Irish Climate Analysis and Research Units

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Ollscoil na hÉireann Má Nuad

INFORMATION AND DECISION-SUPPORT FOR ROBUST ADAPTATION OF IRISH WATER RESOURCES TO CLIMATE CHANGE

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Abstract

Anticipatory adaptation to climate change in the water resources sector is essential to reduce or avoid expected impacts on water resources availability and management. Anticipating how water systems are likely to respond to a changing climate is a challenging task, due to the difficulties in detecting clear signals of anthropogenic climate change from hydrological observations, along with uncertainties in future climate change impacts. To date in Ireland, studies with regard to climate change have focused on the traditional top-down, climate-scenario-driven impact assessments. Little research has gone beyond this traditional approach and examined how uncertain information on the future resource availability and on the vulnerability of water supply systems to climate change, can be incorporated into decision-making.

In addressing these challenges this thesis first examines observations of river flows from a network of near-natural catchments for evidence of climate-driven trends. Selected flow indicators relevant to water resource management are extracted and analysed for climate-driven trends, using different approaches including fixed periods of record and moving windows tests, to explore the nature of change in observations. Results indicate that the derived time series of median and low flow indicators in Ireland are dominated by natural variability, which makes the detection of a climate change signals in river flows rather difficult. The trends obtained for observed summer flows indicate a disagreement with established Irish climate change projections of drier summers and more extreme drought conditions. Given the shortage of coherent trends, the magnitude and amount of time required for change to be detected suggest that change signals will not be detected, using conservative significance levels, in the time frame required for adaptation. Therefore, anticipatory adaptation in the water resources sector cannot only rely on observed flow information but also needs to be based on the assessment of vulnerabilities to projected future changes.

In developing a tool to support water resources decision-making in Ireland, a physically based hydrological model (HYSIM) is coupled with a water resources model (WEAP) and applied to 12 different case study surface water abstraction points in Ireland to explore the effectiveness of selected adaptation options. The tool incorporates uncertainties in Irish future climate scenarios and hydrological model application. To facilitate application to un-gauged river reaches, from which water is abstracted, the tool incorporates a proxy-basin method, incorporating hydrological model uncertainty to obtain feasible ranges of future hydrological conditions. Non-climatic pressures such as population growth projections are also included in the modelling framework. Threshold-based indicators are employed to assess the water resources system performance for selected robust adaptation options of demand and leakage reductions.

Results indicate that the sensitivity of individual water resource systems to future changes and adaptation decisions is context specific. This is due to the particular hydrological and water supply system characteristics and requires case-by-case analysis. For a number of abstraction points examined in the east of the country, the tested scenarios are not sufficient to reduce vulnerability for a considerable proportion of the uncertainty space considered. Additional or different adaptation options will be required in these situations to increase system performance. The development and application of this tool marks a first attempt at using climate scenarios and their associated uncertainties for decision appraisal and marks a first step in this direction in Ireland, thereby providing a bridge in transitioning to a fuller methodology for decision appraisal. In developing a future research agenda priorities are distilled.

Acknowledgements

The research undertaken in this thesis is the culmination of two research projects over the past four years. The first part of this thesis is derived out of the 'HydroDetect' project, which sought to establish a reference network of hydrometric gauges for monitoring and analysing climate change. The second part was derived from the 'CoCoAdapt' project, specifically the work package on Climate Change and Water Resources. Funding for both projects by the Irish Environmental Protection Agency (EPA) under the Climate Change Research Programme 2006–2013 is gratefully acknowledged.

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List of Abbreviations

API	Application Programming Interface
BAU	Business as Usual
CORINE	Co-ORdination of INformation on the Environment
CCRR	Climate Change Research Programme
CMIP3	Coupled Model Intercomparison Project Phase 3
DTM	Digital Terrain Model
EC	Efficiency Coefficient
EPA	Environmental Protection Agency
GCM	Global Climate Model
GIS	Geographical Information System
GLUE	Generalised Likelihood Uncertainty Estimation
GSI	Geological Survey of Ireland
HA	Hydrometric Area
HYSIM	Hydrological Simulation Model
IPCC	Intergovernmental Panel on Climate Change
IRN	Irish Reference Network
LOESS	Local Polynomial Regression Fitting
MAE	Mean Absolute Error
MAF	Moving Average Flow
MK	Mann-Kendall
NAO	North Atlantic Oscillation
NI	Northern Ireland
OPW	Office of Public Works
PBIAS	Percent Bias
PE	Potential Evapotranspiration
PUB	Prediction in Un-Gauges Basins
RBD	River Basin District
RCM	Regional Climate Model
RMSE	Root Mean Square Error
RRV	Reliability Resilience and Vulnerability Indices
RSR	Root Mean Square Error-Observations Standard Deviation Ratio
S	Satisfactory Time Step
SD	Statistically Downscaled
SLF	Sustained Low Flow
SRES	Special Report on Emission Scenarios
$STDEV_{obs}$	Standard Deviation of the Observed Flow
SDSM	Statistical Down-Scaling Model
TC	Threshold Criterion
T_{min}	Minimum Trend Magnitude
U	Unsatisfactory Times Step
UK	United Kingdom
URR	Water Use-to-Resource Ratio
WEAP	Water Evaluation And Planning System
WGEN	Weather Generator
WRF	Water Framework Directive
Y_{detect}	Detection Time

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1 Introduction

"Water is essential to human life - for basic health and survival, as well as food production and economic activities." UN (2003); pp.1.

1.1 Introduction

A changing climate has the potential to have a significant impact on water resources availability and management. To be able to better cope with the expected changes anticipatory adaptation is necessary to prepare water supply systems and to minimise potential impacts. Parts of the work presented in this thesis are a result of an Irish Environmental Protection Agency (EPA) funded project through the Climate Change Research Programme (CCRR) 2007–2013, and are published as Report Series No. 16 by Hall *et al.* (2012). The work presented in this thesis is centred on the difficulties and potential of extracting and generating information to inform climate change adaptation decisions in the Irish water sector.

The first chapter introduces the topic of water resources in Ireland and the challenges of obtaining information for adapting water resources and their management to a changing climate. In Section 1.2 the rationale of this thesis is set out. The research aims and objectives are explained in Section 1.3. The description of the thesis structure in Section 1.4 concludes this chapter.

1.2 Rationale

Climate is the main driver influencing the long-term availability of raw water resources. Changes in the climatic regime of an area are apparent through changes in mean and extreme precipitation and its timing, frequency, intensity and location, which can have a significant impact on the hydrological system and therefore on the availability of water resources. Any changes in the hydrological system will have large implications for water resources management. For example, as a consequence of increasing temperature, climate models suggest an approximate global average precipitation increase of 3.4% per degree Kelvin of temperature (Allen & Ingram, 2002), leading to more intense but less frequent precipitation periods. These projected changes are global averages; however, at a regional scale such changes can manifest themselves at different magnitudes. Nevertheless, anticipating how projected changes will affect future water availability is an important for any water management decision.

Historically, pressure was put on the management of water supply systems mainly from increasing water demand or extended drought conditions; however, with a warmer climate, water demand could further increase while water supply may be reduced. Therefore, a changing climate will be a key driver of the future availability of raw water resources, resulting in the necessity of including climate change considerations in the planning approach.

A changing climate and the associated changes in the hydrological cycle challenge the traditional approach in water resource planning which is based on the assumption of stationarity of the climate system and thus on a stationary hydrological system (Milly *et al.*, 2008). This traditional view implies that raw water availability for water abstraction is more or less constant over time, with some inter-annual or inter-decadal variability. However, with a changing climate, the assumption that the past climate and hydrological system will be the key to the future conditions is no longer valid. Changes in the hydro-climatic system might already be take place and could result in changes in the observed flow regimes. This uncertain hydrological future is problematic when planning decisions and anticipatory adaptation measures have to be agreed upon to avoid expensive mal-adaptation. This is of particular importance in planning and managing water supply policies and infrastructure, with a long time required for planning and operationalisation, as well for the long design life of such infrastructure projects, where mal-adaptation can be expensive (Hall & Murphy, 2011).

