mean basin altitude property ALTBAR, this formally compares two nested models: $b = \alpha$ (b and ALTBAR not related) and $b = a + \beta\ ALTBAR$ (linear relationship between b and ALTBAR); see 3.3.6.2. For properties significantly related to the HG coefficients (p value ≤ 0.05), the R^2 of the corresponding single linear regressions were extracted as a measure of property influence on HG. Secondly, six sets of multiple regressions (one for each HG coefficient as the dependent variable and the retained basin properties as predictors) were fitted using MMI (see 3.3.4.3) to assess the relative influence of those properties.

5.7 Results and discussion

5.7.1 HG class spatial patterns

The mapping of HG classes (Figure 5.4) does not suggest any dominant geographical patterns (for example, like in the previous chapter where regional clusters could be identified), which suggests that any HG class pattern would be more likely related to basin or river types.

5.7.2 Associations between HG classes and physical properties

Results of the ANOVA/Tukey's HSD analysis for HG classes are featured in Table 5.2. For each basin property in this table, the HG classes listed in the second column are significantly different from the classes in the third column (e.g. property altitude of site, HG class 2 is different from 4, 5, and 6), and the class property averages are given in the last two columns. Notable properties that did not meet the significance threshold are the FEH descriptors related to basin permeability (BFIHOST and SPRHOST).

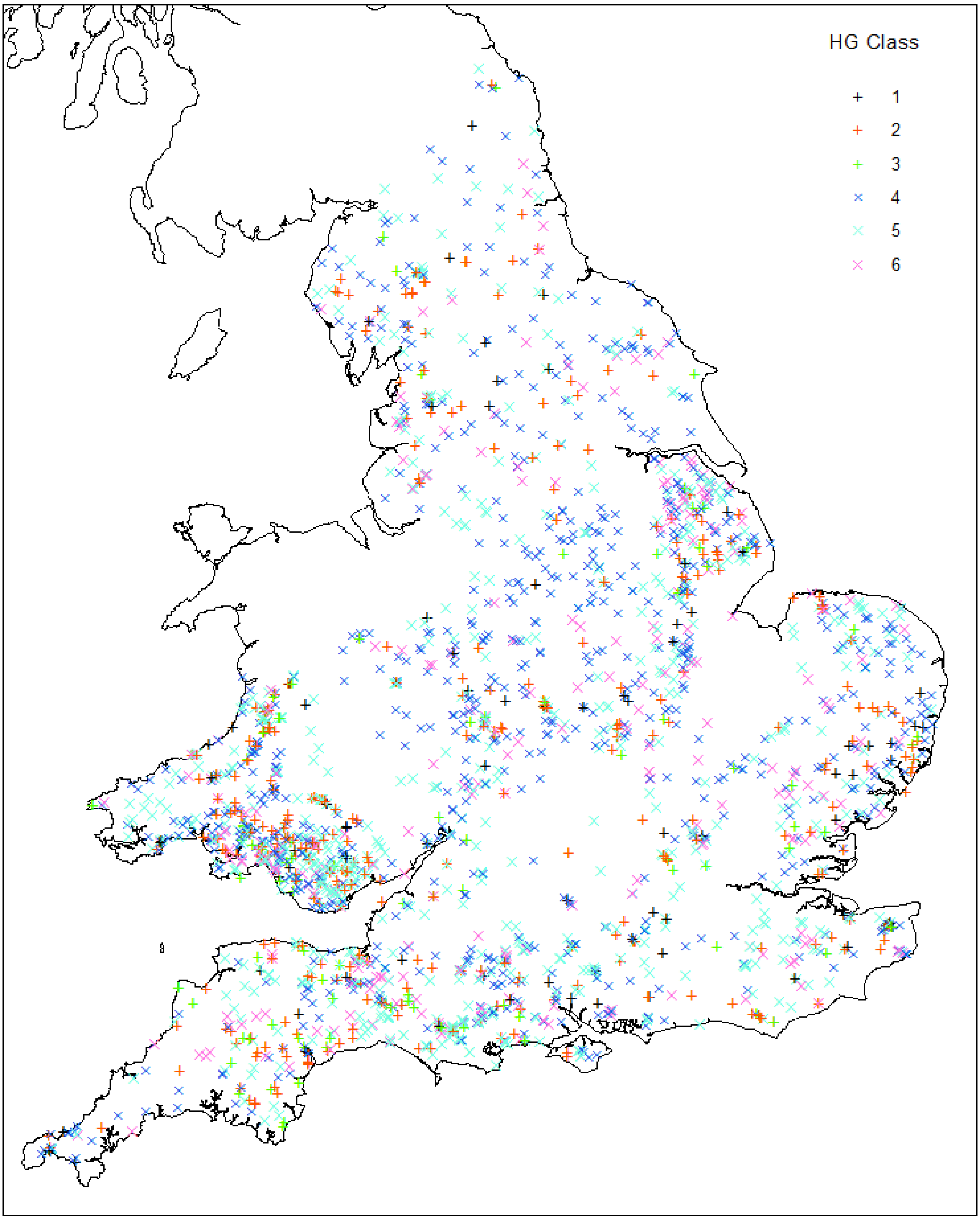

Figure 5.4: Spatial distribution of HG classes.

5.7.3 Relation between basin properties and HG coefficients

Results of the univariate ANOVA tests to identify significant associations between physical properties and HG coefficients are presented in Tables 5.3 (exponents b, f, and m) and 5.4

(multipliers a, c, and k). The tables give the sign of the slopes ('Association') and the R^2 of the corresponding single linear regressions; the higher the R^2 is, the stronger the association is. If a property was not found significantly related to one of the HG coefficient, it is flagged with 'N/S'; if it was not found significant for any coefficient at all, it is simply not featured in the tables (e.g. BFIHOST).

Table 5.2: HG classes with significantly different property averages (ANOVA & Tukey's HSD; $p \leq 0.05$).

Physical Property	Differing HG Classes ($p \leq 0.05$)		Property Class Averages	
ALTBAR	2	6	167.93	128.64
Altitude of site	2	4, 5, 6	75.85	51.82–59.57
	3	4, 6	74.56	51.82 & 54.17
AREA	2	6	67.68	218.47
ASPVAR	2, 3	4, 5, 6	0.33	0.26–0.29
	3	1	0.35	0.27
	4	5	0.26	0.29
Distance from source	2, 3	4, 6	8.82 & 11.32	18.30 & 20.33
DPLBAR	2, 3	4, 6	6.13 & 7.11	11.52 & 12.87
	2	5	7.11	10.58
DPSBAR	2	4, 6	86.80	68.98 & 74.39
LDP	2, 3	4, 6	11.80 & 13.39	21.73 & 24.12
	2	5	13.39	19.81
PROPWET	2	6	0.41	0.37
RMED1D	2	4, 5, 6	39.85	36.22–37.37
RMED1H	2, 3	4, 5, 6	11.49 & 11.52	11.12–11.20
RMED2D	2	4, 5, 6	52.54	47.10–48.82
SAAR4170	2	4, 6	1066.09	922.77 & 963.80
SAAR6190	2	4, 5, 6	1052.79	905.86–951.51
Slope	2, 3	4, 5, 6	12.01	5.65–7.49
	3	1	14.45	6.30
Strahler	2, 3, 5	4	2.42–2.91	3.20
	3	5	2.42	2.91
	2, 3	6	2.42 & 2.59	3.11
Total length upstream	2	6	82.35	239.73

The main finding is that many statistically significant associations have been identified. However, regarding HG exponents, the actual influence of physical properties is limited. The low values of R^2 for each exponent in Table 5.3 mean that physical properties do not explain much of the exponent variability. The a and k multipliers obtain higher R^2 with some properties related to size (R^2 up to about 0.4). These results are consistent with those of Booker (2010) who modelled wetted width using basin properties as predictors, obtaining similar R^2, but still managed to predict *W* reasonably well by using the multipliers. Similar performance could be achieved here for *W* and *V* (and *D* to a lesser extent).

Table 5.3: Significant associations between HG exponents and physical properties (ANOVA *p* value ≤ 0.05) and R^2 of corresponding linear regression ('N/S', not significant).

Physical Descriptor	HG Exponent					
	b		f		m	
	Association	R^2	Association	R^2	Association	R^2
ALTBAR	Positive	0.0030	N/S		N/S	
Altitude site	Positive	0.0214	N/S		Negative	0.0091
AREA*	Negative	0.0727	Positive	0.0085	Positive	0.0295
ASPVAR	Positive	0.0379	Negative	0.0030	Negative	0.0160
Distance source	Negative	0.0168	Positive	0.0081	Positive	0.0043
DPLBAR	Negative	0.0197	Positive	0.0127	Positive	0.0038
DPSBAR	Positive	0.0038	N/S		N/S	
LDP	Negative	0.0210	Positive	0.0130	Positive	0.0042
PROPWET	Positive	0.0023	N/S		N/S	
RMED1D	Positive	0.0104	N/S		Negative	0.0041
RMED1H	Positive	0.0295	N/S		Negative	0.0118
RMED2D	Positive	0.0105	N/S		Negative	0.0039
SAAR4170	Positive	0.0064	N/S		Negative	0.0024
SAAR6190	Positive	0.0070	N/S		Negative	0.0027
Shreve	Negative	0.0039	Positive	0.0047	N/S	
Slope	Positive	0.0314	N/S		Negative	0.0139
Strahler	Negative	0.0361	Positive	0.0070	Positive	0.0127
Total length upstream	N/S		Positive	0.0075	N/S	

*tested on natural log

Table 5.4: Significant associations between HG multipliers and physical properties (ANOVA *p* value ≤ 0.05) and R^2 of corresponding linear regression ('N/S', not significant).

Physical Descriptor	HG Multiplier					
	a		c		k	
	Association	R^2	Association	R^2	Association	R^2
ALTBAR	Positive	0.1068	Negative	0.0109	Negative	0.0192
Altitude site	Negative	0.0030	Negative	0.0173	Positive	0.0067
AREA*	Positive	0.3712	Positive	0.0691	Negative	0.2328
ASPBAR	Positive	0.0031	N/S		N/S	
ASPVAR	Negative	0.1518	Negative	0.0263	Positive	0.1341
BFIHOST	Negative	0.0662	Negative	0.0024	Positive	0.0329
Distance source	Positive	0.4260	Positive	0.0832	Negative	0.1114
DPLBAR	Positive	0.4442	Positive	0.0942	Negative	0.1195
DPSBAR	Positive	0.0630	Negative	0.0182	Negative	0.0073
LDP	Positive	0.4457	Positive	0.0960	Negative	0.1221
PROPWET	Positive	0.1206	Negative	0.0208	Negative	0.0267
RMED1D	Positive	0.0546	Negative	0.0169	Negative	0.0125
RMED1H	Negative	0.0062	Negative	0.0169	Positive	0.0025
RMED2D	Positive	0.0576	Negative	0.0170	Negative	0.0150
SAAR4170	Positive	0.0734	Negative	0.0223	Negative	0.0164
SAAR6190	Positive	0.0665	Negative	0.0224	Negative	0.0140
Shreve	Positive	0.3691	Positive	0.0329	Negative	0.0426
Slope	Negative	0.0166	Negative	0.0155	Positive	0.0413
SPRHOST	Positive	0.0657	N/S		Negative	0.0323
Strahler	Positive	0.4073	Positive	0.0432	Negative	0.2050
Total length upstream	Positive	0.2729	Positive	0.0284	Negative	0.0444

*tested on natural log

5.7.4 Redundancy analysis of physical properties

As discussed in section 3.2.5 and in the previous chapter, many of the physical properties co-vary, often substantially, and are best interpreted as groups of properties ("meta-properties") rather than on their own. Descriptor specifications, pair plots, and correlation matrices (Kendall *tau* ≥ 50%; see 3.3.6.1) were checked to identify the following groups of descriptors:

1) Elevation/wetness ('elevation' hereafter): as noted in Laizé and Hannah (2010) and in previous chapters, basin elevation and wetness are very strongly correlated in the UK;

the meta-property ‘Elevation’ includes ALTBAR (mean basin elevation), DPSBAR (overall basin steepness, correlated with ALTBAR), rainfall descriptors (SAAR4170, SAAR6190, RMED1D, and RMED2D), PROPWET (proportion of time basin is wet; correlated to rainfall descriptors), and the site altitude.

2) Size: AREA, DPLBAR (mean drainage length), LDP (longuest drainage path), which are correlated by design, ASPVAR (basin aspect variability; correlated with AREA as smaller basins tend to be oriented toward specific direction), distance from source, Strahler and Schreve indices, and the total length of upstream rivers.
3) Permeability: BFIHOST and SPRHOST (negatively correlated).

Three properties were kept separate: ASPBAR (mean basin aspect), RMED1H (median hourly rainfall), and slope at the site. Basins with higher RMED1H values tend to have a larger amount of short high-intensity rainfall events, which could occur regardless of basins being otherwise generally dry or wet as measured by other wetness descriptors like SAAR6190. This type of peak rainfall events can have a huge impact on physical habitat and river ecosystems (e.g. flushing out organisms, sediments or debris, altering channel shape).

5.7.5 Synthesis of influence of physical properties on HG classes

Based on the redundancy analysis, results were synthesized per group of properties (Table 5.5). All descriptors within each meta-property were checked to confirm they have consistent associations with HG classes. The main distinction is between classes 2 and 3 on the one hand, and classes and 4, 5, and 6 on the other hand. This corresponds to the division along the vertical line (b = f) on Figure 5.3: classes 2 and 3 are channels getting comparatively wider and shallower as discharge increases (b > f, increasing *W/D*) while classes 4, 5, and 6 become narrower and deeper (b < f, decreasing *W/D*). There are also distinctions between classes 3 and 1, and between classes 5 and 4: these correspond to the horizontal line split (m = b + f).

Classes 3 and 5 are for sites where the wetted area increases faster than velocity, conversely for classes 1 and 4. To summarise the trends, sites with higher elevation, smaller and wetter basins, and steeper slopes tend to become wider and shallower with increasing discharge and they tend to have their wetted area increasing faster than their velocity (and conversely for lower elevation, larger, drier basins, and milder slopes).

Table 5.5: Synthesis of HG classes with significantly different physical characteristics.

Physical Meta-Property	Differing HG Classes ($p \leq 0.05$)		Class Physical Characteristics	
Elevation	2 or 3	4, 5 or 6	Higher	Lower
Size	2 or 3	4, 5 or 6	Smaller	Larger
	3	1		
	5	4		
Slope	2, 3	4, 5, 6	Steeper	Milder
	3	1		
RMED1H	2, 3	4, 5, 6	Wetter	Drier

Referring back to the concepts of depth and velocity suitability indices, and the proportion of usable physical habitat presented in section 2.3 (Figures 2.1 and 2.2), the site types that have been identified would have very different sensitivity to flow change. For example, the smaller, higher elevation sites become wider and deeper rather than faster flowing, so that they would reach the top plateau on the depth suitability curve (all habitat suitable) than they would move towards, or from the peak of the velocity curve.

5.7.6 Synthesis of influence of physical properties on HG exponents and multipliers

As above, results were synthesized per meta-properties (Tables 5.6 and 5.7). All descriptors within each meta-property were checked to confirm they have consistent associations with HG coefficients. In one case only, there was a discrepancy: the site altitude, although 55% correlated with mean basin elevation ALTBAR, has opposite associations for multipliers a and k (Table 5.4). It is possibly due to site altitude being also negatively correlated to area, although in a much more limited extent, so that when site altitude increases, basin size decreases. As a consequence, site altitude was kept separate from the elevation meta-property (italics in Table 5.7). To interpret these tables, it is easier to refer to the log-transformed version of the HG equations, which are linear, where the exponents correspond to the slopes, the multipliers to the intercepts. For example, taking wetted width *W* (coefficients a and b), higher elevation sites tend to have a steeper slope (higher sensitivity to flow change) and a higher intercept (overall wider sections), but sites with larger basins tend to have a milder slope (lower sensitivity to flow change) and a higher intercept. The depth exponent f is only associated with size (slope increasing with basin size).

Table 5.6: Synthesis of significant associations between HG exponents and physical meta-properties.

Physical Meta-Property	HG Exponent		
	b	f	m
Elevation	Positive	N/S	Negative
Size	Negative	Positive	Positive
Slope	Positive	N/S	Negative
RMED1H	Positive	N/S	Negative

Although some properties were kept separate, there are still some correlations with the other groups; for example, slope is approximately 30% correlated with elevation (upland basins tend to be steeper). The relative role of each meta-property was assessed by testing multiple linear regressions using the MMI approach (see 3.3.4.3), which identifies sets of best models with similar performance (top models within 4 AIC points). Properties that are included in all models have more influence than the ones that were only included in some of the best models (Table 5.8). Typically, the variables that are included in only some of the best models are the ones co-varying with the more influential predictors, and only adding limited information value to the model. Exponent f was not analysed as it only relates to one property.

Table 5.7: Synthesis of significant associations between HG multipliers physical meta-properties.

Physical Meta-Property	HG Multiplier		
	a	c	k
Elevation	Positive	Negative	Negative
Altitude of site	*Negative*	*Negative*	*Positive*
Permeability	Negative	Negative	Positive
Size	Positive	Positive	Negative
ASPBAR	Positive	N/S	N/S
RMED1H	Negative	Negative	Positive
Slope	Negative	Negative	Positive

Table 5.8: Inclusion of physical meta-properties in multiple linear regression models of HG coefficeints.

HG Coefficient	Meta-Property	
	In All Models	In Some Models
b	Size, slope, RMED1H	Elevation
m	Size, RMED1H	Elevation, slope
a	Elevation, permeability, size, slope	Site altitude, RMED1H
c	Elevation, permeability, site altitude, size	Slope, RMED1H,
k	Elevation, permeability, size, slope	Site altitude, RMED1H

5.8 Conclusions

This chapter analysed the river hydraulic response to flow variability for more than 2,500 cross-sections in England and Wales (UK), covering most of the basin types in the country, and quantified the relationship between hydraulics and a wide selection of basin and site properties. Firstly, the ‘physiographic region’ assumption mentioned in section 2.3 was not found to apply conclusively in the study area (as indicated by the lack of regional patterns in Figure 5.4). Secondly, the study demonstrated there are statistically significant associations between hydraulics and physical properties, although the magnitude of these associations is limited. The main finding is the distinction between different channel hydraulic types (based on HG classes; see 5.7.5) corresponding to different site or basin types (e.g. wider/shallower rivers, higher, smaller basins). Overall, basin elevation and size were found to be the properties capturing most of the hydraulic variability. Basin permeability was however not significantly related to HG exponents, only to HG multipliers and in a limited way, which is inconsistent with the common view that basin permeability influences HG via it controls on basin hydrological behaviour (Keaton *et al.*, 2005; Booker, 2010).

The findings of this study however support the views of authors such as Park (1977) or Ridenour (2001), who argue that hydraulics is controlled by much more local variables than regional or basin characteristics (eg bed material; Rhodes, 1987). It could be hypothesized that regional hydraulic curves, as used in the USA (Keaton *et al.*, 2005), can only be derived at broader geographical scales and in countries with larger homogenous landscape units (e.g. comparing European countries).

6. CLIMATE AND WATER TEMPERATURE

6.1 Introduction

This chapter addresses the research objectives identified in section 2.4 by quantifying the relative importance of different climatic drivers of WT across a set of UK 'benchmark' monitoring sites, and assessing the effect of basin properties as modifiers of the climate/WT association. Section 2.4 also identified the following research gaps: (1) limited number of WT sites and climate explanatory variables, and/or limited geographical extent; (2) limited knowledge of role of basin properties; (3) need for alternative method. This study addresses the issue of driving data availability by using a comprehensive and consistent set of modelled climate data. With a period of records within 1984–2007, for a total of 35 sites located on 21 rivers within 16 basins, providing a Great Britain geographical extent, six distinct modelled climatic variables were taken within 1 km of the sites. The study focuses on broad spatio-temporal patterns, hence is based on three-month averaged data (i.e. seasonal). Such a temporal scale addresses issues of temporal auto-correlation often found in water temperature time series. The study also investigates a much wider range of basin properties than previous studies. ML modelling (see 3.3.3.2) is applied as an alternative to site-specific or to classification-based analyses because it allows to pool all site data together while taking into account data structure (i.e. observations at site, sites within same basin) as well as not losing any information. In addition, model selection used MMI (see 3.3.4.3), another state-of-the-art technique, which provides more robust models based on sets of good models rather than selecting a single best model.

6.2 Data and methods

The research methodology follows the work flow summarised in Figure 6.1: (1) water temperature (WT) observed data linked with (2) modelled climate variables, then (3) all converted to seasonal (three-month) average series used within (4) a ML modelling / MMI framework to produce (5) five output models (individual seasons and all seasons).

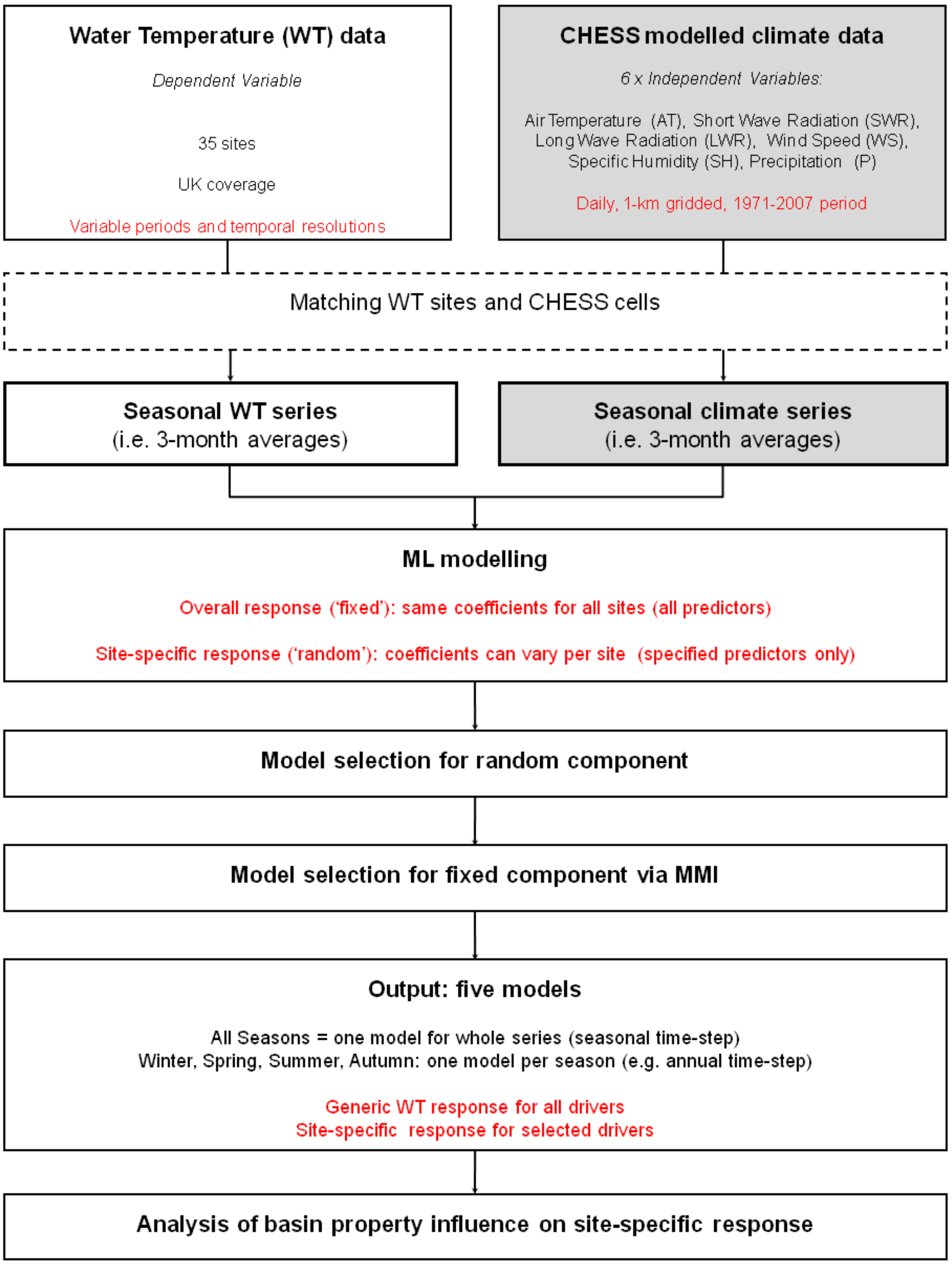

Figure 6.1: Methodological flow chart.

6.2.1 Water temperature data

The water temperature data used therein (see 3.2.4) totals 41 sites but six were dropped from the analysis because they are either duplicates (i.e. same site and same data included in several datasets) or spatially too close to one another (e.g. the Tadnoll has six sites located 50 meters apart along the river stretch; only the first and last sites were used) so that 35 sites were used (see Figure 6.2 and in Appendix I, Table 3). Notably, two sites, both named ‘Frome at East Stoke’ appear in the Frome and in the LOCAR datasets. Despite being geographically close, their datasets are different in terms of period of record (see summary of the datasets in Table 6.1) and completeness, as well as featuring value differences when they overlap; they were therefore kept as separate sites rather than merged or dropped.

Table 6.1: Summary table of datasets.

Dataset	Start	End	Recording	Frequency	Number of Sites Used
Frome	1991	2009	logger	15 minutes	1
Great Ouse	1989	1993	logger	hourly	1
Tadnoll	2005	2006	logger	15 minutes	2
Plynlimon	1984	2008	manual	weekly (approx.)	4
UKAWMN	1988	2008	manual	monthly (approx.)	10
LOCAR	2002	2011	logger	15 minutes	17

6.2.2 Climate data

Climate drivers were characterised by six CHESS variables (AT, LWR, P, SH, SWR, WS), which were extracted as six daily time series for the 1971–2007 period of record (see 3.2.1.4 and Table 3.2). Each CHESS cell was matched spatially to the study temperature site(s) it contained.

6.2.3 Seasonal series derivation

Firstly, sub-daily water temperature datasets were averaged at a daily time step (Frome, Great Ouse, Tadnoll, LOCAR) while spot measurements (Plynlimon, UKAWMN) were assumed representative of the day they were taken, although it is worth keeping in mind that they are only representative of daylight conditions. Secondly, daily temperature data were matched by date to the daily climate data. Thirdly, seasonal averages were computed from the daily data for all seven variables (see 3.3.1). Lastly, five time series were compiled: one series per season at an annual time step (i.e. winter year *y*, winter year *y*+1, etc.), and one series with all seasons at a seasonal time step (i.e. autumn year *y*, winter year *y*, spring year *y*, etc). These series and their related models will be thereafter referred to as 'autumn', 'winter', 'spring', 'summer', and 'all seasons'.

6.2.4 Basin properties

Basin properties were selected from the FEH descriptors (see 3.2.5), which cover all aspects of basin physiography, and in particular characteristics related to elevation, permeability, and size, which are known to modify hydroclimatological links (see Chapter 4; Laizé and Hannah, 2010; Garner *et al.*, 2013).

6.3 Methodology

6.3.1 Multi-level modelling

In order to take into account the hierarchical nature of the water temperature dataset (e.g. sites located on the same river), ML modelling (see 3.3.3.2) was used to build linear models with water temperature as the predicted variable, and the six climate variables as explanatory variables. A three-level data structure was applied: individual observations (level 1) nested within monitoring sites (level 2) nested within river stretches (level 3). In addition, a time variable was included as a predictor to take into account any linear trend in the time series. In order to avoid instability issues when fitting models, the predictors were centred (i.e. their mean subtracted).

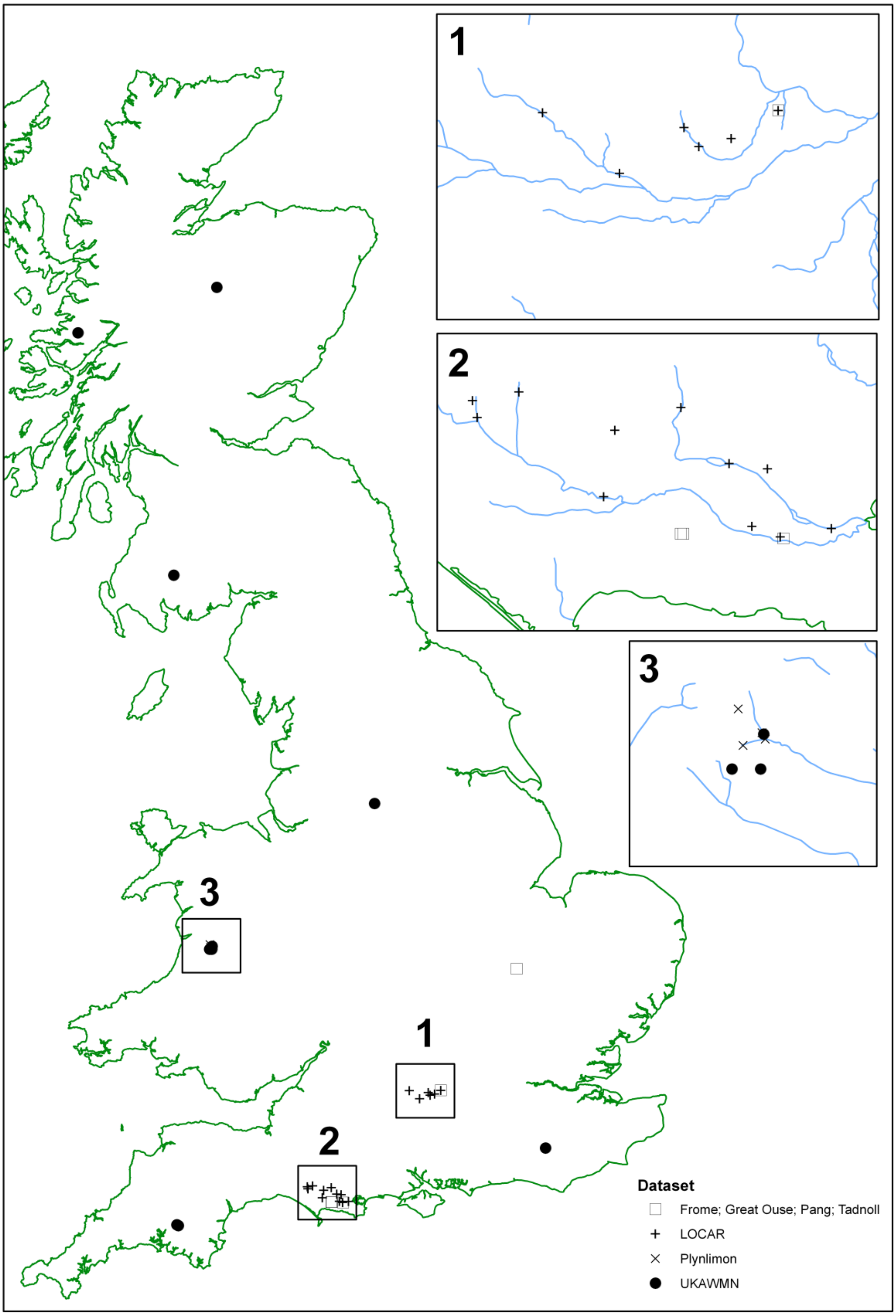

Figure 6.2 Location map of the study sites.

6.3.2 Model selection with multi-model inference

Following standard ML modelling practice (e.g. Zuur *et al.*, 2009), the model selection was done in two stages. First, with all predictors included in the fixed component, models with the various combinations of predictors in the random component were ranked using AICc (see 3.3.4.1). This was done for the four seasonal series and the 'all season' one. In each case, the random component giving the lowest AICc was retained.

With the random component selected, modelling then followed the MMI approach, which selects sets of good models rather a single best one (see 3.3.4.3). All possible combinations of the predictors in the fixed component were fitted and the resulting models ranked based on their AICc.

Akaike weights (Burnham and Anderson, 2002) were also calculated; weights are basically re-scaled AICc scores, and give an indication of the relative importance of each model within a set (if only one model was tested, the weight would be one; models with similar AICc scores have similar Akaike weights); this is used when reporting on MMI outputs. Then, following recommended statistical usage, all models within four points of the lowest AICc were selected (Zuur *et al.*, 2009). Note that in some cases, there is only one model selected as its AICc is lower by more than four points than the next second model in line, and it would also have the higher Akaike weight.

6.3.3 Analysis of basin property influence

For those explanatory variables that were included in the random effects (i.e. different sites can have different coefficients), any relation between site-specific coefficients and site basin properties was investigated by (i) using maps and scatter plots of coefficients against basin properties, and (ii) applying ANOVA (see 3.3.6.2) to confirm observed patterns. A basin property is considered having significant influence on the WT–climate variable relationship when the ANOVA p value is below 0.05. To quantify the influence of these properties, either alone or combined, linear regressions of the site-specific coefficients were fitted.

6.4 Results

6.4.1 Model selection and performance

The number of models included in each final set as selected by MMI was: all seasons = 2; winter = 4; spring = 12; summer = 6; autumn = 14. From a practical perspective, reporting on each set of models would be cumbersome so reporting is done on the 'average model', in which the coefficient of a given variable is the average of the variable coefficients in all the models in the selected set (Table 6.2). For example, the winter AT coefficient (0.3955) is the average of the four AT coefficients from the four models included in the winter set. Thereafter, 'model' means the average model of a given set of selected models. Because the study main objective is to develop explanatory models, model performance was simply assessed by plotting fitted against observed water temperature data, and was deemed satisfactory for all models (Figure 6.3).

6.4.2 Overall responses: relative importance of climatic drivers

With MMI, the role of each explanatory variable is assessed using its relative importance (RI). For a given predictor, RI is calculated as the sum of the AICc weights of the models in which that predictor is included. RI ranges from 0 (variable never included) to 1 (included in all models). For example, the 'all seasons' model is based on two models with AICc weights 0.74 and 0.26; the explanatory variable P is only included in the model with weight = 0.26, hence its RI of 0.26, while the other predictors are in both models and have a RI equal to 1 (Table 6.2).

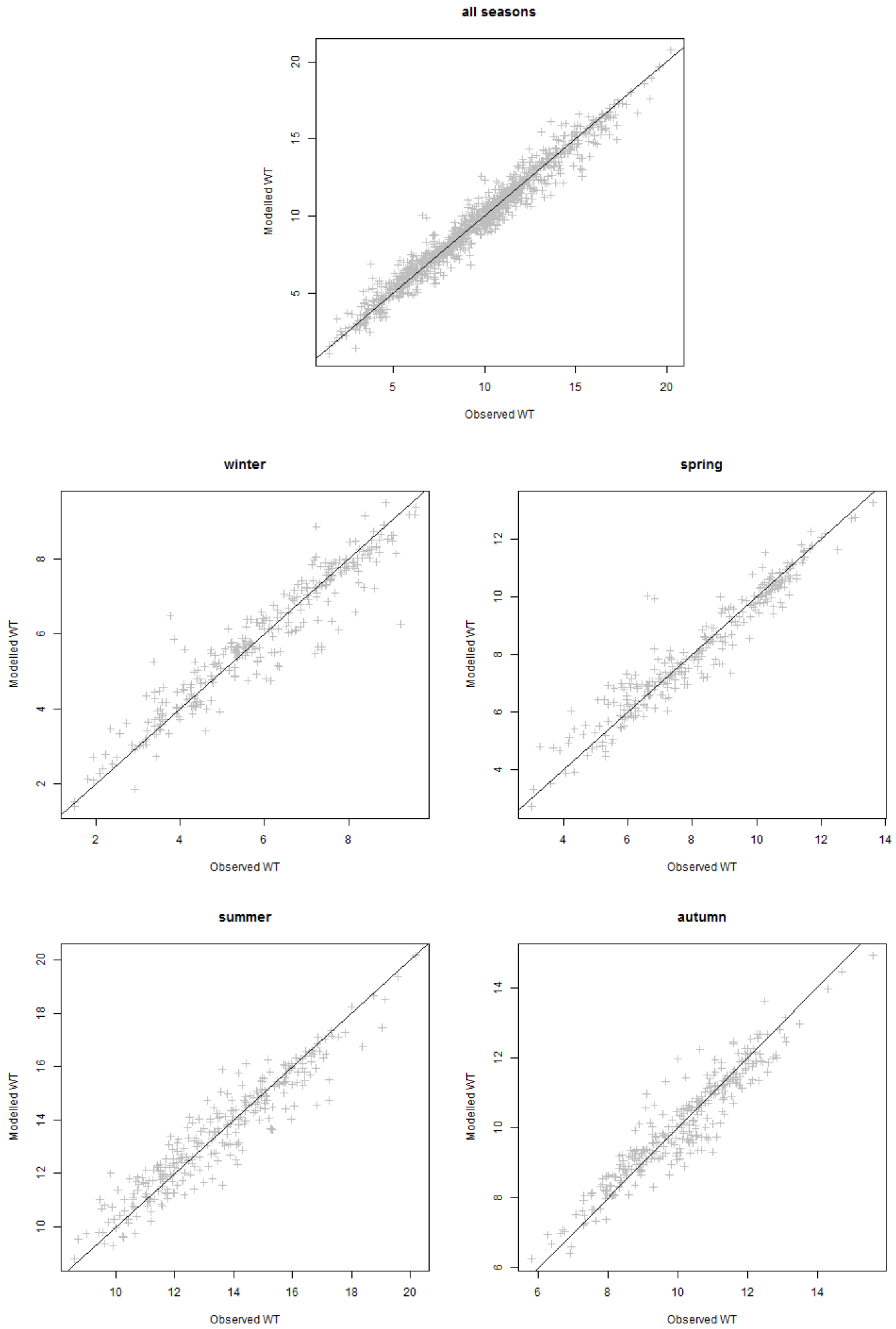

Figure 6.3: Plots of observed and modelled water temperature for the five models.

Table 6.2: Generic response for the five average models.

	all seasons		winter		spring		summer		autumn	
	Coef.	*RI*	Coef.	*RI*	Coef.	*RI*	Coef.	*RI*	Coef.	*RI*
AT	0.5824	*1.00*	0.3955	*1.00*	0.6815	*1.00*	0.4969	*1.00*	0.6860	*1.00*
SWR	0.0055	*1.00*	0.0193	*1.00*	0.0073	*1.00*	0.0077	*0.64*	0.0003	*1.00*
LWR	-0.0149	*1.00*	0.0008	*0.13*	0.0107	*0.18*	-0.0246	*0.52*	-0.0053	*0.25*
WS	-0.1348	*1.00*	-0.1014	*0.68*	-0.1228	*0.63*	-0.3028	*1.00*	0.0552	*0.33*
SH	0.4664	*1.00*	0.6658	*1.00*	0.2241	*0.34*	0.2903	*0.53*	0.1360	*0.37*
P	0.0011	*0.26*	0.0049	*0.15*	-0.0107	*0.38*	-0.0004	*1.00*	-0.0111	*0.41*

First, focusing on the RI of the predictors, none of them has a zero RI in any model. This means all predictors are useful for all models, although it is variable across models. All models considered, AT (RI = 1 for all models) and SWR (RI = 1 for four models and 0.64 for the fifth) are the most important variables. Seasonal models tend to have one or two particularly important predictors in addition to AT and SWR; taking RI above 0.5, these are: winter, SH and WS; spring, WS; summer, all other predictors; autumn, none.

Focusing on the variable coefficients, AT, SWR and SH have positive coefficients for all models, i.e. a consistent warming effect on water temperature, while LWR, WS and P have positive and negative coefficients, i.e. a warning or cooling effect depending on season.