The effect of a changing climate on raw water resources and water supply systems will not only depend on the degree of changes in the hydrological system but also on the water supply system itself. Depending on the main characteristics of water supply systems, the same type of change in a climatic variable can have very different effects on diverse water supply systems. For example, systems with plenty of excess headroom are robust and likely to cope with larger changes, compared to water supply systems that are already under pressure and operating at, or close to, their design capacity, where a small change can have large effects (Hall & Murphy, 2012). Therefore, an assessment of the balance of future water supply and demand of individual water supply systems or even single water abstraction points is crucial by taking future climate and future development of non-climatic pressures into account.

In Ireland, the national water supply system is structured as follows: the majority of the population (80%) receives its water from public water supplies, which are operated by 939 Water Services Authorities spread across the country. Private wells serve 12.3% of the people, whereas private group water schemes and public group water schemes account for 4.7% and 2.3% or the population respectively. The majority (81.9%) of Irish drinking water originates from surface water sources such as lakes and direct in-stream abstractions. Water abstractions from groundwater account for 10.5% and springs 7.6% of the potable water (EPA, 2012). However, regional differences on the main sources and key characteristics of the water supply systems exist.

As shown above, an important characteristic of the Irish water supply systems is that surface water is the main raw water source for public water supplies, which supply the majority of the population (EPA, 2012). Often, particularly for water supply systems serving smaller communities, the water is directly abstracted from the river, without any storage facilities such as reservoirs. This characteristic makes these water supply systems particularly vulnerable to any changes affecting in-stream river flow, such as possible flow reductions induced by a changing climate.

Therefore, an understanding of possible impacts of climate change on surface water resources is of high importance. In the Irish context, little work has been conducted on climate-driven changes in river flows, with exception of high- and mean- flows (Murphy *et al.*, 2013). Though, a systematic study on observed changes in low-flows is still needed to inform water management. With regard to future changes, a number of case studies have analysed the effects of climate change on stream flow at a catchment scale (e.g. Charlton *et al.* (2006), Steele-Dunne *et al.* (2008), Bastola *et al.* (2011a) and Bastola *et al.* (2012)). However, none of these studies have analysed such impacts for individual water abstraction points and such information would be needed to inform adaptation decisions,

1.3 Research Aims and Objectives

The motivation for this thesis is driven by the challenges faced by water managers in adapting to climate change and their need for information and tools to support decision-making. Water and therefore a reliable and sustainable water supply are important to sustain and to develop our society. In the light of challenges posed by climate change in the form of possible changing rainfall patterns and altered water demands, it is critical that water management in Ireland can adapt to a changing climate in a timely fashion. However, the task of formulating adaptation measures is not straightforward. Challenges originate amongst others, from the lack of clear anthropogenic climate change signals in observational data on hydro-climatic variables and wide ranges of uncertainty in projections of future impacts stemming from various sources. This thesis takes an Irish context and specifically uses data and information readily available to water managers in Ireland. The aim of this thesis is to address the issues presented above and offers a practical approach and a tool for more robust adaptation option appraisal in the water sector in Ireland.

The key aims of this thesis are two-fold, built around the analysis of observational data and the development of a modelling and decision-support tool, to inform robust climate change adaptation decision-making in the Irish water supply sector.

Each research aim and supporting objectives can be summarised as follows:

1) Examine the utility of traditional trend analysis in river flow observations for informing decision-making for anticipatory adaptation to climate change in the water sector.
    a. Analyse the observational river flow records in Ireland for evidence of trends in flow indicators relevant to water resource management.

b. Investigate the challenges involved in extracting a robust anthropogenic climate change signal from hydrological records.

c. Identify whether a linear climate change signal will be statistically detectable in the time-frame required for adaptation with regard to both magnitude and timing.

2) Develop a decision-support tool for the water sector in Ireland through coupling available and widely used models, in order to appraise the utility of selected adaptation options in the context of robustness to uncertainty. This tool will:

    a. Incorporate national climate change scenarios that are currently used in impacts and adaptation assessment in Ireland. In addition, provide the flexibility in the model setup to allow future incorporation of larger ensembles of climate change scenarios.

    b. Integrate uncertainties derived from the application of hydrological models. In particular, in a real world application where many points of interest for water management are without observed flow records, the tool shall incorporate uncertainties associated with deriving stream flow in un-gauged settings - particularly model parameter uncertainty.

    c. Include non-climatic drivers that affect water resources, such as population growth and supply network characteristics.

    d. Provide a framework for model output analysis and result presentation of equally possible multiple future outcomes of the water resource model, in a practical context.

The tool developed here will be the first adaptation assessment that goes beyond traditional climate change impact assessment in Ireland. In achieving these research aims, this thesis offers a bridge to support the transition from top-down climate change impact assessments to an approach centred on anticipatory adaptation. Insights gained from this research can inform directions for the future development of information and decision-support tools for tackling the important challenge of adapting water supply systems to a changing future.

1.4 Thesis Structure

In addressing the research aims and objectives outlined above this thesis is split into seven chapters and structured as outlined in the Schematic in Figure 1.1.

In Chapter 2, a review of the scientific literature on climate change impacts on the water sector is presented examining the role of observations and future projections in providing information for anticipatory adaptation under climate change uncertainty. In addition, findings from previous studies are outlined and recent advances in approaches to informing adaptation are reviewed.

The first research aim of the thesis is addressed in Chapter 3. Observational flow records are examined for evidence of a changing climate in a network of Irish hydrometric stations. To investigate the challenges associated with the extraction of climatic change signal in hydrological records, a number of low-flow and low-flow spell indicators are analysed for changes using different trend analysis approaches. Detection times for climate change signals to emerge as statistically significant are established and the utility of observations to inform anticipatory adaptation is discussed.

The second key research aim is addressed in Chapters 4-6.

In light of findings from Chapter 3, in Chapter 4 the need for a tool for informing adaptation decisions in the water resources sector is established. Using data and information currently available to decision makers in Ireland, Chapter 4 describes in detail the framework, methods and data used in the following chapters to form a decision-support tool.

In Chapter 5, the hydrological modelling approaches which underpin the water resources decision-support tool are detailed for illustrative case study areas and gauged and un-gauged water abstraction points.

Chapter 6 provides an assessment of different low-regret adaptation options within a water resource model, by using a threshold-based approach to evaluate the water system and selected adaptation option performance under the range of projected future uncertainties considered.

The thesis concludes in Chapter 7 with an overall summary and discussion of the main research findings, acknowledges the current limitations and suggest future research in the Irish water resources sector.