The variable effect changes in strength depending on season. Comparing the absolute value of the seasonal coefficients for each variable (not between variables as they have different scales): AT, lowest in winter, highest in spring and autumn; SWR, lowest in autumn, highest in winter; LWR, lowest in winter, highest in summer; WS, lowest in autumn, highest in summer; SH, lowest in autumn, highest in winter; P, lowest in summer, highest in spring and autumn.

6.4.3 Site-specific responses

The following variables were included as random effects (i.e. variables for which different sites have different coefficients): all seasons, AT and SWR; winter, SH; summer, P; autumn, SWR; spring, no variables retained. Table 6.3 features the site-specific coefficients for these predictors. For example, the Devils Book at Dewlish Village site (Piddle basin) has an 'all seasons' AT coefficient of 0.5914, i.e. very close to the overall AT coefficient, while the Great Ouse at Lees Brook site has a slope of 0.918; i.e. at Lees Brook WT is comparatively more influenced by AT than at Dewlish Village. The site-specific coefficients of AT are all positive, and those of P are either positive or negative; both variables are thus consistent with the overall pattern shown previously. However, SWR, and SH have both positive and negative site-specific responses, unlike the overall pattern (positive coefficients).

Table 6.3: Site-specific model coefficients (random slopes).

Dataset	Site	Random Slope				
		All AT	All SWR	Au SWR	Su P	Win SH
Frome	Frome at East Stoke	0.570	0.010	0.008	-0.046	0.332
Great Ouse	Great Ouse at Lees Brook	0.918	0.011	0.028	-0.053	1.402
LOCAR	Frome at Chilfrome	0.518	0.003	-0.001	-0.030	0.023
	Frome at East Stoke	0.551	0.011	0.009	-0.049	0.299
	Frome at Loudsmil	0.498	0.009	0.004	-0.046	0.120
	Frome, Sydling Water at Sydling St Nicholas	0.362	0.001	-0.009	-0.008	-0.368
	Frome, Hooke at Maiden Newton	0.568	0.002	0.000	0.000	0.106
	Frome, Bovington Stream at Blindmans Wood	0.647	0.004	0.006	0.007	0.330
	Lambourn at East Shefford	0.199	0.004	-0.017	-0.010	-0.764
	Lambourn at Shaw	0.405	0.008	-0.001	-0.014	-0.145
	Pang, below Blue Pool	0.202	0.004	-0.018	-0.003	-0.825
	Pang at Bucklebury	0.598	0.008	0.006	-0.006	0.344
	Pang at Frilsham	0.562	0.010	0.006	-0.014	0.270
	Pang at Tidmarsh	0.440	0.007	-0.002	-0.006	-0.127
	Piddle at Baggs Mill	0.518	0.006	0.002	0.002	0.083
	Piddle at Briantspuddle	0.479	0.002	-0.004	0.009	-0.072
	Piddle at Little Puddle	0.528	0.007	0.005	-0.003	0.154
	Piddle, Bere Stream at Snatford Bridge	0.336	0.007	-0.004	-0.039	-0.345
	Piddle, Devils Book at Dewlish Village	0.594	0.008	0.007	-0.025	0.327
Plynlimon	Lower Hafren	0.609	-0.004	-0.005	0.043	0.024
	Lower Hore	0.719	0.006	0.011	-0.023	0.606
	Upper Hafren	0.508	-0.003	-0.006	0.026	-0.201
	Upper Hore	0.677	-0.002	0.001	0.006	0.223
Tadnoll	Tadnoll, Logger 1	0.349	0.008	-0.002	-0.012	-0.249
	Tadnoll, Logger 6	0.351	0.007	-0.002	-0.011	-0.256
UKAMN	Allt a Mharcaidh, 2	0.671	-0.001	0.002	0.017	0.285
	Allt na Coire nan Con, 3	0.774	0.005	0.009	-0.023	0.677
	Dargall Lane, 9	0.866	0.008	0.017	-0.044	0.927
	River Etherow, 12	0.679	0.010	0.013	-0.048	0.425
	Old Lodge, 13	0.626	0.002	0.003	0.020	0.108
	Narrator Brook, 14	0.348	0.003	-0.003	-0.011	-0.482
	Afon Hafren, 17	0.635	-0.004	-0.002	0.040	0.156
	Nant y Gronwen, 18	0.902	0.015	0.024	-0.068	1.349
	Narrator Brook, 23	0.312	0.000	-0.009	-0.003	-0.475
	Afon Gwy, 24	0.732	0.010	0.016	-0.066	0.657

6.4.4 Role of basin properties

6.4.4.1 Significant basin properties

The site-specific coefficients were initially mapped against elevation and permeability to explore basin modification of the WT–Climate relationship, and any pattern linked to easting/northing. While there was no clear easting/northing pattern, the maps showed some potential associations between coefficients and basin properties. ANOVA (see 3.3.6.2) was then run on the FEH descriptors to identify descriptors significantly associated with the model coefficients; results are presented in Table 6.4.

Table 6.4: FEH basin descriptors significantly related to site-specific model coefficients (ANOVA; p≤0.05).

Model	Predictor	Descriptor	Type of Association
all seasons	AT	ALTBAR	Positive
		AREA*	Negative
		ASPVAR	Positive
		BFIHOST	Negative
		DPLBAR	Negative
		DPSBAR	Positive
		LDP	Negative
		PROPWET	Positive
		SPRHOST	Positive
		RMED1D	Positive
		RMED2D	Positive
		SAAR4170	Positive
		SAAR6190	Positive
all seasons	SWR	ALTBAR	Negative
		AREA	Positive
		DPLBAR	Positive
		LDP	Positive
		SAAR6190	Negative
autumn	SWR	AREA*	Negative
		BFIHOST	Negative
		SPRHOST	Positive
winter	SH	AREA*	Negative
		BFIHOST	Negative
		SPRHOST	Positive
		DPLBAR*	Negative
		LDP*	Negative
		PROPWET	Positive

*tested on natural log

6.4.4.2 Redundancy analysis of basin properties

The basin properties featured in Table 6.4 are the ones significantly associated with the site-specific coefficients. However, as explained in section 3.2.5 and in Chapters 4 and 5, due to the correlation between properties, they need to be interpreted as groups of properties (“meta-properties”). Similarly to the previous chapter, descriptor specifications, correlation matrices (Kendall; see 3.3.6.1), and pair plots featuring the 35 study sites were checked to identify the following meta-properties: (1) elevation/wetness ('elevation' hereafter): ALTBAR, DPSBAR, SAAR4170, SAAR6190, RMED1D, RMED2D, and PROPWET; (2) size: AREA, DPLBAR, LDP, ASPVAR; (3) permeability: BFIHOST and SPRHOST. Descriptors for each meta-property were checked to confirm they have consistent associations with each model predictor. One descriptor was retained per group, depending on which were flagged as significant (Table 6.5).

Table 6.5: Simplified basin descriptors significantly related to site-specific model coefficients.

Model	Predictor	Basin Meta-property	Retained Descriptor	Type of Association
all seasons	AT	Elevation	ALTBAR	Positive
		Permeability	BFIHOST	Negative
		Size	AREA	Negative
all seasons	SWR	Elevation	ALTBAR	Negative
		Size	AREA	Positive
autumn	SWR	Permeability	BFIHOST	Negative
		Size	AREA	Negative
winter	SH	Elevation	PROPWET	Positive
		Permeability	BFIHOST	Negative
		Size	AREA	Negative

6.4.4.3 Regression models of site-specific coefficients

To quantify the influence of the properties, either alone, or combined, simple linear regressions of the site-specific coefficients were fitted and ranked with AICc as per MMI. Models are featured in Table 6.6. The model with the lowest AICc is displayed in bold; models within 4 points of the lowest AICc are considered equally good.

Table 6.6: Linear regressions of site-specific coefficients as function of basin properties (models ordered by increasing AICc; best model in bold; models within 4 AICc points of best model in standard font, those outside in italics).

WT Model	Coefficient	Linear Regression	R^2	AICc
all seasons	AT	**BFIHOST**	**0.370**	**-31.3**
		BFIHOST+ALTBAR	0.403	-30.1
		BFIHOST+ln(AREA)	0.381	-29.3
		BFIHOST+ln(AREA)+ALTBAR	0.411	-28.3
		ln(AREA)	*0.284*	*-26.8*
		ln(AREA)+ALTBAR	*0.288*	*-24.5*
		ALTBAR	*0.127*	*-19.9*
all seasons	SWR	**ALTBAR**	**0.177**	**-277.5**
		ALTBAR+ln(AREA)	0.183	-275.2
		ln(AREA)	0.089	-274.0
autumn	SWR	**BFIHOST**	**0.125**	**-223.1**
		ln(AREA)	0.115	-222.6
		BFIHOST+ln(AREA)	0.136	-220.9
winter	SH	**BFIHOST**	**0.192**	**48.7**
		ln(AREA)	0.162	50.0
		BFIHOST+ln(AREA)	0.203	50.8
		BFIHOST+PROPWET	0.192	51.3
		PROPWET	0.123	51.6
		PROPWET+ln(AREA)	0.178	51.9
		PROPWET+ln(AREA)+BFIHOST	*0.203*	*53.6*

6.5 Discussion

6.5.1 Overall response

All models flag a close association between AT and WT: (i) AT RI is always equal to 1; (ii) AT coefficient is within 0.3955–0.6860, which, given that both variables have the same unit, means that WT is roughly equal to 40–70% of AT. This finding is consistent with the literature: it is well documented that AT and WT are both influenced by climatic drivers, and tend to achieve thermodynamic equilibrium (Caissie, 2006). Both variables consequently tend to co-vary positively, making AT a very useful predictor, although the association is partly causal only.

Equally, SWR, i.e. direct sunshine, is physically a positive input of energy, and is appropriately captured in the models with positive coefficients. Its effect is stronger in winter (highest coefficient), possibly because climatic conditions are generally at their coolest, so that heating due to SWR is comparatively more noticeable.

SH is in this context a proxy for the amount of evaporation, hence cooling due to evaporation (the more humidity in the air, the less evaporation, thus the less water cooling). The positive coefficients are therefore consistent although the process captured by this predictor is more the absence of cooling rather than warming.

Three predictors—LWR, WS, and P—have positive or negative coefficients depending on the model, i.e. a warming or cooling effect on WT. The interpretation for P is that when rainfall occurs, its temperature may be higher or lower than that of the river depending on the season. For WS, the interpretation is more complex: wind has a cooling effect by increasing evaporation at the water surface, which would be captured by a negative coefficient, but WS also plays a significant role in air–water energy exchanges (increased mixing), which would be captured by a positive coefficient given AT has a positive coefficient. For most models, the cooling effect seems to be predominant, hence the overall negative coefficient, while in autumn, mixing seems to take precedence. One can theorise that the primary effect of WS is to increase evaporation, and the secondary effect is to increase mixing. In autumn, given that the conditions are usually wetter with more air moisture, the primary effect is weaker and the secondary effect manifests itself more. This would be consistent with WS having both its lowest absolute coefficient and RI (0.0552 and 0.33, respectively) in autumn (within 0.1228–0.3028 and 0.63–1.00 otherwise).

However, for LWR, alternating coefficient signs is inconsistent with theory. LWR is physically an energy input to the river (warming) so its coefficient should be always positive. LWR corresponds to radiation diffused by clouds so is co-varying with cloud cover, and inversely co-varying with direct sunshine (SWR). As a consequence, high LWR is associated with more clouds and less sunlight, which is consistent with generally colder climatic conditions, and in turn colder water. The negative coefficients would therefore most likely be an artefact with LWR acting as a proxy for processes driving colder water temperatures.

6.5.2 Site-specific response

First of all, it is worth reminding why different models include different predictors in the random component. The presence of a variable in the random component means that different sites have different responses to that variable. In theory, it is conceivable that all predictors should be included. However, the model selection was based on an information criterion; if a variable was not included in the random component, it means that the site-specific response was not substantially different from the overall response and that the benefit of adding it was outweighed by the increase in model complexity.

As shown in the results, the site-specific coefficients for AT and P are consistent with the overall pattern, and with a physical interpretation, but it is not the case with SWR and SH. Some sites exhibits negative coefficients for SWR, which is apparently conflicting with the overall pattern (positive coefficient) and with the physics: SWR is represents an input of energy so should warm up water. For SH, as seen above, the more humidity, the less evaporation hence the less cooling; coefficients should similarly be positive. This inconsistency can be explained by: (1) the site-specific response relating to fewer data-points (i.e. data at each site) than the overall response (all sites pooled); (2) the water temperature signal being also controlled by many other variables not included in the model (see section

2.4). It is likely that those sites with negative coefficients are actually capturing another effect with SWR acting as a proxy (or more simply they are an artefact). However, both SWR and SH coefficients are significantly linked with basin properties in a consistent manner; for example, for the autumn model, the smaller the SWR coefficient is, including negative values, the higher is the permeability. In any case, this should be investigated in further research.

6.5.3 Influence of basin properties

6.5.3.1 Elevation

In the 'all seasons' model, the higher (lower) the elevation is, the higher (lower) the AT coefficient is but the lower (higher) the SWR coefficient is. Given the association between AT, SWR and WT (i.e. SWR heating up both WT and AT when it is sunny, WT and AT exchanging heat any time), this result means that high elevation basins are comparatively more influenced by atmospheric heat exchanges and less by direct sunlight, than lower elevation ones. For the winter model, the higher the elevation, the higher the SH coefficient. Similarly, this means that uplands basins are more controlled by atmospheric processes than lowlands ones.

6.5.3.2 Permeability

For all models and for all predictors (all seasons AT, autumn SWR, winter SH), the more (less) permeable the basin, the lower (higher) the coefficients. Water temperature in impermeable basins is more influenced by climate than in permeable basins. Indeed, in permeable basins, the temperature regime is comparatively more influenced by the groundwater input to the river; groundwater temperature tends to have more inertia and groundwater to have a damper effect. This is consistent with findings reported in Garner et al.

(2013), which used different temperature monitoring sites and basin properties to investigate air–water temperature associations only.

6.5.3.3 Size

For the ‘all seasons’ model, the smaller (larger) the basin is, the higher (lower) the AT coefficient is but the lower (higher) the SWR coefficient is. This is a similar result as with elevation (see 6.5.3.1), but in this case, smaller basins are comparatively more influenced by atmospheric heat exchanges and less by sunlight than larger ones. However, the association between size and SWR for the ‘autumn’ model goes the opposite way, i.e. the smaller the basin, the higher the SWR coefficient. Although seemingly contradictory, the interpretation lies in the fact that smaller basins are more influenced by the climate drivers than larger ones. In the ‘all seasons’ model, AT and SWR, being closely associated as noted earlier, are somehow competing to explain between-site variability. In the autumn model, only SWR was retained in the random component, possibly because of the generally cooler temperatures in that season, which make AT–WT exchanges less notable compared to radiative inputs. SWR is consequently the only variable explaining the higher control on smaller basins, in this case.
The winter SH model supports this conclusion (the smaller the basin, the higher the SH coeffcient).

6.5.3.4 Overall pattern

The regression models of site-specific coefficients presented in Table 6.6 provide some quantification of the influence of basin properties. Depending on the site-specific coefficient, the R^2 range from 0.125 (autumn SWR) to 0.411 (‘all seasons’ AT). In each case, a single regression (on BFIHOST or ALTBAR) is the best model AICc-wise, although most of the multiple regressions are within 4 AICc points so equally valid models.

These meta-properties are themselves not independent in the UK: (i) high upland basins are generally impermeable in the UK (permeable geology occurs in the lowlands); (ii) there are comparatively more small basins at higher elevation. Results in Table 6.6 demonstrate this. For the 'all seasons' AT coefficient models, single regressions on BFIHOST, ln(AREA), and ALTBAR achieve a R^2 of 0.370, 0.284, and 0.127, respectively, but the multiple regressions with either two or all of them only achieve R^2 within 0.381–0.411. The comparatively small gain when adding several predictors is due to the three properties co-varying. Similar comments can be made on the other models.

At one end of the spectrum, small, upland, and/or impermeable basins are thus the most exposed to atmospheric heat exchanges, at the other end, large, lowland, and/or permeable basins are the least exposed. Intermediate basin types occur less frequently or hardly (e.g. upland permeable).

6.6 Conclusions

Of the six predictors investigated in this study, the modelling exercise showed that all of them play a role as a WT control. AT and SWR are important for all models/seasons, although their coefficients vary depending on model, while LWR, SH, and WS are important for some models/seasons only. Their coefficients also vary. This probably reflects the fact that depending on the season, the main processes driving WT differ. P has a small influence in all models.

From an explanatory modelling perspective, the effect of the LWR predictor is not necessarily following a physical process. However, from a predictive modelling perspective, and although this was not the primary objective of the study, the series of models have some potential as seasonal water temperatures could be generated for the whole spatial and temporal extent of the CHESS datasets (whole country, 1971–2007 period of records), for example, allowing to investigate broader geographical patterns.

The analysis of site-specific responses and their association with basin properties showed that small, upland, and/or impermeable basins are the ones most influenced by atmospheric heat exchanges, therefore the most at risk due to climate change, while the larger, lowland and permeable basins are least at risk.

7. FUTURE ENVIRONMENTAL FLOWS

7.1 Introduction

The research objectives identified in section 2.5 are to assess river ecological risk due to future flow alteration at the broad pan-European scale; and to identify which parts of Europe or which types of basins are most/least at risk.

This study was undertaken as part of the European Union (EU) SCENES (water SCenarios for Europe and for NEighbouring States) project. SCENES was a four-year Integrated Project under the EU 6th Framework, which investigated the future of freshwater resources up to the 2050s in 'Greater' Europe (defined as EU countries and neighbours i.e. Iceland, Norway, Belarus, Ukraine, Moldova, Turkey, non-EU Balkan countries, and Switzerland) and including the Mediterranean rim countries of north Africa and the near East, from Caucasus to the White Sea (see Figure 7.1). Innovatively, the project considered both climate-induced future change and also scenarios integrating socio-economic and policy drivers. SCENES provided a reference point for long-term strategic planning of pan-European freshwater. SCENES investigated impacts on different water use sectors (industry, food, energy, recreation, domestic use, etc). This chapter focuses on impacts on water for the environment (Duel and Meijer, 2011). In this context, the study addresses the pressing need to better quantify broad scale future environmental flows in European rivers and thus yield robust information to formulate European water policies.

The overall aim of this chapter is to project the risks to European river ecosystems caused by river flow regime change under possible future climate and socio-economic/policy scenarios. This aim is achieved through four objectives:

1. To quantify the degree of flow regime alteration in terms of ecologically relevant hydrological indicators (supported by the development of the new ERFA method)
2. To identify spatial patterns of these indicators in the pan-European study area
3. To assess the consistency of these patterns across the different scenarios
4. To identify the main drivers (climate, socio-economics) and modifiers (basin properties) of these patterns

In addition, this study is putting the UK-focused findings from the previous chapters into a broader geographical scope and a longer-term time horizon, allowing to gauge how transferable those findings may be.