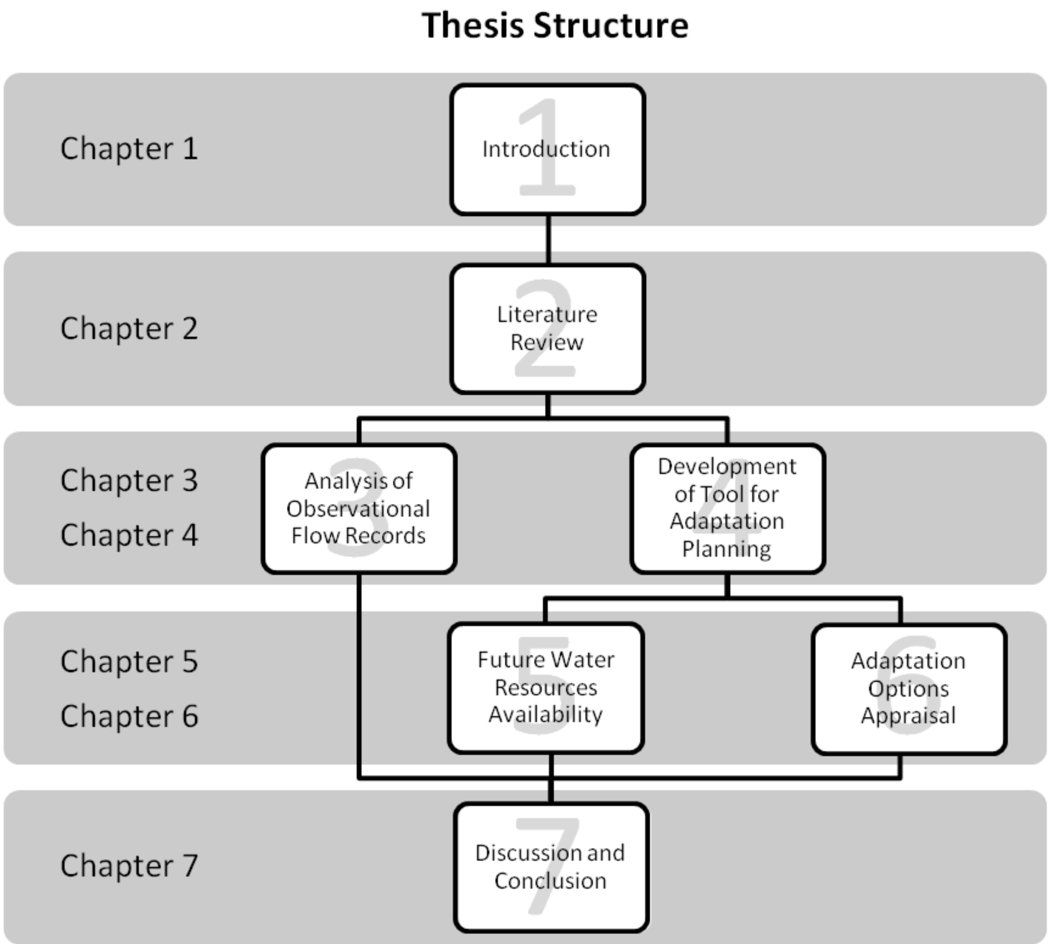


Figure 1.1 Schematic of thesis structure and chapters.

2 Review of Scientific Literature

2.1 Introduction

This chapter presents and summarises the literature on water resource management and climate change with the aims of summarising recent approaches, identifying gaps in research so far and distilling research objectives to be investigated in this thesis.

The chapter starts out by providing an overview on water resources and climate change (Section 2.2). In Section 2.3, the role and challenges associated with the use of observations in providing information for future water management are presented. In section 2.4, future climate projections and hydrological scenarios and their associated uncertainties are examined together with a critical appraisal of traditional, top-down approaches in Section 2.5. Alternative approaches to climate change adaptation are presented in Section 2.6 followed by sample applications in Section 2.6.1. This chapter finishes with a summary (Section 2.7) which identifies gaps in knowledge and how this thesis is addressing these.

2.2 Water Resources and Climate Change - An Overview

Management of future water resources faces many challenges. Water management needs to take into account various dynamic processes affecting water demand and water supply such as changes in population, land-use changes, inter-annual weather variability and climatic change.

The energy of the sun drives the climate system, which is the key driver of the hydrological cycle. Both systems are intrinsically linked with each other so that a change in one can induce a change in the other due to their in-depth inter-connection (Kundzewicz, 2004). However, the energy balance of the Earth has been modified due to human action , mainly through greenhouse gas emission and land use change. Forster *et al.* (2007) highlight the strong likelihood of humans having extensively influenced the warming of the global climate, since 1750.

The Intergovernmental Panel on Climate Change (IPCC) considers anthropogenic greenhouse gases emission as a very likely cause of the increase in global temperatures over the course of the 21st century (IPCC, 2007a). They also estimate that global mean surface temperatures have increased by 0.74°C ± 0.18° C (linear trend) over the last ~100 years (1906-2005) (Trenberth *et al.*, 2007). It is expected in theory that a warmer climate leads to increases in evaporation and a higher specific humidity resulting in an intensification (or acceleration) of the hydrological cycle (Huntington, 2006). A changing climate also has the potential to affect the intensity, timing and frequency of precipitation events and their translation into runoff (Bates *et al.*, 2008).

Such projected changes can have both positive and negative effects, as outlined below. Expected changes in precipitation will be more variable then the expected future changes in temperature, as precipitation is very site specific and highly influenced not only by the topography but also by local and regional atmospheric patterns (IPCC, 2007a). Thus, precipitation changes will not be translated linearly into hydrological changes (e.g. in infiltration or surface runoff), as these again depend on the catchment characteristics. Therefore, due to this nonlinearity, possible changes can have both positive and negative effects on the hydrological system (or no effects at all) depending on the sign, magnitude of the change and the geographical location. For example, temperature increases can result in increased evapotranspiration through increased atmospheric water holding capacity and larger water loss from the soil surface (Dai *et al.*, 2004) or water surface or an increasing demand for potable water for domestic or agricultural use. Whereas an increase in the magnitude of a rainfall event has the potential to cause damaging floods or increased erosion and might adversely affect water supply systems and water abstraction due to decreased water quality, high turbidity and disrupted systems.

Localised information on possible future impacts is needed, to anticipate changes and to devise appropriate adaptation measures, to reduce exposure or develop coping strategies. However, the local scale is also the one at which the greatest uncertainties and challenges exist in detecting regional climate change signals (Stott *et al.*, 2010) and in modelling future impacts (Milly *et al.*, 2005; Nohara *et al.*, 2006).

Hydro-climatic information and historical records from monitoring networks have always played an important part in informing decision-making in water management, especially for planning and operating water resource systems. However, with anthropogenic induced climate change and the possibility of experiencing new or changing hydro-climatic conditions, alternatives in addition to the traditional approaches in water resources planning and management are needed to adapt successfully to these anticipated changes. Long-term hydrological observations will always play an important role in providing data for detecting and quantifying changes along with possible trends in the hydrological system, informing hydrological modelling (calibration and validation), evaluating projected future hydrological conditions and appraising possible adaptation strategies for informing planning and decision-making in the context of climate change.

2.3 The Role of Hydrological Observations

Data from river flow observations is the basis of effective water resources management and provide basic information for resource assessments, regulation and policy development. In the context of changing climatic conditions such measurements can provide key information for understanding variability within observations, the detection and attribution of emerging climate change signals (Burn *et al.*, 2012). Nevertheless, observations are also important for the validation of climate change scenarios and the provision of reliable information for training models that can be used to generate future predictions. For such purposes, high quality low data from time series that span the time period of interest are required.

Observational hydro-climatological data has always played an important role in informing decisions in water resource sector to assess different planning options. For example, past hydrological records have been used to provide information about future water availability and to design water infrastructure together with other factors, such as current and expected water demand increases due to population growth. Traditionally, water resource systems have been designed based on historical hydro-climatological information, assuming that stream flow will remain unchanged in future, with some inter-annual or inter-decadal variability, according to the principle of stationarity. In hydrology, stationarity refers to the perception that stream flow varies within un-changing lower and upper bounds, defining the maximum variability extent (Milly *et al.*, 2008). However, if climate - the main driver of the hydrological cycle - is changing, this assumption of stationarity may no longer be valid and additional information on whether and how the hydrological system is changing is needed.

In hydro-climatic data, changes in time series can affect all parts of the flow regime, for example high, mean and low flows and/or the timing and frequency of river flows of a certain magnitude. In the hydrological community, such changes are generally thought to manifest themselves as a trend (gradual change over time), which can occur as a linear change, as several smaller step changes or in a curved manner (Hirsch *et al.*, 1991; Kundzewicz & Robson, 2004). Changes can also happen as step changes/regime shift (rapid change of the magnitude of trend at one (change point) or multiple points in the time series). Additionally, oscillations with or without period clusters can be present in the time series as shown in Figure 2.1.

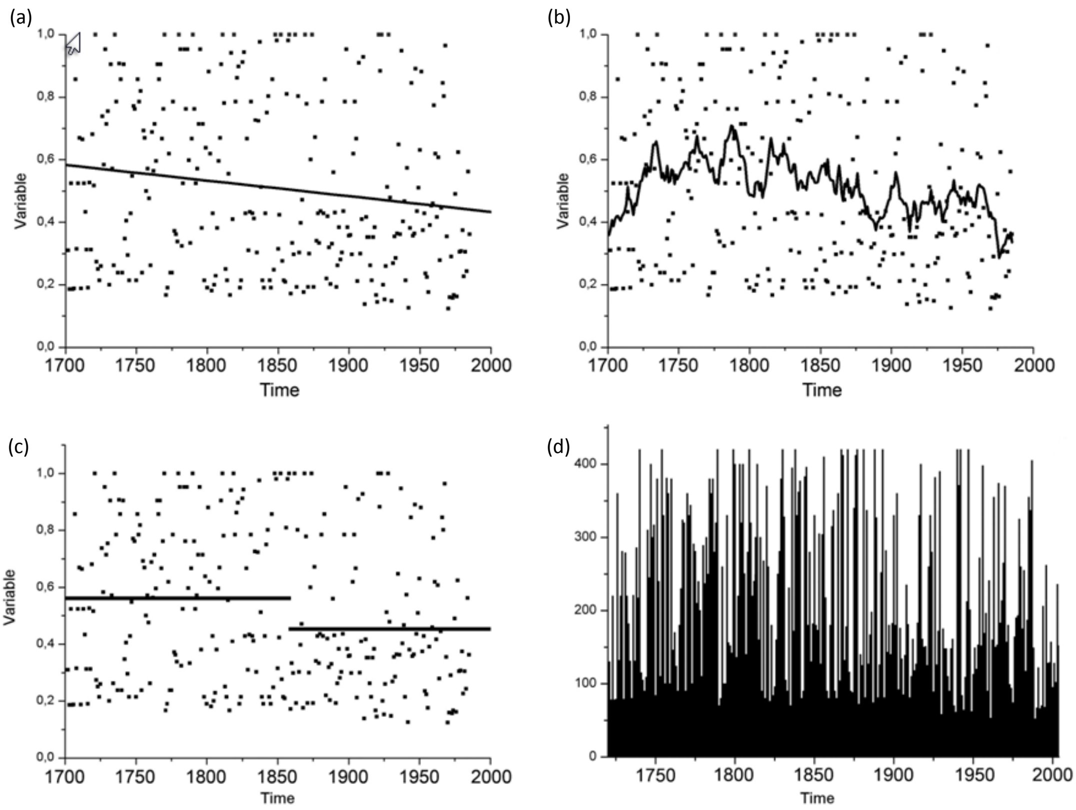


Figure 2.1 Time series with possible characteristics of a) trend, b) oscillation, c) regime shift or d) noise (Omstedt, 2005).

Internationally several studies have aimed to assess climate-driven changes in hydrological data records from existing monitoring networks. However, only few studies have actually established and used data from a hydrometric network of specific stations selected for the purpose of monitoring the effects of climate variability and change on hydro-climatic variables (e.g. Birsan *et al.* (2005), Hannaford & Marsh (2006, 2008), Hodgkins & Dudley (2006), Khaliq *et al.* (2008, 2009), Hannaford & Harvey (2010) and Burn *et al.* (2010)). Even without assigning these stations a special network status, the results from a review of 128 international studies on climate-driven changes by Burn *et al.* (2012) showed that only ~30% of the studies used data from pristine catchments or near-natural catchments with limited disturbances such as land-use change or water abstractions.

The main advantage of using stations from an active network is that already existing data can be analysed for long-term changes without the need to setup new stations to collect data and to wait until the time-series has reached an appropriate length for any analysis to be meaningful. A shortcoming of such an approach is that these networks were often established for monitoring purposes other than hydro-climatic changes such as recording high or low flows (Burn *et al.*, 2012). Depending on the monitoring purpose, some parts of the flow regime will have better accuracy than others. Therefore, only few hydrological monitoring stations perform well across the entire range of flows (Hannaford & Marsh, 2008). Consequently, the quality of data might not be ideal for the purpose of monitoring an anthropogenic induced climate change signal. Consequently, a rigorous quality control process, including meta-data information for the time series used should be employed (Kundzewicz & Robson, 2004) and only appropriate data should be included for further analysis. Such a thorough selection process of measuring stations and their associated time series can limit the number of usable sites and might affect the coverage, if regional analysis is performed and spatial representativeness of study sites over large areas is needed.

Reference hydrometric networks can provide quality controlled data sets for the detection of climate-driven changes in stream flow. Therefore some countries have specifically assigned stations to such networks, to allow the assessment and identification of such changes. The networks consist of either existing and/or new hydrological monitoring sites or have capitalised on existing sites for monitoring and detection of climate-driven trends in hydro-climatic records. Examples of reference networks include the Hydro-Climatic Data Network (HCDN) in the USA (Slack & Landwehr, 1992), Canada's reference hydrometric basin network (RHBN) (Harvey *et al.*, 1999), the UK Benchmark Network (Marsh, 2010) or the Irish Reference Network (IRN) (Murphy *et al.*, 2013).

However, not only hydrometric sites can be analysed to better understand changes in the hydro-climatic cycle. Several studies have analysed various types of indicators of hydro-climatic variables of interest. For example, Alexander *et al.* (2006) investigated global changes in temperature and precipitation extremes and reported statistically significant changes (at the 5% level) for minimum temperatures and precipitation, although with less spatial coherence for the latter. Precipitation changes differ in magnitude and sign from region to region, reducing the average global signal of change (Zhang *et al.*, 2007). Therefore, regional analyses are more appropriate. For example, Osborn & Hulme (2002) analysed precipitation patterns in the United Kingdom (UK) from 1961 to 2001 and found daily precipitation tends to become more intense in winter and less intense in summer. These findings are also supported in an updated analysis of the data up to 2006 (Maraun *et al.*, 2008).

In Ireland, changes in climatic driven variables such as precipitation have been analysed by previous studies. For example, Sheridan (2001) analysed Irish rainfall records for trends in rain-days and wet-days (precipitation ≥ 1.0 mm) and found two significant trends, namely increases at many stations in March and decreases in July, August and September. An analysis of annual rainfall from 1960 onwards by McElwain & Sweeney (2007) indicated increases for the north and west of the island, while decreases or slight increases were detected for the south and east. According to a study by Kiely (1999), extreme rainfall events have become more common in Ireland since 1975 and a correlation with an increase in the positive phase of the North Atlantic Oscillation (NAO) Index was found. Additionally, Leahy & Kiely (2011) highlighted that annual and seasonal precipitation totals changed for synoptic stations in the west and northwest of Ireland. This change is marked by a transition to increased rainfall levels around mid-1975. While change points related to natural variability have been detected along with consistent trends in recent decades, no long-term monotonic trends have been identified and attributed to climate change. This has also been the case for studies in other countries such as North America (Ziegler *et al.*, 2005), Canada (Burn & Hag Elnur, 2002) and the United Kingdom (Wilby, 2006).

However, the way changes in precipitation and temperature are translated into changes in stream flow cannot be considered as being linear and are rather highly dependent on catchment characteristics. Therefore, regional assessments utilising long-term stream flow records have been conducted for several studies around the globe. Although currently there is little evidence of a climate change signal at regional scales in hydrologic variables, a trend analysis of up to date data can provide a first insight (Bordi *et al.*, 2009). On a European scale, several studies have identified changes at regional scales for different parts of the flow regime (low, mean and high flows) (Dixon *et al.*, 2006; Hannaford & Marsh, 2008; Klavins & Rodinov, 2008; Bordi *et al.*, 2009; Petrow & Merz, 2009; Burn *et al.*, 2010; Fiala *et al.*, 2010; Korhonen & Kuusisto, 2010; Wilson *et al.*, 2010; Montanari, 2012). However, due to the caveats encountered when performing a trend analysis (see Section 2.3.1) the results of the example studies presented here will need to be treated with caution.

In this thesis, only examples of studies analysing the lower part of the river flow regimes are presented as these have the highest importance for long-term water management decisions. For example, Hisdal *et al.* (2001) investigated stream flow droughts in Europe using data from the Europe Water Archive (including catchments with high human influences) and found for the period 1962-1990 an increasing deficit volume during droughts for large parts of the UK, Eastern Europe and Spain, and decreasing volumes in Central Europe, although most of changes were reported to be not statistically significant. Hisdal *et al.* (2001) highlight the fact that these trends could be explained by changes in precipitation patterns and/or human influences in the investigated catchments.