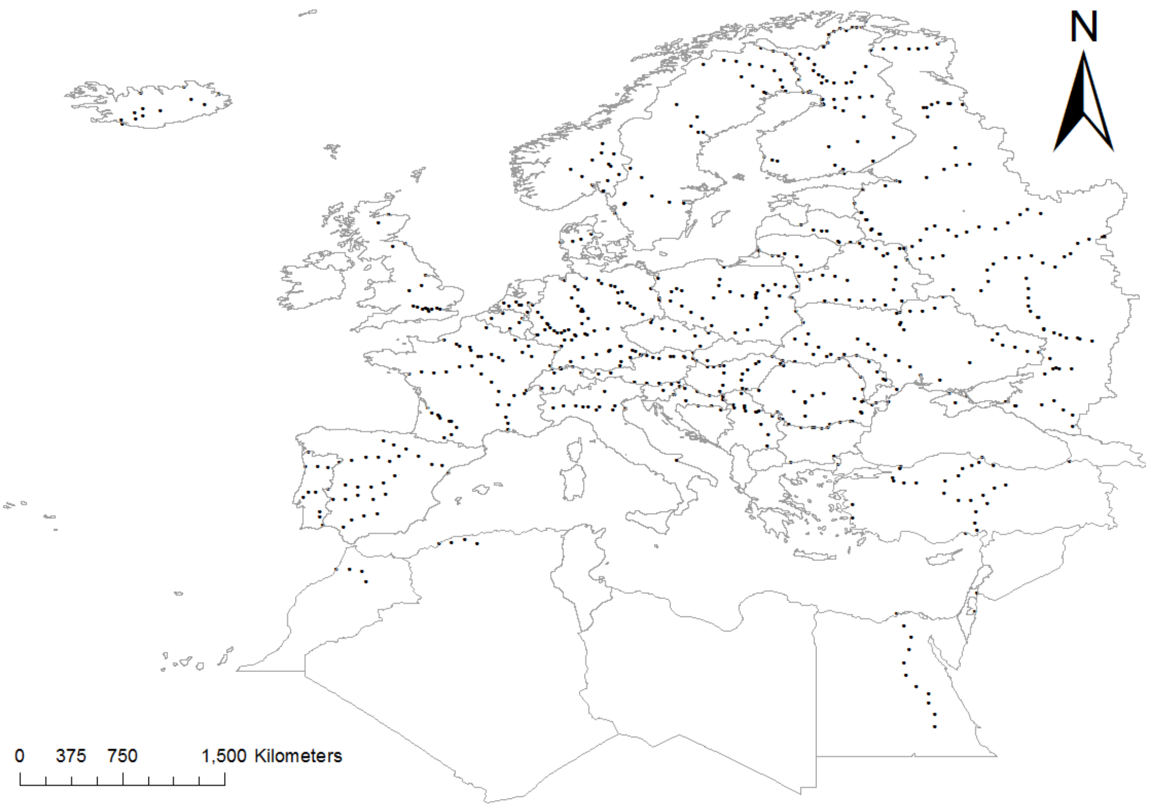

Figure 7.1: Study geographical extent (grey outlines); WaterGAP cells used for method testing (black dots).

Research gaps identified in the literature review were: few studies on impact of climate change on freshwater ecosystems; studies have limited number of sites, geographical extent, and/or resolution; studies are most often qualitative rather than quantitative, and focus only on climate change; not all ecologically-relevant aspects of the flow regime are investigated. They are addressed in this study, which is the first assessment of river ecological risk due to flow alteration to provide pan-European geographical coverage, to use a detailed (given the geographical extent) river network based on 33,368 cells with a 5' x 5' resolution, to consider explicitly a set of ecologically-relevant hydrological indicators (i.e. all facets of the flow regime), and to consider not just climate-induced change, but combined climate and socio-economic pressures.

7.2 Data and Methods

The research methodology includes five main components (as numbered in Figure 7.2): (1) climate data (observed historical and modelled future) used on their own or linked with (2) a set of socio-economic scenarios within (3) a large-scale hydrological and water use model (WaterGAP) to produce (4) sets of monthly flow time series (baseline and future) that serve as inputs for (5) the new Ecological Risk due to Flow Alteration (ERFA) screening method that compares future flows against baseline flows. As this study was part of a wider collaborative project: components 1 and 2 (selection of climate data and development of socio-economic scenarios) were carried out by a pan-European panel (PEP) of experts following the Story-And-Simulation (SAS) approach (Alcamo, 2008) by which narrative storylines of plausible futures and modelling work are linked iteratively within a participatory process; components 3 and 4 (WaterGAP model runs with and without socio-economic scenarios) were carried out by colleagues from the University of Kassel, Germany. The modelled time series for a bespoke selection of sites constitute the actual input data to the ERFA method development and analysis (component 5), which is the core of this chapter (also Laizé *et al.*, 2014). The following sections detail each component.

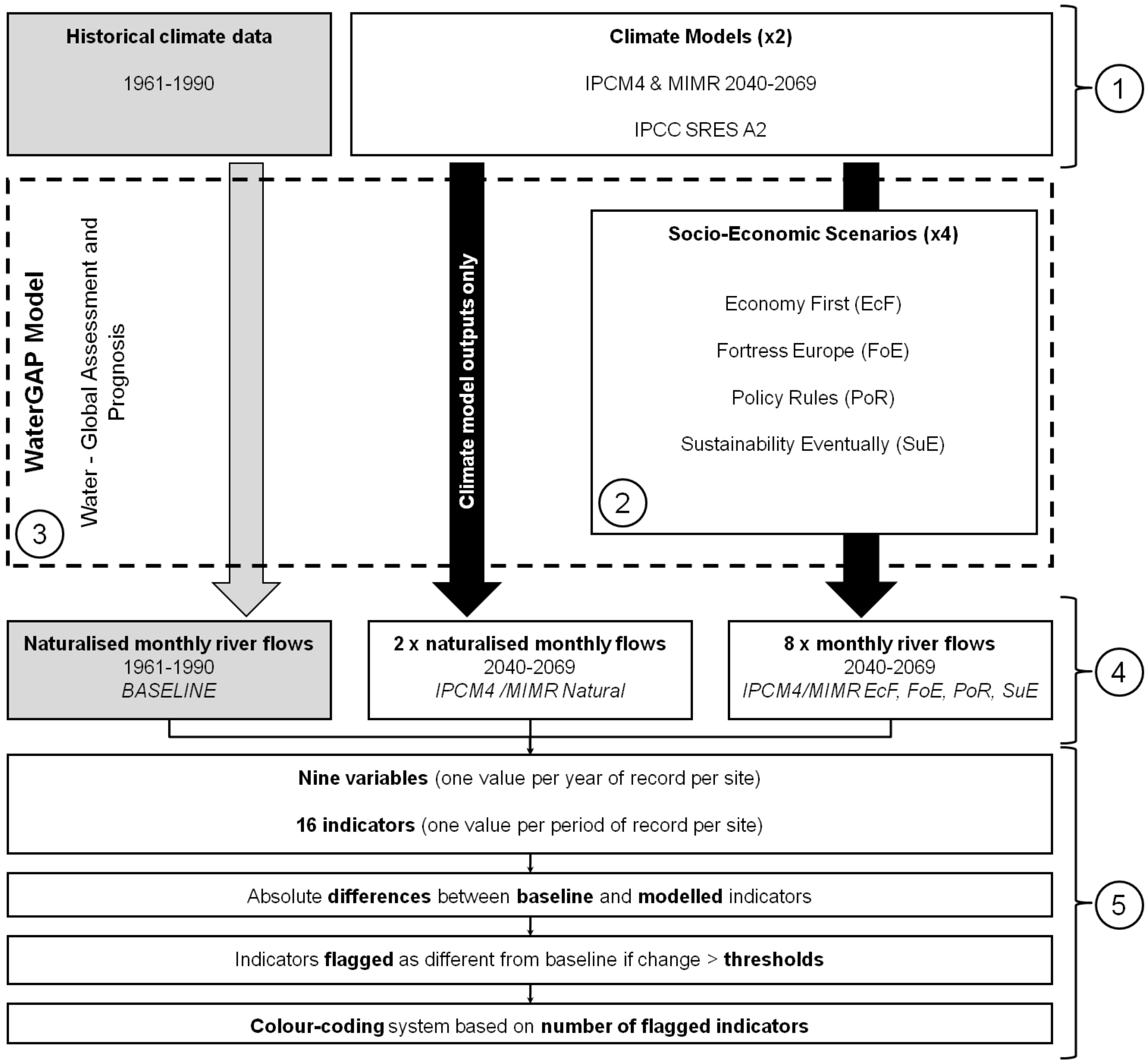

Figure 7.2: Methodological flow chart.

7.2.1 Observed historical and modelled future climate data

Observed historical climate data for the reference period 1961–1990 were collated from the Climate Research Unit (University of East Anglia, UK). Projected future climate data for the period 2040–2069 (i.e. '2050s') were taken from two Global Circulation Models (GCMs): (i) IPSL-CM4, Institut Pierre Simon Laplace, France ('IPCM4' thereafter), and (ii) MIROC3.2, Center for Climate System Research, University of Tokyo, Japan ('MIMR' thereafter). These two GCMs were chosen after comparing nine GCMs from the IPCC Fourth Assessment (Intergovernmental Panel on Climate Change, 2007); they were considered representative of the variability between GCMs (Bärlund, 2010). For both GCMs, the IPCC SRES A2 emission scenario (Intergovernmental Panel on Climate Change, 2007) was selected; it describes a very heterogeneous world with high population growth, slow economic development and slow technological change (global greenhouse gas emissions projected to grow steadily during the whole 21st century and possibly to double by 2050 compared to the year 2000). Under SRES A2, IPCM4 predicts a high temperature increase and a low precipitation increase/decrease ("warm and dry") while MIMR predicts a high temperature increase and a high precipitation increase or a low decrease ("warm and wet"). Climate change scenarios were selected by PEP to be consistent with their socio-economic narrative storylines (see below).

7.2.2 Socio-economic scenarios

The PEP defined four different visions of future pan-European freshwaters (taking into account socio-economic and environmental settings, and possible consequences for water quantity and quality) up to the year 2050 described as narrative storylines (i.e. qualitative), which were then turned into quantitative scenarios based on Fuzzy sets and modelling results according to the SAS approach:

- Economy First (EcF), economy-oriented towards globalisation and liberalisation with intensified agriculture and slow diffusion of water-efficient technologies
- Fortress Europe (FoE), closed-border Europe concentrating on common security issues with food and energy independence as the main focus of the European coalition
- Policy Rules (PoR), stronger coordination of policies at the European level, driven in part by high energy costs and reduced access to energy supplies, expectation of climate change impacts and increasing water demand
- Sustainability Eventually (SuE) transition from globalising, market-oriented Europe to environmental sustainability with quality of life as a central point

The detailed methodology for the socio-economic scenarios is provided by Kok *et al.* (2010), Kok and van Vliet (2011) and Kok *et al.* (2011).

7.2.3 WaterGAP model

The continental-scale water model WaterGAP is a semi-distributed water resource model consisting of two main components: a global hydrological model (Alcamo *et al.*, 2003; Döll *et al.*, 2003) to simulate the terrestrial water cycle and a global water use model (Döll and Siebert, 2002; Flörke and Alcamo, 2004; aus der Beek *et al.*, 2010) to estimate water withdrawals and water consumption of five sectors (domestic, electricity production, manufacturing industry, irrigation, and livestock). This study used WaterGAP version 3.1 that performs its calculations on a 5' x 5' grid (i.e. about 6 x 9 km^2 in central Europe). This version has been used in a variety of recent studies, e.g. Okruszko *et al.* (2011), wetland ecosystem services; Schneider *et al.* (2011a), bankfull flows; Schneider *et al.* (2011b), floodplain wetlands; Flörke *et al.* (2011), power plant water needs. Built into the model are 590 European dams from the European Lakes and Reservoir Database (ELDRED2, EEA) including management rules (Hanasaki *et al.*, 2006) to account for human alteration of water storage and transfer. WaterGAP calculates daily water balances for the land areas and open freshwater bodies for each individual grid cell then runoff from each cell is routed as river discharge along the modelled drainage network. Natural cell discharge is then reduced by consumptive water uses as calculated by the water use component of WaterGAP. The model is calibrated and validated independently against measured annual discharge data from the Global Runoff Data Centre (GRDC) at 221 gauging stations across Europe (Döll *et al.*, 2003). For this study, Laizé *et al.* (2014) selected a subset of the WaterGAP cells corresponding to all major European rivers and their tributaries (excluding tributary cells with fewer than 20 upstream cells due to limiting computer resources), thus totalling 33,368 cells (for example, see Figure 7.4). These cells are the outlets of as many basins and nested sub-basins, with the smallest basin represented being 63 km^2.

7.2.4 Model runs

In total, eleven sets of modelled monthly flow series were generated using different combinations of climate data inputs and socio-economic scenarios. Naturalised flows for 1961–1990 were generated by running WaterGAP with the hydrological component only (i.e. no water usage) and the historical climate data from CRU as input. This naturalised run is the baseline for the subsequent analysis (termed 'Baseline'). In addition, ten model runs representing future flows under various water usage conditions were generated: five runs for each GCM (termed 'IPCM4' and 'MIMR'; see above), including one for naturalised flows (termed 'Natural') and one for each of the four socio-economic scenarios (termed 'EcF', 'PoR', FoE', 'SuE'; see above). For all projected runs, the period of record is 2040–2069 (termed the '2050s').

7.2.5 ERFA screening method

The new ERFA screening method was based conceptually on the Range of Variability Approach (RVA) using Indicators of Hydrological Alteration (IHA), a technique for defining ecologically appropriate limits of hydrological change introduced by Richter *et al.* (1996, 1997). The underlying assumption of the IHA/RVA is that, if a river ecosystem exists under given baseline hydrological conditions, then any impact causing departure from these baseline conditions, beyond some thresholds, will alter the ecosystem. Example impacts could be: the building of a hydraulic structure, the creation of an abstraction point or, as in the present study, climate and socio-economic change. The IHA/RVA recognises that all characteristics of the flow regime—their magnitude, duration, timing, frequency and rate of change—are ecologically important.

ERFA relies similarly on a series of indicators describing the flow regimes, which are calculated for the baseline (i.e. naturalised flows 1961–1990) and for every future projection. Presenting the results of the departure from baseline of every single indicator would involve displaying a very large amount of information so to enable ready interpretation, the ERFA method aggregates information as a simple colour-coded risk classification based on how many indicators differ from the baseline by more than a set threshold.

The IHA are based on 32 different variables derived from daily flow statistics (one value per year of record) as shown in Table 7.1; the IHA themselves are indicators of the magnitude and variability of the variables, derived for the pre- and post-impact periods (or baseline and future periods in this study). Given this study focuses on an extensive pan-European river network (>33,368 sites) and 30-year long records, there is a significant cost (mostly computing time) in using the daily IHA as the basis for deriving ERFA classes. Therefore, the approach was adapted to use monthly flow statistics, thereafter referred to as Monthly Flow Regime Indicators (MFRIs). This also provides a methodology for wider application when only monthly data are available, which is common. For testing purposes, two versions of the ERFA method were implemented using the MFRIs (MFRI/ERFA) and the IHA (IHA/ERFA) and were compared for a subset of 683 WaterGAP grid cells (Figure 7.1). The following section gives background on the IHA, details the development of the MFRIs, and of both ERFA implementations, and gives the results of their comparison. Note: in this study, river flow data (m^3s^{-1}) were converted to runoff (mm) to allow ready comparison across all basins of different sizes.

7.2.5.1 Defining the MFRI variables

A summary of the original 32 daily time-step variables is given in Table 7.1. The list of nine monthly time-step variables (listed in Table 7.2) was selected to maintain a similar structure of regime characteristics and by taking into account:

- Redundancy within the 32 IHA variables due to their interdependence; information from the published literature (Olden and Poff, 2003; Monk *et al.*, 2007) was supplemented by a rank-based correlation analysis (*tau*; Kendall, 1938) applied to the test subset of 683 sites
- Daily variables not computable at the monthly time step by definition (e.g. 1-day minimum or maximum flows) or less meaningful (e.g. rates of rise between months only showed seasonal patterns year after year)
- Expert ecological knowledge (e.g. Acreman *et al.*, 2008)

Table 7.1: Variables for the Indicators of Hydrological Alteration [adapted from Richter *et al.*, 1996].

IHA Variables	IHA Group	Regime Characteristics
Mean value for each calendar month (x12)	1	Magnitude; Timing
Annual minima 1-, 3-, 7-, 30-, and 90-day means (x5) Annual maxima 1-, 3-, 7-, 30-, and 90-day means (x5)	2	Magnitude; Duration
Julian dates of 1-day minimum and maximum (x2)	3	Timing
Numbers of high pulses[a] and low pulses[b](x2) Mean durations of high and low pulses (x2)	4	Magnitude; Frequency; Duration
Numbers of flow rises and flow falls (x2) Mean rise and fall rates (x2)	5	Frequency; Rate of change

[a] number of times flow rises above 75^{th} flow percentile
[b] number of times flow drops below 25^{th} flow percentile

Table 7.2: Monthly Flow Regime Indicators (MFRI).

MFRI Variables (one value per year)	MFRI[c] (one value per record)	Flow Type	Regime Characteristics	Analogue IHA Variables
Number of months above threshold[a]	Median (1) IQR[d] (2)	High flows	Magnitude; Frequency	Number of high pulses
Month of maximum flow (1–12)	Mode (3)	High flows	Timing	Julian date of 1-day maximum
January mean flow	Median (4) IQR (5)	Seasonal flows	Magnitude; Timing	January mean flow
April mean flow	Median (6) IQR (7)	Seasonal flows	Magnitude; Timing	April mean flow
July mean flow	Median (8) IQR (9)	Seasonal flows	Magnitude; Timing	July mean flow
October mean flow	Median (10) IQR (11)	Seasonal flows	Magnitude; Timing	October mean flow
Number of months below threshold[b]	Median (12) IQR (13)	Low flows	Magnitude; Frequency	Number of low pulses
Month of minimum flow (1–12)	Mode (14)	Low flows	Timing	Julian date of 1-day minimum
Number of sequences at least two-month long below threshold[b]	Median (15) IQR (16)	Low flows	Magnitude; Frequency; Duration	n/a

[a]Threshold = all-data naturalised Q5 from 1961–1990 (95th percentile)
[b]Threshold = all-data naturalised Q95 from 1961–1990 (5th percentile)
[c]Indicator identification number between parentheses
[d]IQR: Inter-Quartile Range

7.2.5.2 Indicators

The hydrological variables (one value per year of record per site) are used to derive indicators capturing the magnitude and variability of each variable as one value across the whole period of record for each site or cell. Magnitude could be described by the mean or the median (i.e. 50th percentile), and the variability by the standard deviation or the interquartile range (IQR; i.e. difference between 75th and 25th percentiles) of annual variables (Richter *et al.*, 1997). In this study, the median and the IQR were chosen because: (i) they are less sensitive to outliers than mean and standard deviation and (ii) they better describe the hydrological variables that are not normally distributed. An exception was made for monthly-based flood and minimum flow timing variables; these variables are the months (i.e. integers ranging from 1 to 12) when flood and low flow events happen and, given their discrete range of values, they were found more meaningfully summarised by their mode. The indicators were derived as follows:

- Based on daily flow data, 64 indicators (32 medians and 32 IQR) based on the 32 IHA variables
- Based on monthly flow data, 16 indicators (i.e. the MFRIs; seven medians, seven IQR, and two modes) based on the nine MFRI variables (see Table 7.2)

7.2.5.3 Thresholds and derivation of ERFA classes

Indicators were computed for the baseline data and for all modelled scenarios, then absolute differences between indicators for each scenario and those for the baseline were calculated. Based on expert knowledge (e.g. Acreman *et al.*, 2008), indicators are considered as departing significantly from the baseline if:

- median or IQR indicators are more than 30% different from the baseline
- mode indicators are more than 1 month different

For practicality, ease of display and interpretation, differences were aggregated via a colour-coding system: a cell is assigned blue (no risk) green (low risk), amber (medium risk), or red (high risk) when its number of indicators differing from the baseline is:

- 0, 1–20, 21–40, and 41–64, respectively (IHA)
- 0, 1–5, 6–10, or 11–16, respectively (MFRIs)

7.2.5.4 Method testing

The MFRI/ERFA and IHA/ERFA implementations were compared for the subset of 683 WaterGAP cells (Figure 7.1) representing sites located along major rivers (approximately one site for every 100 km stretch of river). For those daily variables analogous to monthly variables (see Table 7.2) results were similar (e.g. monthly mean flows) or in the same range (e.g. Julian dates falls within the same period as the mode of month). Across all model runs, 60–70% of the sites obtain the same colour code. For 10–20% of sites the IHA/ERFA indicated more severe risks, and for 5–15% of sites less severe risks, than the MFRI/ERFA. Overall, the IHA/ERFA tends to give slightly higher risks, which is consistent with daily variables giving a more detailed description of the hydrological regime. However, for the majority of sites, the results were the same regardless of time step. Hence, the MFRI/ERFA method was retained as it is suitably informative for the scope of this study.