For the HCDN in the US, large-scale increasing trends in low flows (statistically significant) were reported for the Midwest (Douglas *et al.*, 2000), while McCabe &

Wolock (2002) were able to detect increasing stream flow for annual minimum flows and annual median flows in the US, particularly in the east. In the Canadian Prairies, an influence of the temperature change on low streamflow (in catchments with natural flow regimes) was found, resulting in a decreasing tendency for records with varying streamflow data range from 1912-1993 to 1969-1993. (Yulianti & Burn, 1998). Additionally, a later study on the timing of low flows in the RHBN in Canada up to the year 2003, showed that the majority of observed trends indicated a shift towards earlier occurrences of winter low flow, whereas no prevailing signal of earlier or later summer low flows could be detected (Ehsanzadeh & Adamowski, 2010). A pan-European study by Stahl *et al.* (2010) on low flows in near natural catchments over the period 1962-2004 confirmed more recent national and regional trend studies, with increasing trends in winter and decreasing low flows for the regional low flow periods for the majority of catchments investigated, especially in southern parts of Europe.

In the UK benchmark network, few significant positive trends (5% level) have been found for low flows (1973-2002) and these trends lost statistical significance when records were extended beyond a length of 40 years (Hannaford & Marsh, 2006). In Wales, significant increases in low flows for three time periods of different length (minimum of 25 years) up to 2001 were identified by Dixon *et al.* (2006). Regarding Ireland, for the period 1976-2009 Murphy *et al.* (2013) found that high-flows show significant positive trends (5% level), however, for the majority of investigated hydro-climatic indicators, strong temporal variability of trends is apparent, which can mask any climate change signal.

The above studies show that so far there are no common, robust signals of climate change in the investigated flow records to date. This can be caused by regional differences between the investigated areas, but also due to the different methods, periods and statistical significance levels used. Additionally, the studies often use short records (e.g. 30 years), which are strongly influenced by inter-annual and inter-decadal variability. In such short records, extremes (particularly at the start or end of the analysed time series) can cause apparent short-term trends, where no long-term trend exists. Chen & Grasby (2009) provide a summary diagram illustrating the effect of oscillations and selected monitoring window on trends obtained (Figure 2.2). They highlight the need to consider the presence of quasi-periodic climate cycles of 45–60 years, and argue for caution when conducting trend analysis of observed records, on time series with less than 60 years.

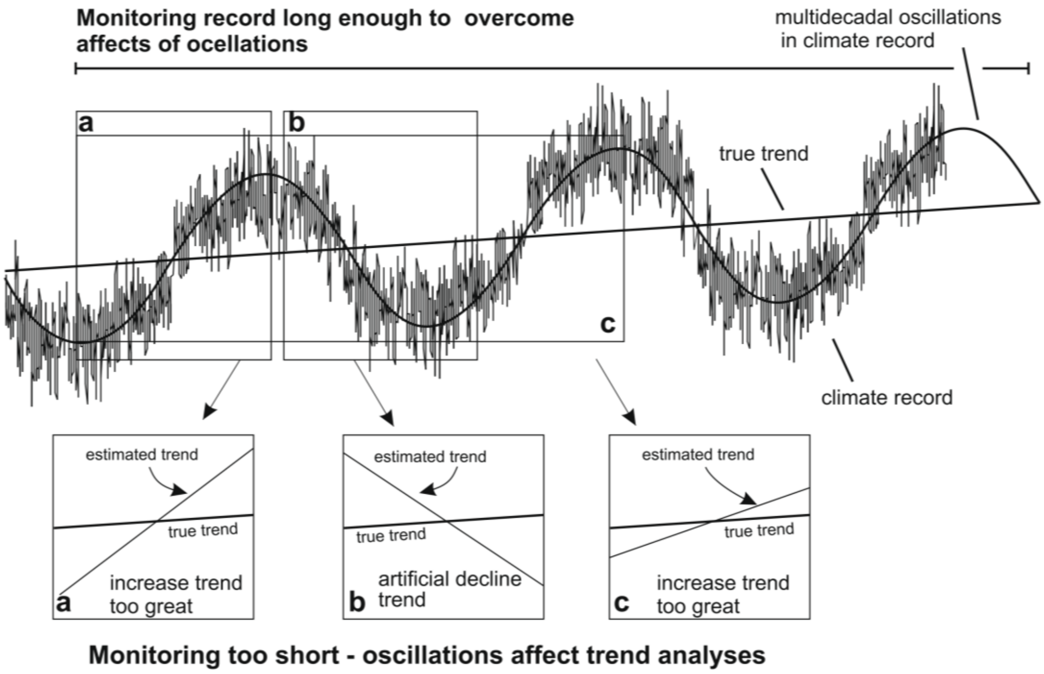


Figure 2.2 Summary diagram showing the effects of oscillations on trend analyses. Main diagram shows a conceptual long-term climate record with a prominent multi-year cyclical component along with a linear increase trends with time. Box (a) shows that if climate monitoring captures ½ wavelength starting at the trough and ending at the peak of a cycle, then the estimated trend will be significantly greater than the true trend. In contrast, (b) shows that a ½ cycle record starting at a peak and ending in the trough of a cycle will give a negative trend, even though the true trend is positive. In (c), even one and half cycle length record will give too great an increase due to the record starting at the low point of a cycle. Graphic taken and caption quoted from Chen & Grasby (2009).

Kundzewicz (2004) noted that from a review of previous research evidence is lacking of any significant large-scale evidence for changes in hydrological data (i.e. floods and droughts) induced by anthropogenic climate change. However, as the effects of human-induced climate change become more pronounced with time, early detection of changes in hydrological regimes is increasingly important, for informing adaptation strategies to minimize negative effects on the environment and society. Therefore, a 'wait and see' attitude until these anticipated changes become detectable in hydrological records to devise policies and responses is not an option (Murphy *et al.*, 2011). This is problematic given the long planning times required in developing adaptation and the long design-life of water infrastructure (Hallegatte, 2009).

2.3.1 The Challenges of Climate-Driven Trend Detection

The following sections will outline the challenges associated with climate-driven trend detection in observational hydrological records. Human induced artificial influences on hydrological records, so called confounding factors, can introduce artificial changes into the record, which are not driven by anthropogenic climate change (Fowler & Wilby, 2010) and can be easily misinterpreted as anthropogenic induced climate-driven trends. Examples for such human induced changes are, but are not limited to land use change (e.g. deforestation, urbanisation, arterial drainage or changes in water infrastructure), shift of the location (upstream or downstream) of the measuring site, change in measuring technique/device or the inability of the device to capture the flow at extreme magnitudes (low flows or high flow). In overcoming some of these challenges when studying river records for a climate change signal, Kundzewicz & Robson (2004) recommend that if possible, only records from near-natural river catchments with long good quality records should be used.

As shown in the previous section, observational data from reference hydrological networks with limited non-climate related disturbances have the potential to provide such records, which can be the base for the analysis of climate-driven changes in hydrological time series. To date, there is no international accepted standard for a common protocol of data collection and analysis in such networks. Different countries use different criteria, variables and analysis methods, which makes comparison of international or global outcomes difficult (Burn *et al.*, 2012). This high diversity of approaches makes it difficult to internationally compare the outcomes of the analyses and assemble the results into conclusive broader scale picture.

However, from a national/regional point of view, this diversity is rooted in the history and therefore in the purpose of the existing network, which defines the spatial distribution, length and quality of data available. The attributes of the existing network then define the station selection criteria that can be applied to form a sub-network for specific purposes. For example, to obtain a geographically representative reference hydrological network in the UK, compromises on the station selection criteria were necessary because of the limited number of stations with a natural flow regime (Bradford & Marsh, 2003).

Additionally, the variables and the time series that could be potentially analysed also depend on network history and the reason for establishment of stations in the first place. Ideally, the entire range and selected parts of the flow regime (e.g. mean, high and low flows), for annual, seasonal and monthly indicators, should be analysed to allow for the fact that catchments within the same region, but with differently properties (e.g. size, soils or aquifers) respond different to climate-driven changes. However, this is not always possible, as for example, in Ireland the hydrometric stations installed by the Office of Public Works (OPW) were mainly for monitoring flood risk, with a focus on high flows (OPW, 2012). Therefore, for some of these stations, the low flows are of poor or unacceptable quality, which limits the potential for good quality assessments of low flow related hydrometric variable.

Apart from the influences of the network history and location on the potential of doing a trend analysis, other factors such record length, missing data, the period of record selected and non-stationarity make the detection of trends challenging. For example, when a trend study with observed time series is being conducted on multiple measuring sites, a common problem encountered are large differences in particularly start but also end dates, depending on when the gauges were installed or ceased to operate. For meaningful interpretation of the outcomes of such a study, the records examined must be coexisting. However, to obtain a representative spatial coverage across a region, often a compromise between concurrent record and inclusion/exclusion of measuring stations might become necessary. This can additionally complicate the analysis as this evokes a trade-off between spatial and temporal coverage driven by the need for long record series and not excluding too many stations with shorter records. Long record lengths are important to detect trends driven by anthropogenic climate change, as shorter records are often dominated by strong natural climate variability (e.g. high inter-annual, inter-decadal and multi-decadal variability). At least 50 years of data are recommended by Kundzewicz & Robson (2000) and Yue *et al.* (2012), whereas Chen & Grasby (2009) even go further and caution the use of time series records with less than 60 years. However, not only the record length, but also the periods of record selected influence the detectability of trend in the data as start and end year of the record can influence the trend magnitude and direction. This is particularly the case when outliers are present at the start and end of the time series (Fowler & Wilby, 2010).

Further complexity in detecting trends is added by missing data, especially if gaps persist over multiple time steps and/or occur over different time periods for different stations. For such situations, Hirsch *et al.* (1991) recommend the use of monotonic trend test procedures, because they allow an easy testing of all records over the common period. However, an objective procedure needs to be established to account for the maximum amount of data missing in total and for consecutive time series points. Additionally, Kundzewicz & Robson (2000) highlight the need to establish whether missing data values occur randomly or happen at certain points of the flow spectrum (e.g. when the measuring device is not able to capture extreme low flows). Such random errors or additionally systematic errors, such as measurement errors leading to a constant under or over estimation of low flow values, can compromise the trend detection.

A common approach for the analysis of trends in hydrological time involves the use of the Mann-Kendall nonparametric test or linear regression based on the assumption of monotonic changes (Burn *et al.*, 2012) and then the significance of the derived trends is assessed. However, there is an on-going controversy over whether hydrological data can be assumed independent or if the presence of long-term persistence (clustering of positive or negative deviations from the mean) violates this assumption (e.g. Khaliq *et al.* (2008, 2009) or Chen & Grasby (2009)). An additional challenge for trend detection is the non-stationarity found in hydro-climatic data. Cohn & Lins (2005) highlight that it is possible to detect the magnitude of trends in non-stationar time series. However, natural variability and long-term persistence within the series make an attribution of statistical significance ambiguous. Therefore, some authors of have opted to present only the magnitudes of change to report regional patterns and not to test for significance of trends (e.g. Stahl *et al.* (2010) or Hannaford & Buys (2012)).

Despite these challenges in detecting trends, the analysis of trend in observational records can provide helpful information to proactive decision makers and water managers. As the results of such analysis allow putting current hydrological phenomena (e.g., droughts or flooding events) in long-term context, i.e. to see the tendency for emerging shorter term linear trends driven by anthropogenic climate change and long-term natural hydro-climatic cycles (Bordi *et al.*, 2009).

Overall, it is important to attribute the physical causes of any trends detected (Merz *et al.*, 2012) in hydro-climatic data to be able to understand how these trends might evolve into to the future, (i.e. whether the trend persists, levels off or reverses). Only when the cause or the multiple causes of the trend single are fully understood, can these signals be extended into the future and used for future planning and water resource management. However, the trend detection and analysis approaches presented above are only able to give planners retrospective indication of what has happened to the hydro-climatic system. For anticipatory adaptation, this partial understanding/interpretation about past and current conditions needs to be amended by information about possible future conditions. For example, this can be achieved by using climate change projections in conjunction with hydrological models to provide projections about the future state of the hydrological system (Burn *et al.*, 2010). The outputs from these models can then be used as a source of additional information to future water resources management and planning. Information on possible future climate becomes especially important when anticipated future trends in hydro-climatic indicators are not statistically detectable within current observations and future planning decisions in the water resources sector have to be made.

2.4 The Role of Future Hydrological Projections

2.4.1 Low Flow & Drought Projections and Future Water Resources

Traditionally, water resources management and planning has been predominately been based on estimated or measured stream flow to assess raw water availability at certain locations. However, anthropogenic induced change in hydro-climatic variables cannot yet be detected in hydrological records with confidence, as discussed in the previous section. Therefore, there is an increasing need for supplementary information to allow better future management and long-term planning of water resource systems.

Several studies aimed to assess possible future impacts of a changing climate on low flow, droughts and water resources at various scales. Stream flow decreases, extended low flow periods and hydrological droughts are caused by precipitation deficit (Stahl *et al.*, 2002). As changes in precipitation characteristics occur at a regional scale, the hydrological characteristics should be studied at a similar scale. The examples of European regional studies of future low flow conditions include, but are not limited to, the following example studies. Blenkinsop & Fowler (2007) examined projected future changes in drought duration, magnitude (severity) and frequency for the British Isles using regional climate models. The results suggested decreases in mean precipitation during the summer months leading to an intensification of shorter duration droughts in most of the investigated regions. Stahl *et al.* (2012) performed a gridded simulation of runoff changes for the European continent to overcome the limited spatial distribution for trend analysis for the period 1963-2000. On a very coarse scale, they found dominating increasing trends in winter flow and decreasing trends in summer flow, in conjunction with a north-south gradient. This divide is in line with future climate projections, which split Europe in a wetter northern part and a drier southern part.

In terms of various climate change impacts on water resources at a global scale published by Bates *et al.* (2008), Hall & Murphy (2012) provide a summary table of the projected effects of climate change and other non-climatic pressures (Table 2.1).

Table 2.1 Future changes, their likelihood and effects on water resources (c.f. Bates *et al.*, 2008).

Change Projection	Likelihood (21st century)	Effects on water resources
Precipitation increases in high latitudes and parts of the tropics	*very likely and likely*	Increase in water resources.
Annual river runoff increase at high latitudes and in some wet tropical areas	*high confidence* (by the middle of the century)	More frequent and more serious floods
Precipitation decreases in some subtropical and lower mid-latitude regions	*likely*	Decrease in water resources
Annual river runoff decrease over some dry regions at mid-latitudes and in the dry tropics	*high confidence* (by the middle of the century)	More frequent and more serious droughts
The frequency of heavy precipitation events increase over most areas	*very likely*	Risk of rain-generated floods.
Increase in continental drying in summer (especially in the subtropics, low and mid-latitude)	*likely*	More frequent and more serious droughts
Decline in glaciers and snow cover (important in regions supplied by melt water)	*high confidence*	Reduced water availability (seasonal shift in stream flow, reductions in low flows)
Higher water temperatures and changes in extremes, including floods and droughts,	*high confidence*	water quality and exacerbate many forms of water pollution
Sea-level rise extends areas of salinisation of groundwater and estuaries,	*high confidence*	Decrease of freshwater availability in coastal areas.
Globally, increase in population and affluence and urbanisation;	*high confidence*	Growing water demand
Regionally, changes in irrigation needs due to climate change and land use change	*high confidence*	Growing irrigation water demand

The quantitative uncertainty is expressed using statements about their confidence levels expressed as the assessed chance of a finding being correct: "very high confidence at least 9 out of 10; high confidence about 8 out of 10; medium confidence about 5 out of 10; low confidence about 2 out of 10; and very low confidence less than 1 out of 10" (Bates *et al.*, 2008).

Uncertainty is expressed using the following likelihood ranges to express the assessed probability of occurrence: "virtually certain >99%; extremely likely >95%; very likely >90%; likely >66%; more likely than not >50%; about as likely as not 33% to 66%; unlikely <33%; very unlikely <10%; extremely unlikely <5%; exceptionally unlikely <1%" (Bates *et al.*, 2008).