7.3 Results

This section identifies the key patterns in departure of the 16 individual MFRIs from the baseline (7.3.1) and then moves on the ERFA for the 10 model runs by: (i) mapping and comparing the overall breakdowns of ERFA classes (7.3.2); (ii) mapping and comparing the geographical location of the risks (7.3.3); and (iii) mapping synthesized results to show where risks are spatially consistent across all model runs (7.3.4).

7.3.1 Hydrological indicator patterns

In accordance with the intended method development, all indicators show varying degrees of departure from the baseline and thus play an active role in the overall ERFA. However, some indicators seem more sensitive than others. Low flow indicators are dominated clearly by the IQR of the number of months below threshold (indicator 13), that is by the variability of low pulses. Figure 7.3 box plot shows for all 16 MFRIs (identified by their number from Table 7.2 and grouped by hydrological type) the percentage of cells (out of 33,368) differing from the baseline across the ten model runs. High flow indicators are dominated by the median and IQR of the number of months above threshold (indicators 1 and 2), that is the magnitude and variability of high pulses. For the seasonal flow indicators, the median/IQR of the mean January flow (indicators 4/5), and of the mean April flow (indicators 6/7) show higher percentages than median/IQR of July and October (indicator 8/9 and 10/11, respectively) so that winter and spring flows seem to dominate over summer and autumn flows.

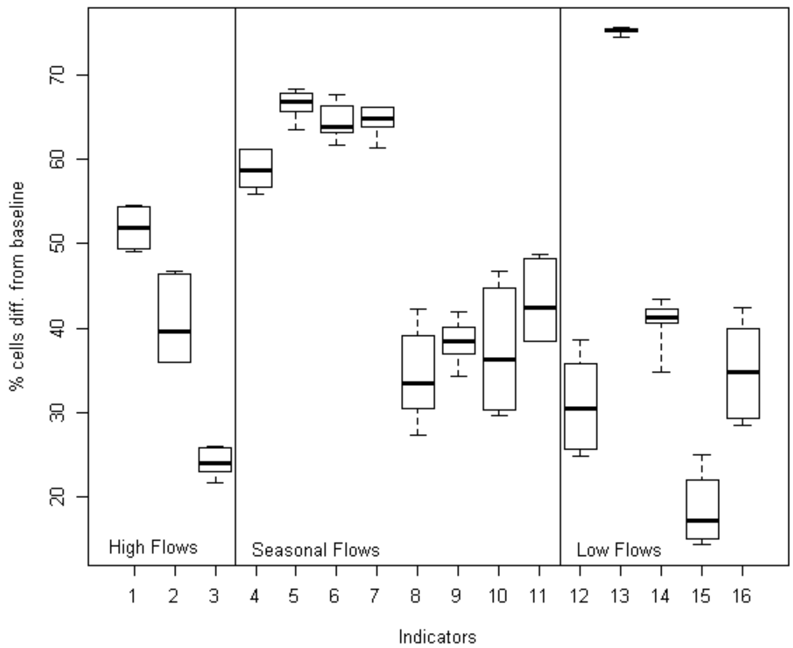

Figure 7.3: Box plot of the percentages of cells (out of ~33,368) for which indicators are different from the baseline across all ten model runs (indicator identification numbers as in Table 7.2).

7.3.2 Breakdown of future ERFA

The picture of future ERFA classes is very consistent between model runs with the different socio-economic scenarios giving similar results and the main differences being between: (i) climate models, see IPCM4 Natural (Figure 7.4) *v* MIMR Natural (Figure 7.5), and IPCM4 *v* MIMR socio-economic runs (Figure 7.6); and (ii) Natural runs and socio-economic runs, see IPCM4 Natural (Figure 7.4) *v* IPCM4 socio-economic runs (Figure 7.6), and similarly for MIMR (Figure 7.5 vs. Figure 7.6). Regardless of scenario, 54–55% of the cells (out of 33,368) are in the medium risk class, and 14–20% in the high risk class (Table 7.3). In terms of the difference between climate models, IPCM4 runs have slightly more high risk cells (16–22%) than MIMR runs (14–17%); whereas MIMR runs have slightly more low risk cells (24–26%) than IPCM4 (18–25%). For both climate models, the socio-economic runs have more high risk and fewer low risk cells than the corresponding Natural run, although this is more subtle for MIMR (difference of 0–3% for high risk, 1–2% for low risk) than for IPCM4 (4–6% for high risk, 5–7% for low risk). As noted above, socio-economic runs are similar but these can be ranked (Table 7.3), for both climate models, by decreasing risk severity as EcF (highest risk), FoE, PoR, and SuE (lowest risk).

Table 7.3: Distribution of ERFA classes per runs (% of cells).

		None	Low	Medium	High
IPCM4	*Natural*	5	25	54	16
	EcF	5	18	54	22
	FoE	5	19	55	21
	PoR	5	20	55	20
	SuE	5	20	55	20
MIMR	*Natural*	5	26	55	14
	EcF	5	24	54	17
	FoE	5	24	55	16
	PoR	5	25	55	15
	SuE	5	25	55	15

7.3.3 ERFA spatial patterns

Although the total numbers of WaterGAP cells within each ERFA class are very similar between model runs, the underlying spatial distribution of risk locations differs between model runs. As in Section 3.2, the main differences are between: (i) climate models, see IPCM4 Natural *v* MIMR Natural in Figure 7.7, which shows where ERFA are the same for both runs (green), and where MIMR is less severe (blue) and more severe (red) than IPCM4; and (ii) Natural and socio–economic runs, see Natural runs *v* their respective socio–economic runs in Figure 7.8, which shows where ERFA classes are the same (green), and different (red).

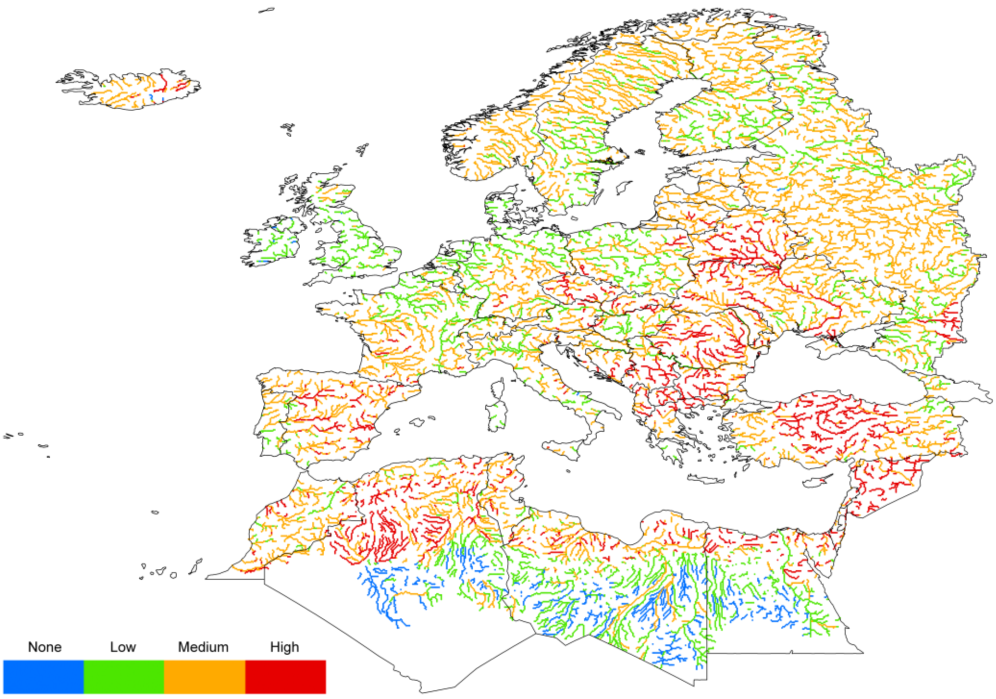

Figure 7.4: Geographical location of ERFA classes for Natural IPCM4 2050s model run: future naturalised flows, i.e. climate model A2–IPCM4 only, no water usage, no socio-economic scenario, 2040–2069 projection period; blue, no risk; green, low risk; amber, medium risk; red, high risk.

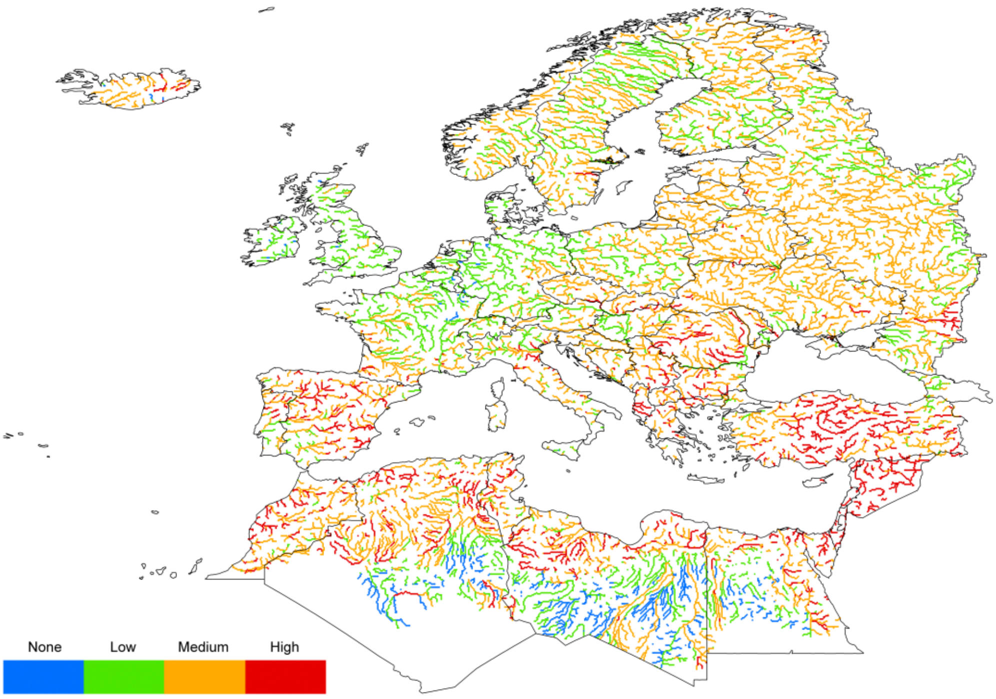

Figure 7.5: Geographical location of ERFA classes for Natural MIMR 2050s model run: future naturalised flows, i.e. climate model A2–MIMR only, no water usage, no socio-economic scenario, 2040–2069 projection period; blue, no risk; green, low risk; amber, medium risk; red, high risk.

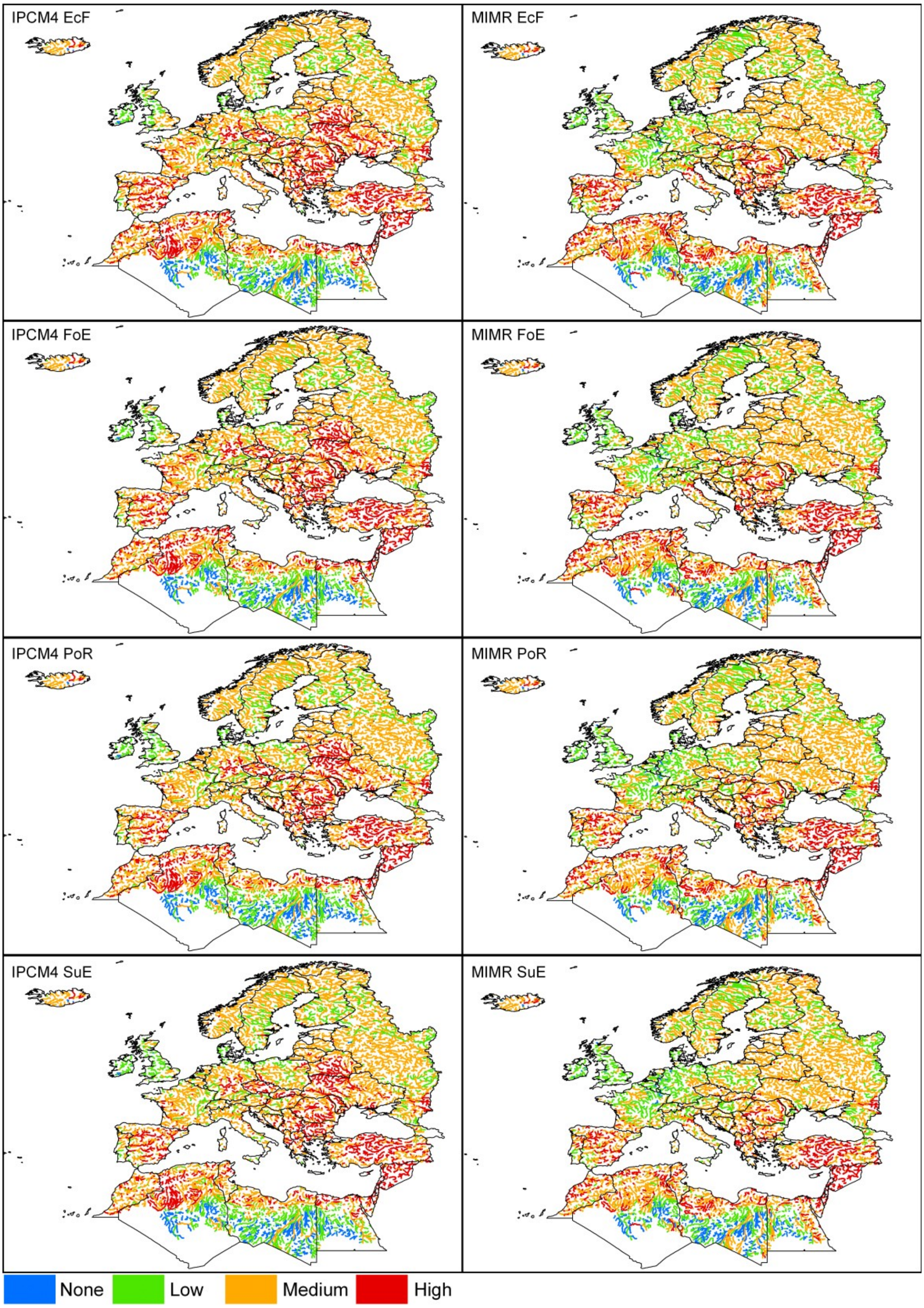

Figure 7.6: Geographical location of ERFA classes for the eight model runs including the four socio-economic scenarios (top to bottom): Economy First (EcF), Fortress Europe (FoE), Policy Rules (PoR), Sustainability Eventually (SuE); climate models, A2–IPCM4 (left), A2–MIMR (right); 2040–2069 projection period; blue, no risk; green, low risk; amber, medium risk; red, high risk.

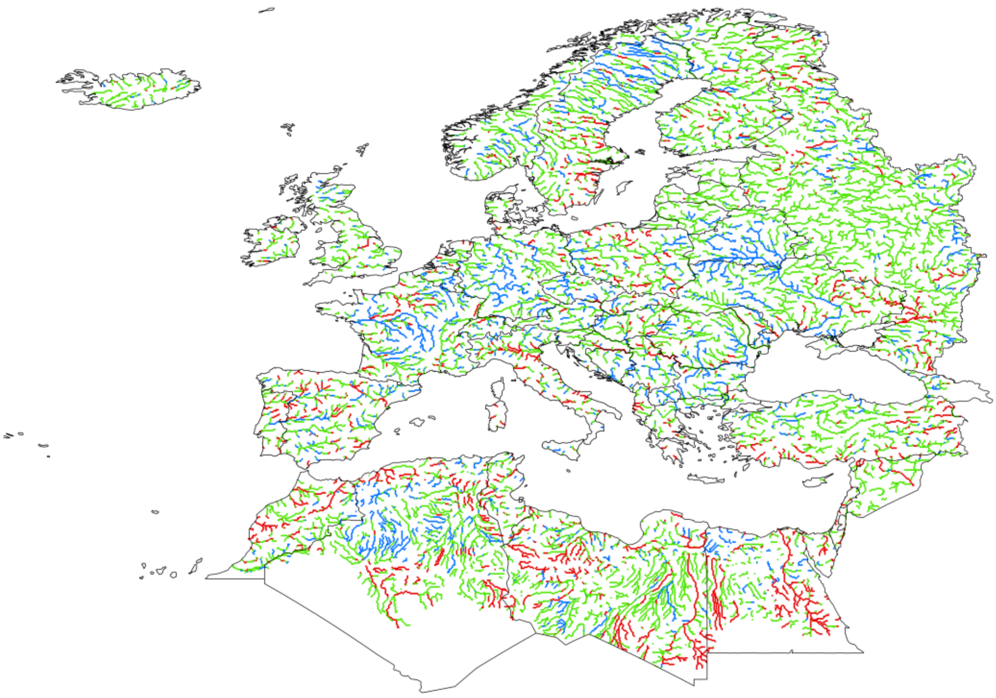

Figure 7.7: 2050s ERFA geographical location changes between IPCM4 Natural and MIMR Natural: green, same ERFA; blue, MIMR less severe than IPCM4; red, MIMR more severe.

Between climate models, MIMR runs are generally about one third different from IPCM4. Table 7.4 summarises the percentage of the cells (out of 33,368) that have different ERFA classes when comparing runs against each other (e.g. IPCM4 Natural differs from MIMR Natural for 36% of the cells). Runs for socio-economic scenarios differ from the Natural run by 17–21% for IPCM4 and 3–9% for MIMR. Differences between socio-economic scenarios are 4–8% under both IPCM4 and MIMR. The relative difference between socio-economic runs is the same for both climate models. EcF runs show the greatest departure from Natural runs, followed by FoE, PoR and SuE (least different from Natural).

There is no distinct geographical pattern across Europe in terms of the differences in risk between climate models. However, the socio-economic scenarios cause locational changes along an east–west 'belt', which is marked especially for IPCM4 runs and consistent for MIMR runs although somewhat less well-defined (Figure 7.8).