Table 2.1 provides a generalised summary of future projected changes and their impacts on water resources on a global scale. However, global change projections have only limited usability for providing information on local impacts. Projections at a more local scale are also affected by a higher degree of uncertainties as discussed later. Therefore, it is a complex assessment to extract catchment specific projections on the impacts of climate change on the hydrological regimes. Hence, Prudhomme &

Davies (2009) concluded that the complexity and uniqueness in individual catchment responses require individual climate change impact assessments on a catchment-by-catchment basis.

Until the last couple of years, most studies concerned themselves with assessing the impacts of climate change on hydrological regimes with only a small number of studies going a step further and examining what these changes could potentially mean for water resources management and planning (Arnell, 2006). Therefore, the example studies presented in the previous paragraph on projected hydrological trends all excluded direct human influences on stream flow and simulate streamflow changes in isolation. Only few studies so far have taken the human influence of the system explicitly into account. For example, Fowler & Kilsby (2007) and Fowler *et al.* (2007) modelled the impacts of climate change on water resources in north-west England and estimated the reduction of the overall yield by 18%, and also projected a large impact on low flows (Q95 - the flow equalled or exceeded 95% of the time) in summer months, with reductions between 40-80%. On a larger scale, Lehner *et al.* (2006) estimate the impact of climate change for Europe using different climate models in conjunction with water use scenarios, which adds another component to the already complex modelling approach. Their model results suggest amongst others, a possible increase in the recurrence of 100-year drought in southern Europe, the UK and Ireland for the 2070s. Although these findings are not too different from the other studies that do not specifically include water resource systems, it is important to bring these two components (streamflow projections and water supply systems) together to obtain a more thorough understanding of possible future changes that have the potential to affect future water resources.

On a global scale, Alcamo *et al.* (2007) investigated long-term changes for three different water stress indicators taking into account both climate change and socio-economic changes such as population growth using a scenario lead approach. In their study, water stress changed (increased or decreased) for all investigated river basins; however, the magnitude and direction depended on the location on the globe.

However, these broad scales (global, pan-European or national) can only provide a rough identification of possible future changes, and merely help to raise awareness of future pressures on water resources. The scale at which water management and planning is operating is the catchment scale (which includes national or trans-boundary river basins), and at this scale information on possible change would be desirable. However, as mentioned before due to the individual characteristics of catchments, each catchment will respond in a unique way to change (Prudhomme & Davies, 2009).This unique response and the uniqueness of the water resource system characteristics increase the complexity of future water resources planning in a changing climate (Hall & Murphy, 2012).

Therefore, future assessment of impacts of climate change on water resources on a catchment-by-catchment basis or even at the scale of individual water abstraction will become necessary, to incorporate climate change into water management plans to allow anticipatory adaptation to expected changes. Because of this complexity, adaptation of the water resources sector to climate change is challenging. Different modelling approaches have been developed to aid anticipatory decision-making. These approaches will be reviewed in the following sections.

2.4.2 Modelling Chain and Propagation of Uncertainties

Traditionally, for climate change impact assessments on the hydrological system, output from a selection of Global Climate Models (GCMs), forced with specific greenhouse gas emissions scenarios are downscaled to regional levels using empirical or dynamical techniques. The downscaled scenarios are then used as input to impacts models, such as hydrological models, to generate future time series of variables of interest that can be further analysed depending on the variables of interest. This traditional, top-down or GCM-led approach shown in Figure 2.3 is subject to a cascade of uncertainty (Viner, 2003; Wilby & Dessai, 2010).

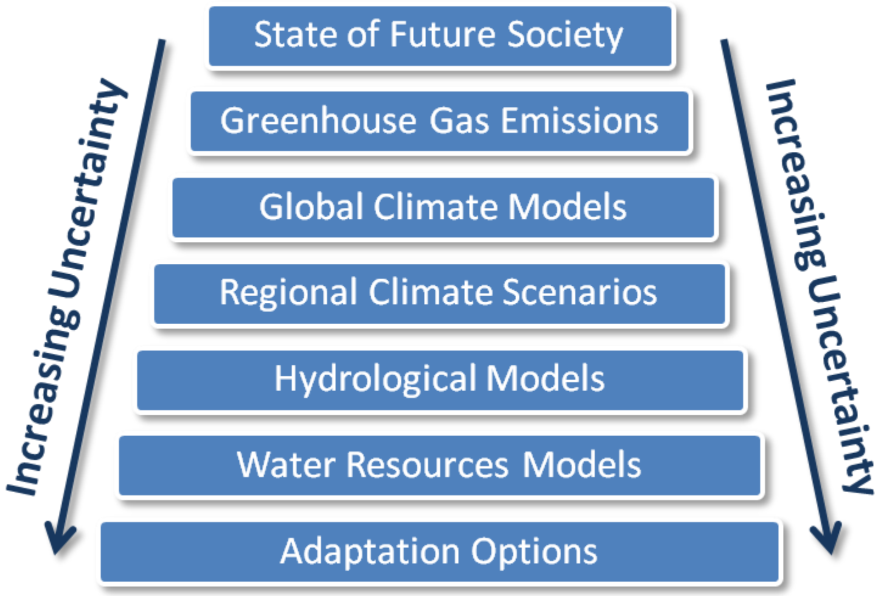


Figure 2.3 Cascade of uncertainty (modified after Wilby & Dessai (2010), c.f. Hall & Murphy (2012)).

Projections of future climate are derived from the state of future society (socioeconomic scenarios) and their transformation into different scenarios of greenhouse gas emissions. The greenhouse gas concentrations in the atmosphere are then used within GCM to model the future climate system. However, the output (e.g. temperature and precipitation changes) of these models is too coarse for impact studies at a regional or catchment scale. Therefore, regionalisation techniques are used to downscale these large-scale simulations to the desired smaller scale.

Hydrological models are then used to translate the Regional Climate Model (RCM) output into a hydrological signal (runoff). The results from the rainfall runoff model can then be used to assess management and adaptation options in the water resource sector. However, each modelling step contains different sources of uncertainty, which are propagated throughout the chain of modelling steps, and with each step, the model output diverges in a non-linear way, resulting in increasing uncertainty ranges. Due to the uncertainties introduced at and propagated through each stage of this methodology, multi-model approaches can result in diverging outputs regarding the timing, location, sign and/or magnitude of change. Such accumulation and spread of model output uncertainties has been described as a '*cascade of uncertainties*' (Viner, 2003; Wilby & Dessai, 2010).

The uncertainties in model output stem from different sources which can broadly be divided into two uncertainty categories, namely aleatory uncertainties (also called unknowable knowledge, natural variability or irreducible uncertainties), and epistemic uncertainties (also called incomplete knowledge, statistical uncertainty or reducible uncertainties) (New & Hulme, 2000; Hall & Solomatine, 2008). However, it is not always possible to separate these two different sources of uncertainty, therefore uncertainties are often presented and analysed based on their occurrence in the individual modelling steps. The uncertainties stemming from the modelling steps involved in an assessment of future water resources are presented in the following sections.

2.4.2.1 Climate Modelling Uncertainties

When analysing the uncertainty sources in a top down modelling approach the 'cascade of uncertainty' starts off with the *forcing uncertainty* (Stainforth *et al.*, 2007), introduced by the choice of anthropogenic greenhouse gas emission scenarios depending on the development of future socio-economic pathways, all of which need to be considered as equally possible future emission scenarios. Different emission scenarios used will result in different magnitudes and ranges of warming, which can be seen in the examples shown in Figure 2.4.