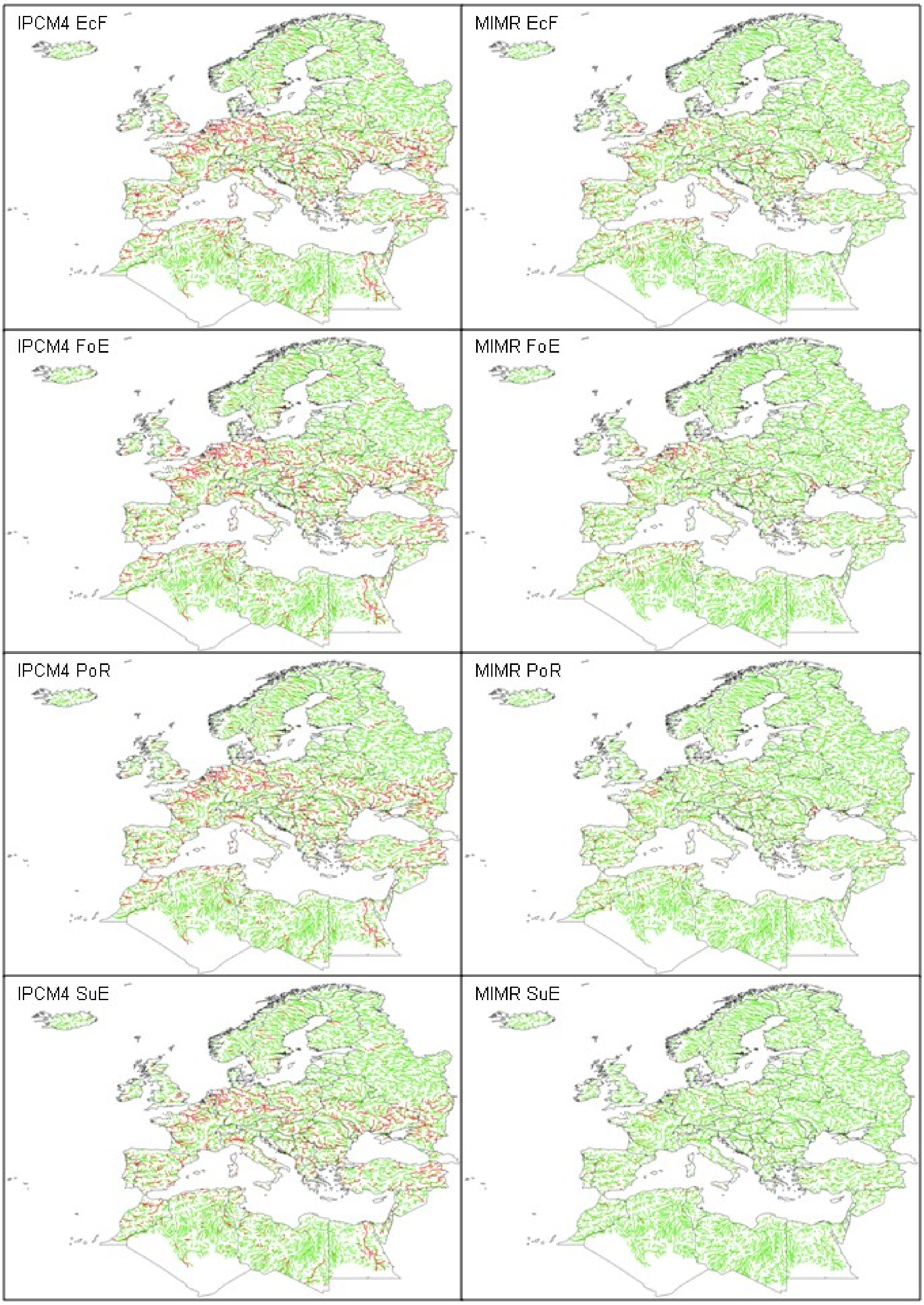

Figure 7.8: 2050s ERFA geographical location changes between Natural and socio-economic scenarios(top to bottom): Economy First (EcF), Fortress Europe (FoE), Policy Rules (PoR), Sustainability Eventually (SuE); climate models A2–IPCM4 (left), A2–MIMR (right); green, same ERFA; red, different ERFA.

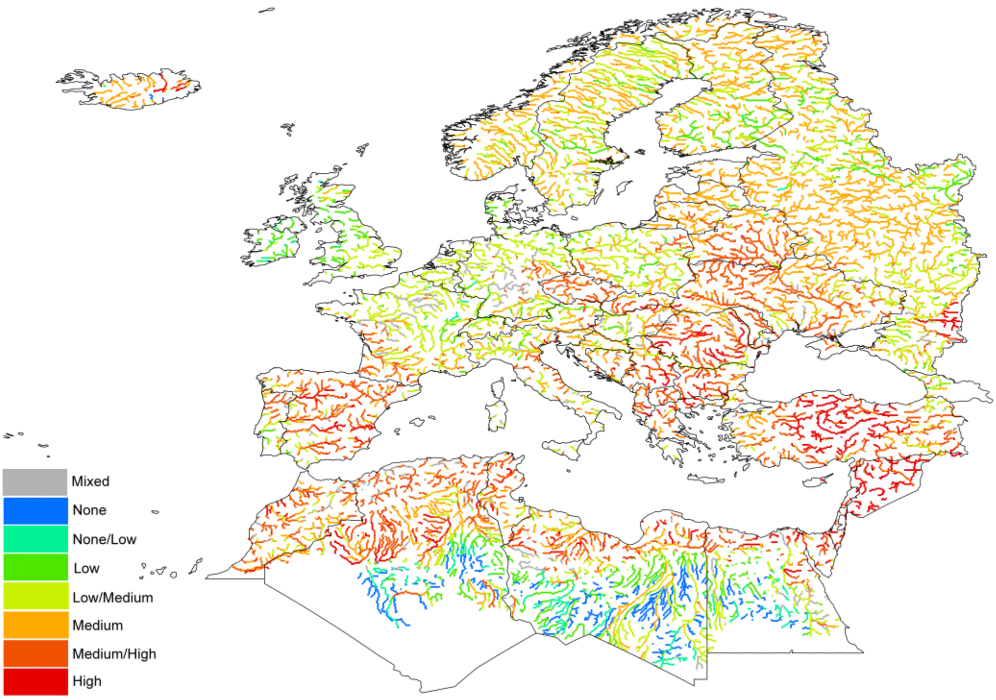

Figure 7.9: Summary of ERFA classes across all 10 model runs: categories ‘None’, ‘Low’, ‘Medium’, ‘High’ for cells with a single ERFA class for all 10 runs; categories ‘None/Low’, ‘Low/Medium’, ‘Medium/High’ for cells with either of the two ERFA classes for all 10 runs; category ‘Mixed’ for cells that are inconsistently classified.

Table 7.4: Summary matrix of differences in ERFA classes between all runs (% of different cells).

		IPCM4					MIMR			
		Natural	*EcF*	*FoE*	*PoR*	*SuE*	*EcF*	*FoE*	*PoR*	*SuE*
IPCM4	*Natural*		21	20	18	17				
	EcF			5	7	8				
	FoE				4	6				
	PoR					4				
	SuE									
MIMR	*Natural*	36	37	36	35	35	9	8	5	3
	EcF	37	34	34	33	33		5	7	8
	FoE	37	35	34	34	33			5	6
	PoR	37	37	36	35	35				4
	SuE	37	37	36	35	35				

7.3.4 Commonality of impacts across all model runs

Based on the overall agreement between the ten model runs, four main zones can be identified: (i) highest risk, Mediterranean rim (bulk of Southern Europe and coastal region of North Africa), southwest part of Eastern Europe, and Western Asia; (ii) medium/high risk, Northern Europe (including Iceland) and northeast part of Eastern Europe; (iii) low/medium risk, Western and Eastern Europe (including Ireland and UK); (iv) lowest risk, inland region of North Africa. Figure 7.9 provides a summary map in which cells with the same ERFA class for all 10 runs are allocated that class (i.e. 'None', 'Low', 'Medium', 'High'), cells with either of two adjacent ERFA classes are designated a joint class (i.e. 'None/Low', 'Low/Medium', and 'Medium/High'), and remaining cells that are inconsistently classified are labelled 'Mixed'.

7.3.5 ERFA and basin properties

Generally, basin properties act as modifiers of climatic inputs (Chapter 4; Laizé and Hannah, 2010). The WaterGAP model captures this by using physical characteristics at cell level (e.g. elevation, slope, land use, geology; Döll and Flörke, 2005). Physical characteristics therefore influence the modelled flows by design, and consequently the ERFA classes. The downstream aggregation of information by cell routing along the drainage network makes it difficult to state, from the model specifications alone, what this influence is at the basin scale. To assess if different ERFA classes have different distributions of basin properties, ANOVA (see 3.3.6.2) followed by Tukey's HSD (see 3.3.6.3) were used as in the previous chapters, on the major basins modelled in WaterGAP (761 basins).

Elevation data are continuous and were summarised as the basin median elevation. For all runs, the low, medium, and high ERFA classes are significantly different with low ERFA associated with lower elevation, medium ERFA with medium elevation, and high ERFA with higher elevation (Appendix I, Table 4).

In WaterGAP, the permeability of the geology is captured by the aquifer factor: the higher the aquifer factor, the more permeable the basin. ERFA classes were significantly related to basin median aquifer factor for all runs. For those pairs of ERFA classes that are significantly different, high ERFA basins always have higher aquifer factors than any other ERFA classes. For low and medium ERFA, the patterns are more variable. Indeed, for IPCM4 Natural and MIMR runs, medium ERFA basins have lower or equal aquifer factor values than low ERFA basins, but for IPCM4 EcF, FoE, PoR, and SuE, the lower aquifer factors correspond to the low ERFA. See Appendix I, Table 5.

Analysing land cover did not yield such clear patterns. Some ERFA classes significantly differ for some runs but there is a huge variability from one land cover type to another (see Appendix I, Table 6). Similarly to findings for the UK (Chapter 4), land cover patterns can be largely explained by elevation; for example, high ERFA associated with higher snow/ice cover (occurring mostly at higher elevation), or low ERFA with urban/suburban areas (mostly present at lower elevation).

7.3.6 ERFA in mainland UK

Cells corresponding to mainland UK were extracted to assess differences with the pan-European patterns (see Appendix I, Table 7; equivalent to Table 7.3). Firstly, there is more variability between model runs, and the main differences are between socio-economic runs rather than between climate models. Overall, 10–43% of the UK cells are classified as medium risk, and none as high risk. IPCM4 runs have slightly more medium risk cells (15–43%) than MIMR runs (10–31%). For both climate models, socio-economic runs have more medium risk and fewer low risk cells than the corresponding Natural run (IPCM4, 8–38 %

points; MIMR, difference of 0–21). Secondly, regarding differences in cell classes between runs (see Appendix I, Table 8; equivalent to Table 7.4), there is less difference between climate models with about one quarter of the MIMR runs differing from IPCM4 runs (against one third for pan-European results). Socio-economic runs differ from the Natural run by 17–37% for IPCM4, and 0–21% for MIMR, while differences between socio-economic runs are similar for both climate models (IPCM4, 6–22%; MIMR, 3–21%). These figures are higher than for the pan-European ones. To summarise, mainland UK has mostly low/medium risk classes, but, given its small size, is highly variable (Figure 7.10).

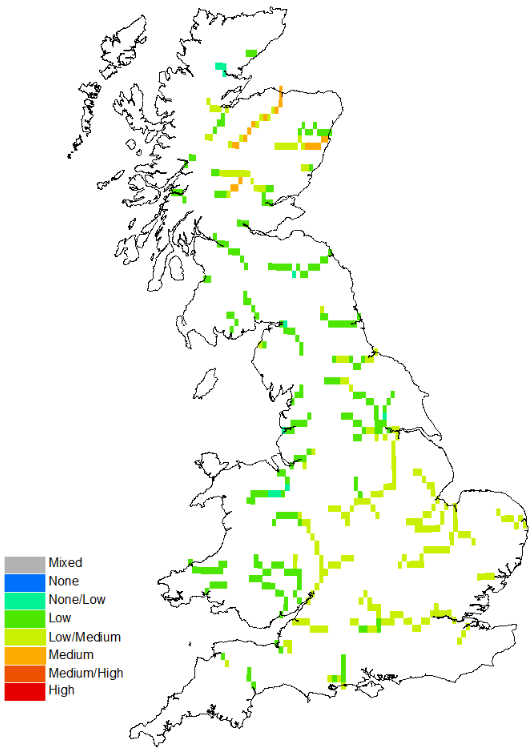

Figure 7.10: Summary of ERFA classes across all 10 model runs for mainland UK (same information and data as in Figure 7.9; map using British National Grid projection).

In terms of association between ERFA classes and basin properties, patterns are consistent with those at the pan-European scale, as shown in Figure 7.11, which features summary ERFA classes from Figure 7.10 on top of elevation and aquifer factor. In the Northwest, higher ERFA are associated with higher elevation, while in the southeast, they are linked to higher permeability.

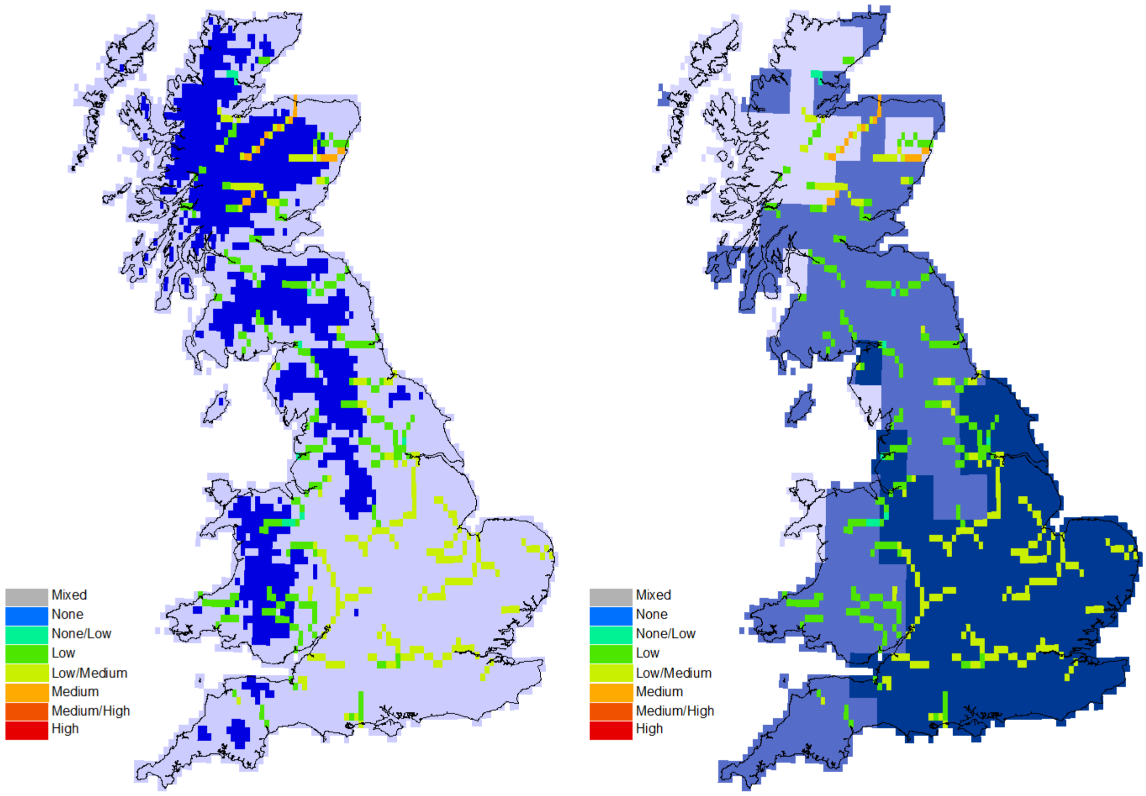

Figure 7.11: Summary ERFA classes *v* physical properties in the UK; left, elevation (light blue, lowlands ≤ 200m; dark blue, uplands > 200m); right, aquifer factor equal to 50 (most impermeable, light blue), 70 (medium blue), 100 (most permeable, dark blue).

7.4 Discussion

As highlighted in the introduction, there are few studies focusing on future ecologically-relevant flow regimes, and existing studies are often either descriptive and/or have limited geographical scope (Wright *et al.*, 2004; Clarke, 2009; Graham and Harrod, 2009; Heino *et al.*, 2009; Johnson *et al.*, 2009; Wilby *et al.*, 2010). The only thematically analogous paper to this study is by Döll and Zhang (2010), although their approaches vary markedly (worldwide geographical extent, much coarser grid resolution, less detailed river network, fewer and broader scale hydrological variables, and lack of integrated climate/socio-economics). This study provides the first, detailed pan-European systematic assessment of future effects of climate and socio-economic change on ecologically-relevant river flow indicators by developing the new ERFA methodology.

7.4.1 Model run inter-comparison

Patterns are reasonably consistent across model runs. However, there are notable differences between climate models and socio-economic scenarios related mainly to the location of risks. In terms of the breakdown of ERFA classes, no socio-economic scenario mitigates climate-induced risks since all socio-economic runs have a few more medium and high risk cells than the Natural runs (see Table 7.3). Although the results of socio-economic scenarios are very similar, subtle differences are noteworthy. Ranking by risk severity shows that highest risks are under EcF, whereas SuE has the lowest risks. This is consistent with the narrative storylines whereby EcF is the market-driven scenario as opposed to SuE that is the environment-driven scenario, i.e. the 'greenest' of all (Kok *et al.*, 2010). In terms of ERFA class location, there is again a strong similarity between socio-economic scenarios; the most notable difference is between the Natural runs and their respective socio-economic runs as shown in Figure 8. Location shifts in ERFA classes for the different socio-economic scenarios occur in a broad east–west swath across the mid-continental Europe. It may be hypothesised that this zonal area corresponds to the more populated and/or more managed areas where changes in socio-economic changes may be more apparent. It is noteworthy that given the geographical extent of the study and the WaterGAP grid resolution (i.e. 33,368 5' x 5' cells) even a few percentage points difference in cell impacts can translate into several hundred km of river.

7.4.2 Spatial patterns and coherence between model runs

Using the new ERFA methodology developed in this study, more than two thirds of the river network (Greater Europe, Near East, North Africa) is at medium or high risk, regardless of the climate model or scenario used. Thus, European river ecosystems are under significant threat in the future. This is likely to be manifested in changes to species and communities and loss of current ecosystem functions and services (Poff and Zimmerman, 2010; Okruszko *et al.*, 2011). Broad regions with contrasting impact levels have been identified (Figure 7.9). The least impacted region is the lower half of North Africa, which has low population (hence low water demand). Focusing on the other, more densely populated, regions, Western and Eastern Europe is the least impacted, while the Mediterranean rim extending up to Western Asia is the most impacted. It could be hypothesised that this is due to the climatology of temperate oceanic regions being less affected by climate change than semi-arid/continental locations (Kundzewicz *et al.*, 2008).

7.4.3 Identifying the main driver

The results show that climate is the primary driver of change by 2050 under the modelled conditions and that climate sets the broad patterns at the pan-European scale. In a previous study on a groundwater and river resources management programme at a European scale (GRAPES; Acreman *et al.*, 2000; Acreman, 2001), the impact of current anthropogenic pressures, such as water abstraction, outweighed the then projected impacts of climate (this may be partly due to the focus of GRAPES on case studies of heavily impacted basins in the UK, Spain and Greece). In contrast, this study shows that climate change impacts dominate over water use impacts at a general level across Europe, while socio-economics is a secondary driver. However, this finding has to be set within the context of the current approach: in WaterGAP, water consumption (i.e. abstracted minus return flows) is lumped at the cell level because the locations of flow abstractions and returns within a cell are not known; this value is relatively low for domestic and industrial usage.

The analysis of the main basin physical characteristics built-in the WaterGAP model showed that high ERFA cells are significantly more associated with higher elevation, or with permeable geology. Land cover patterns are less conclusive, and possibly due to land cover co-varying with elevation, similarly to what was found in Chapter 4.

7.4.4 ERFA Further research and wider implications

The ERFA methodology assesses the absolute departure of the MFRIs from the Baseline. Indicator departure can be due to increase/decrease (e.g. magnitude, duration), or advance/delay (timing). The actual effect on given species or ecosystem services depends on the type of flow (i.e. low, seasonal, or high) being altered, how alteration manifests (e.g. high flows affecting floodplain inundation, migration and channel maintenance, seasonal flows affecting habitat availability for growth and over-wintering, low flows affecting habitat availability for the young) and target organism or service. For example, less variable flows benefit macrophytes, whereas higher flow magnitudes may be detrimental to macrophytes (Bragg *et al.*, 2005); a change in high flow timing may causes a loss of cue for fish with synchronised spawning or migration (Bunn and Arthington, 2002), or for plants and their seed release (Lytle and Poff, 2004). Some ecological responses are the same whether flow indicators are decreasing or increasing. For example, lower or higher magnitudes in extreme high or low flows cause altered assemblages and reduced diversity (Poff and Zimmerman, 2010). In that regard, the present approach should be seen as a screening tool to identify systematically regions of potential impact on which to focus further hydroecological research attention (Piniewski *et al.*, 2012). In addition, the method can be adapted easily to target specific aspects of the flow regime, or to use different models at different spatial and temporal scales, for example, as done on the Narew (Poland) by Piniewski *et al.* (2012) or on the Mekong by Thompson *et al.* (2014).

It would be useful to relate the departure from the baseline hydrological regime to ecological impacts beyond the qualitative rules collated in the literature. Using historical observed data can provide a way to (semi-)quantify these impacts (e.g. broad-scale fish species richness and mean annual flow; Xenopoulos *et al.*, 2005). However, this is complicated by: (i) the fact that flow, although a key variable, is not the only factor affecting river ecosystems (e.g. water temperature has a major influence; Caissie, 2006); (ii) the general mismatch in nature and spatio-temporal scales of hydrological and ecological datasets (Monk *et al.*, 2008a); and (iii) monitoring generally not focusing specifically on ecological responses to flow alterations (Souchon *et al.*, 2008).

The ERFA methodology could be used in relation to the European Water Framework Directive (WFD; European Commission, 2000), which requires EU Member States to achieve and maintain at least 'Good Ecological Status' (GES) in all rivers by 2015. Although flow-based criteria are not used directly to assess GES, it has been recognised that restoration or maintenance of the flow regime is often one of the measures needed to ensure GES and can be set in the River Basin Management Planning process (Acreman and Ferguson, 2010). The present study identifies rivers potentially more susceptible to fail GES due to flow alteration.

More generally, river restoration requires reference conditions to set-up appropriate outcome targets (e.g. Nestler *et al.*, 2010; Stoddard *et al.*, 2006; Palmer *et al.*, 2005), which traditionally relate to past ecological state. However, under changing water availability, whether due to water use or climate, reverting to such reference conditions may be too restrictive as it does not take into account the natural variability of the system (Overton and Doody, 2012). The present study could be used to identify appropriate conditions as targets for restoration in the context of changing climate and socio-economic conditions across Europe.

7.5 Conclusions

This study is the first assessment of river ecological risk caused by the alteration of flow regimes: having a pan-European geographical coverage, using a detailed river network, considering a set of ecologically-relevant hydrological indicators, and combined climate and socio-economic/policy scenarios. With regards to the four objectives of the study:

1. Two thirds of the European rivers are at medium or high ecological risk by 2050s.
2. ERFA classes were mapped and four main zones were identified (Mediterranean rim, southwest part of Eastern Europe, and Western Asia; Northern Europe, northeast part of Eastern Europe; Western and Eastern Europe; inland North Africa).
3. All model runs yield very consistent patterns in terms of breakdowns of risk classes; the main difference relates to the geographical location of the risks.
4. Patterns are primarily driven by climate, with socio-economics being a secondary driver; basins with higher elevation and/or higher permeability tend to be more at risk.

The method provides a screening tool to identify systematically which pan-European regions are more at risk in order to better focus further hydroecological research attention. This is illustrated by the analysis of the UK-focused subset, which showed that the country is comparatively less at risk than most of Europe (low/medium ERFA classes) but has more variability between model runs.

8. CONCLUSIONS AND FUTURE WORK

8.1 Overview of findings

This thesis aimed to disentangle the climate–hydrology–ecology chain of processes (Figure 1.1) by: (1) identifying the drivers of the main linkages (climate–river flows, river flows–river hydraulics, climate–water temperature); (2) identifying where and when rivers are least/most sensitive to changes in these processes; (3) assessing the influence of basins as modifiers of the these interactions. The research was broken down into four components, which are summarised in Table 8.1 (based on Table 3.1). Research gaps that applied to all research components were the lack of studies with extensive geographical coverage, high site density, and long periods of records; the study addressed these gaps. Spatial patterns could only be found for studies involving climate and flow (historical or future projections), for hydraulics and temperature, spatial patterns were related to basin properties. For all components, a small set of basin properties were found to have a significant influence.

Table 8.1: Summary of research components and main findings.

Association	Spatial Extent	Time Scale	Period	Number of Sites	Spatial Patterns	Basin Properties
Climate–river flows	Mainland UK	Seasonal	1975–2005	104	Yes	Elevation Permeability
River flows–river hydraulics	England and Wales	N/A	1993–2006	>2,500	No	Elevation Size
Climate–water temperature	Mainland UK	Seasonal	1984–2007	35	No	Elevation Permeability Size
Climate–environmental flows	Greater Europe	Monthly	2040–2069	>30,000	Yes	Elevation Permeability

The following sections detail the main findings for each component.

8.1.1 Climate–river flows

The understanding of seasonal hydroclimatological associations was refined by investigating records for more than 100 near-natural gauged river basins in mainland UK, in conjunction with AC and RC. Some complex spatial patterns of seasonal flow regimes were found: flow classes varying between seasons, with contiguous clusters of gauged sites for some seasons but not for others. RC exerted a stronger control on flows than AC (the latter only significantly associated with flows in winter and summer). The dominant climate variables varied with season. Climate was a primary driver but physical basin properties relating to elevation and permeability were found to significantly modify the climate–flow associations: upland and impermeable basins are more sensitive to climate control than lowland and/or permeable ones. For the UK, this translates into a northwest–southeast partition (exposure to westerly weather combined with distribution of basin types).

This research (Chapter 4; Laizé and Hannah, 2010) provided general statements about UK hydro-climatic patterns and the influence of basin properties to a wide range of studies: hydrology (Smith and Phillips, 2013; Chiverton *et al.*, 2014; Harrigan *et al.*, 2014), stream temperature (Garner *et al.*, 2013), sediments (O'Callaghan *et al.*, 2013), birds (Royan *et al.*, 2014). More specifically, its findings supported the following studies with regards to: (i) methods, e.g. wetlands in the USA (Schook and Cooper, 2014), river flows in western Europe (Wilson *et al.*, 2013), river flows in the UK (Chiverton *et al.*, 2014); (ii) basin properties influence in general, from droughts in Europe (Parry *et al.*, 2012) and in Great Britain (Kingston *et al.*, 2013) to future global water assessments (Harding *et al.*, 2014), and geology more specifically, e.g. streamflow trends in Europe (Stahl *et al.*, 2010; 2012). reference hydrometric networks for hydro-climatic studies (Burn *et al.*, 2012), drought worldwide (Van

Lanen *et al*., 2013); (iii) importance of investigating patterns at the seasonal time scale (Hannaford and Buys, 2012; Prosdocimi *et al*., 2014).

8.1.2 River flows–river hydraulics

River flows–river hydraulics associations were thoroughly investigated by modelling the responses of wetted width, mean depth, and mean velocity to discharge at more than 2,500 natural cross-sections in England and Wales (UK), representative of the regional basin typology.

Statistically significant associations between hydraulic regimes and physical properties were found, but no evident regional patterns (no 'physiographic region' was conclusively found). Although basin and site properties have a significant influence on hydraulics, this influence is limited in terms of sensitivity to flow change. However, channel hydraulic types were found to correspond to different site/basin types. These findings suggest that hydraulics may be controlled by much more local variables than regional or basin characteristics.

Basin elevation and size were found to capture most of the hydraulic variability. Smaller basins were more sensitive to flow change regarding width but less sensitive regarding velocity and depth. Higher elevation basins were more sensitive for width and less for velocity, but did not show any significant relation to depth. Contrary to the common view that basin permeability influences hydraulics by controlling the basin flow regime, permeability was not found significantly related to hydraulic variability.

8.1.3 Climate–water temperature

A comprehensive set of six climate predictors were investigated for 35 temperature sites across the UK at the seasonal time scale, and were found to control WT. However, which predictors are the main driving variables varies depending on season, probably according to the dominant physical processes for that season. AT and SWR are important regardless of season, while the other predictors are only important for some seasons. Their associations with WT (i.e. model coefficients) also vary with seasons. Climate–WT associations also vary with basin properties: small, upland, and/or impermeable basins are more sensitive to climate than larger, lowland, permeable basins. The series of models developed could be used to generate seasonal water temperatures for the whole spatial and temporal extent of the input datasets, allowing to investigate broader geographical patterns and providing a solution to the issue of mismatched datasets.

8.1.4 Future environmental flows

This study assessed ecological risk to rivers due to flow alteration in a novel way, by having a pan-European geographical coverage, using a detailed river network with more than 30,000 cells, considering ecologically-relevant hydrological indicators, and combining climate and socio-economic change.It was cited by a number of position papers on environmental flows (Acreman *et al.*, 2014b; Moss, 2014; Tonkin *et al.*, 2014).

The main findings are: two thirds of the European rivers are at medium or high ecological risk by the 2050s, with four consistent geographical risk zones (from higher to lower risk: Mediterranean rim, southwest part of Eastern Europe, and Western Asia; Northern Europe, northeast part of Eastern Europe; Western and Eastern Europe; inland North Africa); all model runs are very consistent in terms of breakdowns of risk classes, with differences relating to the location of risk classes; climate is a primary driver, socio-economics a secondary driver; basins with higher elevation and/or higher permeability tend to have high risk classes.

Location shifts in risk classes occurred in a broad east–west swath across mid-continental Europe, possibly reflecting more populated and/or more managed areas where socio-economic changes may be more noticeable. The UK (part of the Western/Eastern Europe risk zone) is comparatively less at risk (low/medium) but has more variability between model runs than Europe as a whole.

8.2 Seasonal patterns and basin properties

Two key aspects emerge from the four components of the thesis: (i) importance of seasonal patterns, and (ii) strong basin property patterns.

With regards to seasonal patterns, studies of climate–flow and climate–temperature associations (Chapters 4 and 6) intentionally split analyses based on seasons, while in Chapter 7, several of the environmental flow indicators were designed to capture seasonal flow magnitude and variability. In the case of the climate–flow and climate–temperature associations, the analyses showed that sensitivity to climate is not constant all throughout the year, nor the main climate controls remain the same; for future environmental flows, there were more flow alterations in winter and spring flows, than in summer and autumn. This has important implications for ecosystems, the response of which depends on timing (for example, in relation to the life cycle of key species).

Strong patterns related to basin properties were found, which bears implications in terms of: (i) the analytical methods used; (ii) the potential application of the findings for screening purpose.

First, analyses were all run with all basin types at once. They highlighted the differences between basin types, in particular, between impermeable and permeable basins. It could be useful to run analyses on subsets based on basin types, in a similar way analyses were done for individual seasons in Chapters 4 or 6. For example, this would allow to investigate non-linear models for groundwater-dominated basins.

Secondly, the identified basin property patterns could provide a useful screening mechanism to identify regions or rivers most/least at risk, especially when environmental data is sparse, but spatial data are increasingly available. To illustrate the concept, Figure 8.1 features a climate–river flow sensitivity map: UK rivers have been classified according to broad physical types (upland/lowland, permeable/impermeable) then assigned a sensitivity flag (most/least sensitive) based on results from Chapter 4. On this example, red rivers are the most sensitive to climate forcing, thus the most vulnerable to climate change. Similar maps could be generated for the other components, either independently, or combined. From a method perspective, formal modelling could use techniques such as Bayesian belief networks.

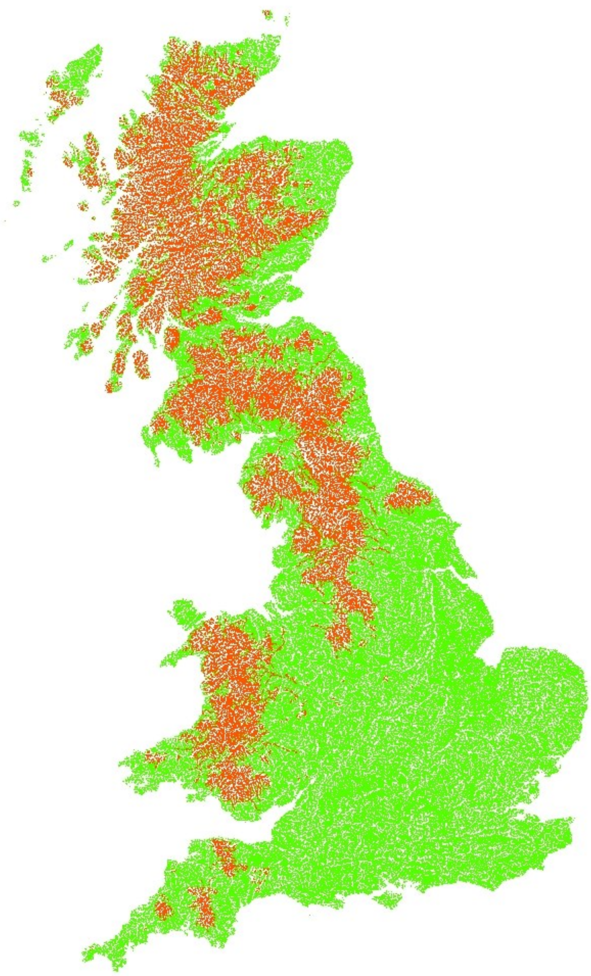

Figure 8.1: Climate–river flow sensitivity map (red, most sensitive; green, least sensitive).

8.3 Future research

8.3.1 Environmental flows

Discharge may indirectly control of river ecology, but, with the flow alteration approach, it still provides a powerful way to explore future conditions at broad geographical scales, due to the generally wider availability of observed or modelled hydrological data. This was demonstrated by the new ERFA method presented in Chapter 7. This approach is very flexible and has been applied across spatial and temporal scales, with different sets of indicators, and with different hydrological models (Narew basin, Poland, Piniewski *et al.,* 2012, 2014; Europe, Schneider *et al.*, 2013; Mekong, Thompson *et al.*, 2014), while other studies drew on it conceptually (India, Mittal *et al.*, 2014; China, Tang *et al.*, 2014). The ERFA method is highly relevant to the European WFD; hydromorphology is key to ensure rivers have good ecology. The method can identify where flow alteration is susceptible to cause poor river ecology, or conversely, can help define appropriate flow targets in the context of changing climate and water usage. One possible future development would be to characterise ecohydrological river types (i.e. ecologically-relevant hydrological regimes) and investigate how this typology may change (rivers may change type, while types may disappear, or new types may appear in the future).

The present approach allows to screen systematically for regions of potential impact, but there is a need to relate outputs from such methods to the environmental flow requirements of actual organisms or ecosystem services (for example, on-going research is relating ERFA classes to historical observed fish data).

8.3.2 Hydroecological models and physical controls

Following on from the previous point, hydro-ecological models are needed to set appropriate environmental flow standards (Klaar *et al.*, 2014). In this study, river ecology was considered through the intermediary of the main physical variables controlling the river environment (environmental flows, hydraulics, and temperature). In the scientific literature there are a number of studies or models linking flows and biota, but flow is a proxy for many other physical processes, including hydraulics and temperature amongst others. It would be useful to relate hydraulics and water temperature to biotic data directly. Doing so is often difficult due to the mismatch in nature and scales of physical and ecological datasets; the modelling work done in this thesis, in particular the water temperature models, can help resolving this.

Once hydraulic– and temperature–biota relationships have been scrutinised, the next stage would be to investigate the interactions between flows, hydraulics, and temperature (there is a longer term need to include water quality as well). Integrating several physical controls, which are not themselves independent (e.g. climate controlling both flows and water temperature), may require more advanced techniques, such as structural equation modelling.

APPENDIX I

Table 1: FEH catchment descriptors used in this thesis.

Descriptor	Full Name	Unit	Comment
ALTBAR	Mean altitude	m	Mean altitude of catchment above sea level
AREA	area	km^2	Catchment area
ASPBAR	Mean aspect	decimal degree	Mean direction of all inter-nodal slopes in the catchment; characterising dominant aspect
ASPVAR	Invariability of slope directions	none	Ranging from 0 (high variability) to 1 (catchment tends to face one particular direction)
BFIHOST	Base Flow Index from Hydrology of Soil Type (HOST)	none	Ranging from 0 (responsive catchment) to 1 (unresponsive)
DPLBAR	Mean drainage path length	km	Mean of distances between each node (on regular 50m grid) and the catchment outlet
DPSBAR	Mean drainage path slope	m/km	Mean of all inter-nodal slopes for the catchment; characterising overall steepness
LDP	Longest Drainage Path	km	Greatest path from a catchment node to defined outlet
PROPWET	Proportion of time catchment soils are wet	%	Based on soil moisture time series classified as wet/dry days
RMED1D	1-day median annual maximum rainfall	mm	
RMED1H	1-hour median annual maximum rainfall	mm	
RMED2D	2-day median annual maximum rainfall	mm	
SAAR4170	Standard-period Average Annual Rainfall 1941–1970	mm	
SAAR6190	Standard-period Average Annual Rainfall 1961–1990	mm	
SPRHOST	Standard Percentage Runoff from HOST	none	Negatively correlated with BFIHOST

Table 2 (a)–(f): Grouping of seasonal flow classes with similar basin properties; (a) FEH descriptors winter/spring, (b) summer/autumn; (c) land use winter/spring, (d) summer/autumn; (e) elevation and geology winter/spring, (f) summer/autumn; for each property, each line represents one group of flow classes for which their average values of that property are not statistically different (ANOVA and Tukey's HSD); 'grouping mean' is the average property value for all classes in each group. [Chapter 4.]

(a)

Property	Season			
	Winter		Spring	
	Flow Class Group	Group Mean	Flow Class Group	Group Mean
FEH				
AREA	1 2 4 7 8	364.85		
	2 3 4 5 6 7 8	179.89		
ASPBAR	1 2 3 4 5 6 7	133.51		
	2 3 4 5 6 7 8	150.26		
ASPVAR	1 2 4 5 6 7 8	0.17	1 2 4 5 6 7	0.17
	3 7	0.25	3 5 6 7	0.22
BFIHOST	1 2 3 4 5 8	0.45	1 2 3 4 6	0.42
	6 7	0.75	5	0.64
			7	0.86
DPLBAR			1 2 3 4 5	22.31
			2 3 4 5 6 7	17.19
DPSBAR	1 8	186.22	1 2 4	164.40
	2 4 8	139.03	3 5 6 7	66.95
	3 5 6 7	55.20		
	2 4 5	106.92		
LDP			1 2 3 4 5	42.30
			2 3 4 5 6 7	32.34
SAAR6190	1 2 4	1431.10	1 3 5 6 7	882.02
	3 5 6 7	752.39	2 4	1709.99
	1 8	1780.10		
SPRHOST	1 2 3 4 8	42.35	1 2 3 4 6	43.60
	3 4 5	35.83	5	26.11
	6 7	20.20	7	13.87

(b)

Property	Summer Flow Class Group	Summer Group Mean	Autumn Flow Class Group	Autumn Group Mean
FEH				
AREA			1	1141.57
			2 3 4 5 6	184.80
ASPBAR				
ASPVAR	1 2 4 5 6 7	0.17		
	1 3 4 5 6 7	0.19		
BFIHOST	1 2 4 5 6	0.45	1 2 4 5 6	0.45
	3 4 5 6	0.51	3	0.77
	7	0.82		
DPLBAR			1	36.56
			2 3 4 5 6	16.09
DPSBAR	1 3 4	107.72	1 2 4	165.93
	2 4	162.39	3 6	44.14
	3 5 6 7	57.44	5	85.41
LDP	1 2 3 4 5 6	34.14	1 2	52.49
	2 3 4 5 6 7	29.85	2 3 4 5 6	30.44
SAAR6190	1	1133.89	1 4 5	1267.60
	2 4	1719.89	2 4	1671.08
	3 5 6 7	744.81	3 5 6	784.06
SPRHOST	1 2 4 6	42.21	1 2 4 6	43.41
	3 5 6	34.17	3	19.10
	7	16.29	1 4 5 6	40.85

(c)

Property	Season			
	Winter		Spring	
	Flow Class Group	Group Mean	Flow Class Group	Group Mean
% Land use				
Woodland				
	1 2 4 8	3.74	1 2 3 4	7.16
Arable	3 5 6	41.98	5 6 7	44.84
	3 7	60.68		
	1 3 6 7	23.35	1 3 6 7	27.70
Grassland	2 4 8	63.55	2 3 5 6 7	37.01
	2 3 5 6	39.86	4	67.37
	1	40.11	1	40.00
Heath	2 3 4 7 8	5.93	2 3	17.84
	3 4 5 6 7 8	3.67	4 5 6 7	2.33
Bog	1 2 4 7 8	3.91	1 2 3	6.29
	1 3 4 5 6 7 8	1.18	1 2 4 5 6 7	1.42
	1	20.56	1	30.76
Montane	2 3 4 5 6 7 8	0.00	2 3 5 6 7	0.94
			3 4 5 6 7	0.00
Inland bare ground			1 2 3 4 5 6	0.80
			1 2 3 4 5 7	1.03
Built-up area				
Inland water	1 2 3 7 8	0.42	1 2 4	0.56
	2 3 4 5 6 7 8	0.17	1 3 4 5 6 7	0.14

(d)

Property	Season			
	Summer		Autumn	
	Flow Class Group	Group Mean	Flow Class Group	Group Mean
% Land use				
Woodland			1 2 5 6	16.50
			1 3 4 5 6	12.46
Arable	1 2 4	6.49	1 2 4	2.38
	3 5 6	41.99	3 6	57.23
	3 6 7	48.84	5	21.24
Grassland	1 2 3 5 6 7	37.94	1 3 6	22.66
	2 3 4	52.61	2 5	46.89
			4	71.02
Heath	1 2 4	14.34	1	37.63
	3 4 5 6 7	2.79	2	18.29
			3 4 5 6	3.34
Bog	1 2 3 4 6 7	2.47		
	2 3 4 5 6 7	1.05		
Montane	1 2 3 6	2.83	1	25.82
	2 3 4 5 6 7	0.54	2 3 4 5 6	0.41
Inland bare ground				
Built-up area	1 2 3 4 6 7	3.27		
	3 5 6 7	6.09		
Inland water				

(e)

Property	Season			
	Winter		Spring	
	Flow Class Group	Group Mean	Flow Class Group	Group Mean
Elevation				
Minimum	1 2 4 7 8	96.29	1 2 3 4 7	105.89
	1 3 4 5 6 7 8	65.77	2 3 5 6 7	62.04
10^{th} %ile	1 2 4 8	196.26	1 3 4	217.48
	3 5 6 7	61.80	2 5 6 7	92.59
50^{th} %ile	1 2	391.28	1	521.82
	3 5 6 7	100.70	2 3 4	286.47
	2 4 8	299.35	5 6 7	114.95
90^{th} %ile	1	696.67	1	780.14
	2 8	490.55	2 3 4	450.01
	3 5 6 7	163.13	5 6 7	175.66
	4	372.14		
Maximum	1	1065.51	1	1146.30
	3 5 6 7	228.65	2	819.70
	2 4	607.79	3 4	596.42
	2 8	724.88	5 6 7	243.43
% Permeability (Bedrock)				
High	1 2 4 5 8	3.33	1 2 3 4 6	9.15
	3 4 6	34.68	1 3 5 6	18.98
	6 7	80.17	7	87.78
Moderate	1 3 4 5 6 7 8	15.16	1 2 4 5 6 7	12.45
	2 3 4 7 8	25.72	3	58.94
Low	1 2 4 5 8	67.94	1 2 4 5 6	69.47
	2 3 4 6 7	33.32	3 7	10.06
% Permeability (Superficial Deposits)				
High			1 2 3 4 6 7	3.01
			1 2 3 5 6 7	4.15
Mixed			1 2 3 4 5 6	36.65
			1 4 5 7	24.61
Low	1 2 6 8	12.96	1 2 3 7	17.32
	1 3 4 5 6 7 8	5.52	2 4 5 6	3.95

(f)

Property	Season			
	Summer		Autumn	
	Flow Class Group	Group Mean	Flow Class Group	Group Mean
Elevation				
Minimum	1 2 4 6	91.29	2 3 5 6	55.89
	2 3 4 5 6 7	59.70	1 2 4 6	101.23
10th %ile	1 2 4	185.42	1 2 4	206.89
	2 3 5 6 7	88.06	3 5 6	78.92
50th %ile	1 2 4	313.80	1	484.76
	3 5 6 7	108.79	2 4	309.91
			3 6	97.70
			5 6	134.98
90th %ile	1 2 4	477.48	1	744.70
	3 5 6 7	174.55	2 4	478.63
			3 6	141.22
			5	268.65
Maximum	1 2 4	710.81	1	1131.44
	3 5 6 7	247.55	2 4	712.59
			3 6	180.70
			5	400.00
% Permeability (Bedrock)				
High	1 2 3 4 5	8.84	1 2 4 5 6	8.90
	1 3 6	24.29	3	77.75
	7	83.90		
Moderate	1 3	41.76	1 2 3 5 6	13.30
	2 3 4 5 6 7	12.65	1 2 4 5 6	19.18
Low	2 3 4 5 6	65.66	1 2 4 5 6	68.22
	1 6 7	27.66	3	9.31
% Permeability (Superficial Deposits)				
High	1 2 4 5 6 7	3.54		
	3 5 6 7	6.65		
Mixed	1 2 3 6	44.26	1 2 3 4 5	31.45
	3 4 5 7	20.44	1 2 4 6	42.02
Low	1 2 3 4 6 7	8.31		
	2 3 4 5 6 7	5.30		

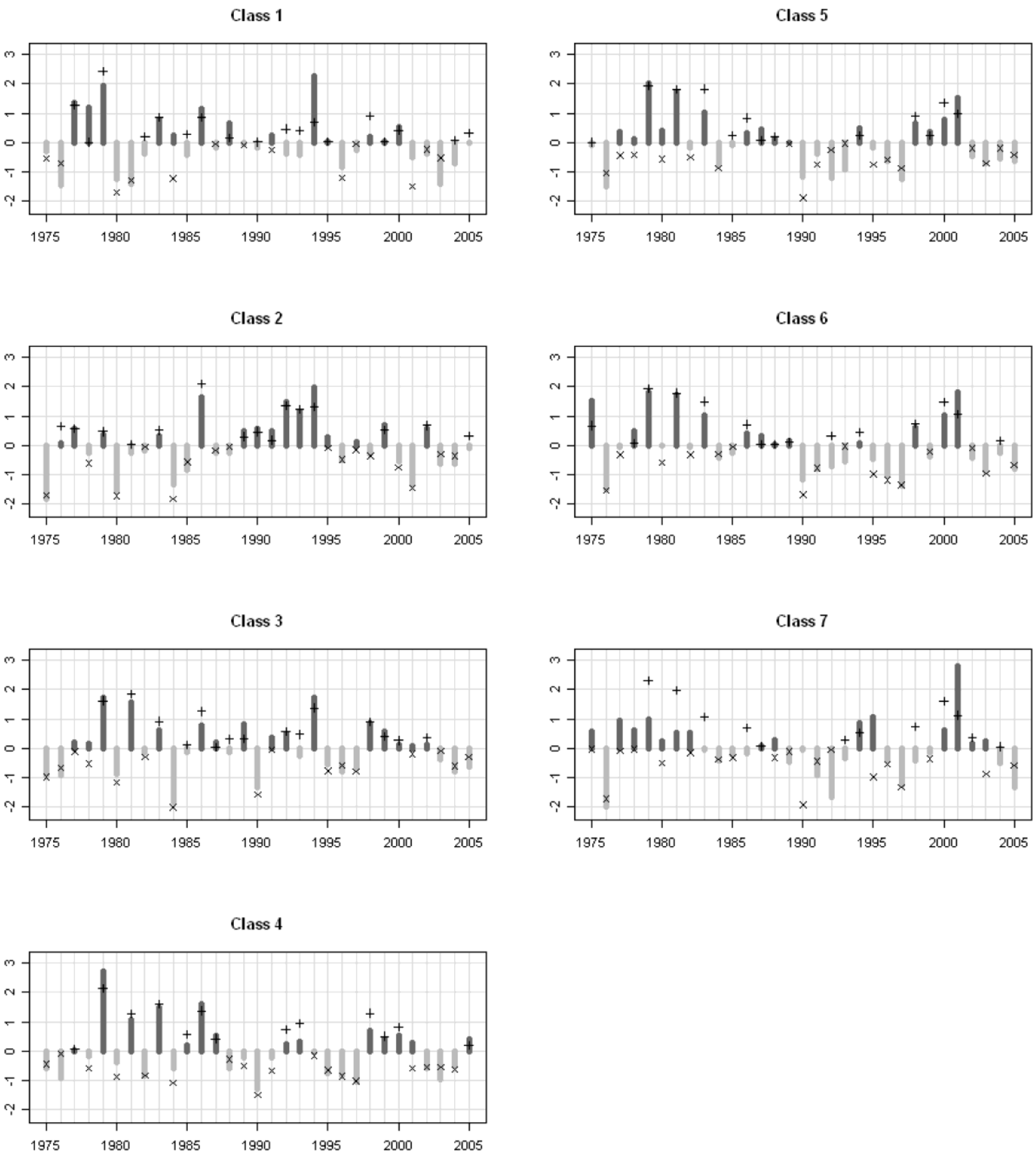

Figure 1: Spring composite river flow (dark and light grey bars denote positive (i.e. wetter) and negative (i.e. drier) *z*-scores, respectively) and rainfall (+ and x symbols denote positive and negative *z*-scores, respectively) by class for 1975–2005. [Chapter 4.]

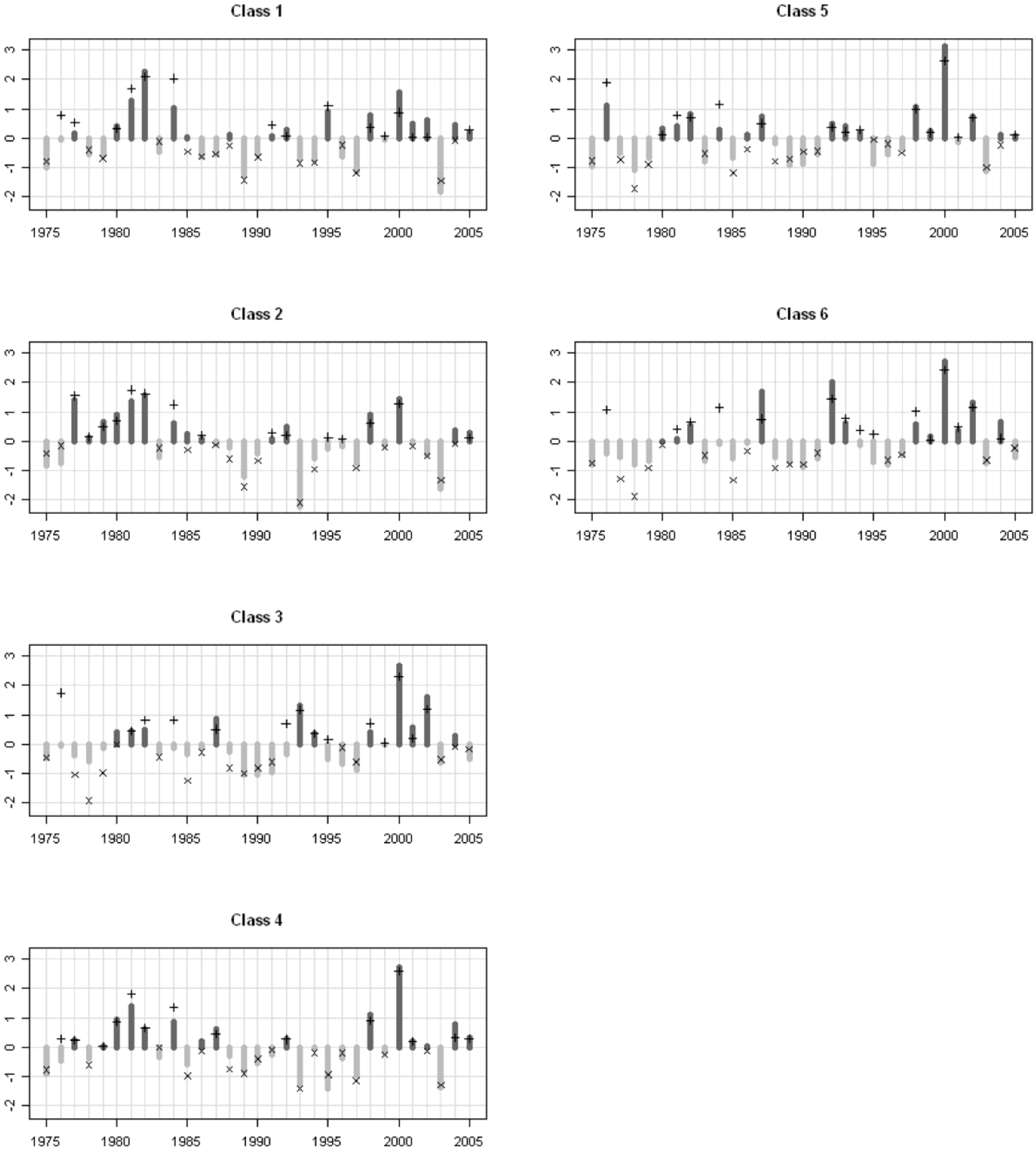

Figure 2: Autumn composite river flow (dark and light grey bars denote positive (i.e. wetter) and negative (i.e. drier) z-scores, respectively) and rainfall (+ and x symbols denote positive and negative z-scores, respectively) by class for 1975–2005. [Chapter 4.]

Table 3: Water temperature sites used in study. [Chapter 6.]

Dataset	Site	Easting	Northing
Frome	Frome at East Stoke	387000	86700
Great Ouse	Great Ouse at Lees Brook	522900	270100
LOCAR	Frome at Chilfrome	359050	99125
	Frome at East Stoke	386725	86850
	Frome at Loudsmil	370850	90475
	Frome, Sydling Water at Sydling St Nicholas	363225	99900
	Frome, Hooke at Maiden Newton	359475	97600
	Frome, Bovington Stream at Blindmans Wood	384175	87800
	Lambourn at East Shefford	438950	174550
	Lambourn at Shaw	447000	168200
	Pang, below Blue Pool	458675	171850
	Pang at Bucklebury	455300	171000
	Pang at Frilsham	453750	173000
	Pang at Tidmarsh	463600	174775
	Piddle at Baggs Mill	391325	87600
	Piddle at Briantspuddle	382125	93450
	Piddle at Little Puddle	371850	96450
	Piddle, Bere Stream at Snatford Bridge	385575	92975
	Piddle, Devils Book at Dewlish Village	377800	98500
Plynlimon	Lower Hafren	284300	287700
	Lower Hore	284500	287300
	Upper Hafren	282800	289200
	Upper Hore	283100	286900
Tadnoll	Tadnoll, Logger 1	377771	87130
	Tadnoll, Logger 6	378000	87133
UKAMN	Allt a Mharcaidh, 2	288100	804500
	Allt na Coire nan Con, 3	179300	768800
	Dargall Lane, 9	254300	578700
	River Etherow, 12	411600	399600
	Old Lodge, 13	545600	129400
	Narrator Brook, 14	257900	68600
	Afon Hafren, 17	284400	287600
	Nant y Gronwen, 18	282400	285400
	Narrator Brook, 23	256800	69200
	Afon Gwy, 24	284200	285400

Table 4: Ranges of average basin median elevations for all model runs. [Chapter 7.]

ERFA class	Average Basin Median Elevation (m)	
	Min	Max
Low	81	95
Medium	175	221
High	306	464

Table 5: Significantly different ERFA classes relative to basin aquifer factor. [Chapter 7.]

Run		Differing ERFA Classes* ($p \leq 0.1$)		Average Basin Aquifer Factor per ERFA Class (%)			
				None	Low	Medium	High
IPCM4	Natural	M	L, H		79	72	81
	EcF	L M	M, H H		73	77	86
	FoE	N, L, M	H	70	74	77	87
	PoR	L, M	H		75	76	86
	SuE	L, M	H		76	76	85
MIMR	Natural	N L M	H M, H H	71	79	73	86
	EcF	N, L, M	H	62	76	76	87
	FoE	N, L, M	H	63	76	75	86
	PoR	N, L, M L	H M	69	78	73	86
	SuE	N, L, M L	H M	71	79	73	85

*None, Low, Medium, High abbreviated as N, L, M, H

Table 6: Significantly different ERFA classes relative to land cover. [Chapter 7.]

GLCC	Run*	Differing ERFA Classes** ($p \leq 0.1$)		Average Basin % per ERFA Class		
				Low	Medium	High
Barren/sparse vegetation	All	L	H	6.41		40.81
	I: F/P/S	M	H		23.64	43.05
Closed shrubland	M: All	L	M	12.64	34.95	
	I: E/S; M: E/P	M	H		34.17	10.63
Cropland	All	L	M, H	86.88	69.59	58.51
	I: E/F/P/S; M: E	M	H		72.87	58.36
Cropland/ natural vegetation	I: E/F/P/S; M: E	L	M	52.56	36.55	
	I: E/F/P/S	L	H	53.63		34.35
Evergreen needle leaf forest	M: E	M	H		64.10	30.62
Grassland	All	L	H	4.98		37.95
	M: All; I: N/F/P/S	M	H		15.82	38.76
Mixed forest	I: N; M: N/P/S	L	M	22.02	34.38	
	I: E/F/P/S; M: E/F/P	M	H		33.76	12.38
Open shrubland	I: N/P M: All	L, M	H	11.45	17.72	32.22
Others	M: E/F	L	M	2.03	0.56	
	I: F/P/S; M: All	L	H	1.78		4.88
	I: N/F/P/S; M: All	M	H		0.80	4.79
Snow/ice	All	M	H		22.11	63.00
Urban/built up	I: N/P/S; M: N/P/S	L	M	42.16	10.49	
	I: N	L	H	39.37		3.76

*IPCM4, MIMR, EcF, FoE, PoR, SuE abbrevaited as I, M, E, F, P, S
**None, Low, Medium, High abbreviated as N, L, M, H

Table 7: Distribution of ERFA classes per runs (% of cells); UK cells only. [Chapter 7.]

		None	Low	Medium	High
IPCM4	*Natural*	1	84	15	0
	EcF	0	56	43	0
	FoE	0	63	36	0
	PoR	0	71	29	0
	SuE	0	77	23	0
MIMR	*Natural*	2	88	10	0
	EcF	2	67	31	0
	FoE	2	73	25	0
	PoR	2	85	13	0
	SuE	2	88	10	0

Table 8: Summary matrix of differences in ERFA classes between all runs (% of different cells); UK cells only. [Chapter 7.]

		IPCM4					MIMR			
		Natural	*EcF*	*FoE*	*PoR*	*SuE*	*EcF*	*FoE*	*PoR*	*SuE*
IPCM4	*Natural*		37	30	22	17				
	EcF			7	16	22				
	FoE				10	15				
	PoR					6				
	SuE									
MIMR	*Natural*	19	37	33	28	25	21	16	3	0
	EcF	36	20	21	23	24		7	18	21
	FoE	32	24	23	22	21			13	16
	PoR	21	34	31	26	23				3
	SuE	19	37	33	28	25				

APPENDIX II

Laizé, C. L. R. and Hannah, D. M. (2010). Modification of climate-river flow associations by basin properties. *Journal of Hydrology,* 389(1-2), 186-204.

APPENDIX III

Laizé, C. L. R., Acreman, M. C., Schneider, C., Dunbar, M. J., Houghton-Carr, H. A., Florke, M. and Hannah, D. M. (2014). Projected Flow Alteration and Ecological Risk for Pan-European Rivers. *River Research and Applications,* 30(3), 299-314.

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