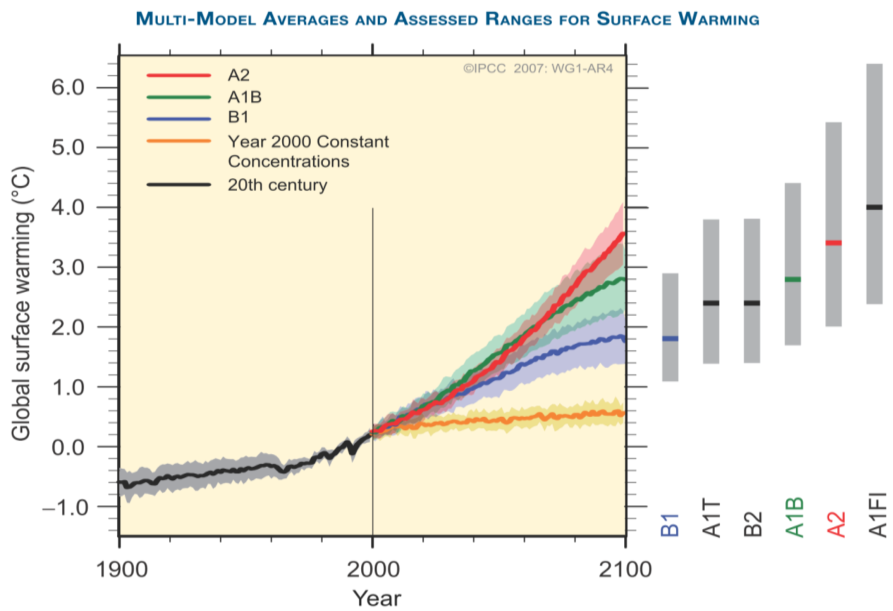


Figure 2.4 Figure from the IPPC report showing the ranges of surface warming obtained from the emission scenarios used in the IPPC Fourth Assessment Report (IPCC, 2007b).

In addition, to the different forcing obtained from greenhouse gas concentrations scenarios, the output of climate models is dependent on their initial state variable (*initial condition uncertainty*) (Viner, 2003; Stainforth *et al.*, 2007) and the uncertainties stemming from *model imperfections* (encompassing both *model inadequacy* and *model uncertainty*) (Stainforth *et al.*, 2007). These uncertainties attached to the output of each of the individual GCM's results in a unique future climate projection, resulting in an increasing spread of the uncertainties in the model output variables with the number of GCM's employed. Particular uncertainties exist for the spatial distribution and amount of precipitation obtained from climate models, compared to temperature projections. For example, in many areas of the globe, less than 66% of the models used in the 4th IPCC report agree on the sign of precipitation change, see Figure 2.5 (IPCC, 2007b).

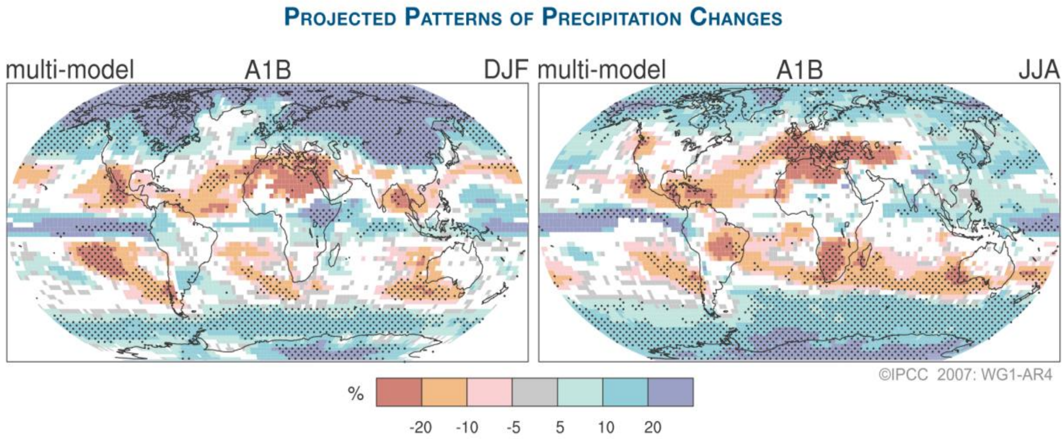


Figure 2.5 Relative changes in precipitation for the period 2090–2099, relative to 1980–1999. Values are multi-model averages based on the SRES A1B scenario for December to February (left) and June to August (right). White areas are where less than 66% of the models agree in the sign of the change and stippled areas are where more than 90% of the models agree in the sign of the change. (Figure caption quoted from IPCC (2007b)).

Another source of uncertainties is brought about by the fact that the output of GCMs is typically very coarse (100-300 km^2 grid), which is too coarse to be used for many types of impact assessments particularly for hydrological assessments at a regional or catchment scale. For future climate projections to be used for future water resources planning and to obtain a finer resolution, post-processing of the output in form of downscaling techniques is performed (Chen *et al.*, 2011). Advantages and disadvantages of the different downscale techniques have been extensively researched (Chen *et al.*, 2011). Depending on the technique employed the results obtained for future climate projections will differ (Chen *et al.*, 2011) increasing the layer of uncertainties. Especially with regard to the later use of the generated climate scenarios to drive rainfall runoff models, Wilby *et al.* (2000) and Wood *et al.* (2004) highlight the sensitivity of the hydrological model response to the downscaling methods employed.

2.4.2.2 Hydrological Modelling Uncertainties

In addition to the uncertainties from the climate modelling steps, hydrological models add another layer of complexity and uncertainty to the assessment. Different rainfall-runoff models can generate ranges of possible future outcomes, although they were able to model historical conditions equally well (Butts *et al.*, 2004; Jiang *et al.*, 2007). The different outcomes of the hydrological modelling process are a result of the combination and interaction of various sources of uncertainties in the hydrological modelling approach.

For example, input data errors introduce uncertainties in the model output data. ‘*Input data uncertainty*’ results from the inability to precisely measure observed phenomena such as precipitation and soil data (Post *et al.*, 2008). For example, precipitation data is used as the primary input to drive hydrological models. However, precipitation is highly variable across time and space and is measured only at specific locations. Approximation, interpolation or correction factors are used to derive precipitation input that can be representative for the catchment area considered in the hydrological model.

Additionally, errors in records of river discharge can be caused by errors in the rating curves, which are used to establish a stage-discharge relationship, by imprecise measurements of extreme (high or low) flows (Hudson *et al.*, 1999) or by missing data records. Such imperfect flow data can increase the uncertainties associated with hydrological model calibration, which is described in the following paragraphs.

Even with perfect (error free) raw data input into hydrological models, the fact that the system under consideration is a dynamic one and the related processed need to be simplified and approximated, introduces another layer of uncertainty. The different formulations in different hydrological models of how hydrological processes are simulated and reproduced result in *'model structure uncertainty'* (Liu & Gupta, 2007; Bastola *et al.*, 2011b). Some of this model structure uncertainty is epistemic and reducible through improvement of the hydrological modelling tools through continuous research and improvement of models. However, some aleatory uncertainty will remain due to the fact that the complex hydrological system needs to be represented by mathematical equations, which requires simplification and approximation of the physical processes involved.

As processes within a hydrological model need to be simplified, models use estimates of parameters to represent certain variables in the mathematical equations. The need for parameterisation is another source of uncertainty, which is called *'model parameter uncertainty'* (Vrugt *et al.*, 2003; Bastola *et al.*, 2008). Parameter estimates are derived through the process of model calibration where the model output is adjusted to optimise the goodness of fit with the observed data, which normally involves the use of objective functions or performance matrices.

However, different combinations of parameters within the same hydrological model can have the same predictive value and simulate the output equally well as defined by performance matrices (*parameter equifinality*) (Beven & Binley, 1992; Beven & Freer, 2001). The existence of multiple optima caused by multiple behavioural parameter sets makes the process of parameter calibration uncertain. Additionally, as highlighted by Beven (2006), over-parameterisation (too many model parameters) and over-conditioning (trained for a specific period) of hydrological models in the model calibration process can also lead to uncertainties in the choice of the optimum parameter set. Therefore, the selection of a single model parameter set by the modeller results in additional uncertainty. To incorporate this kind of uncertainty in the hydrological modelling approach, the scientific community increasingly uses multiple parameters sets.

Model parameter uncertainty can also occur in the absence of the need for parameter estimation. For example, uncertainty arises when parameters are derived from field measurements in physically based hydrological models or when expert judgement is used to obtain parameters due to the absence of measured values. This parameter uncertainty is particularly important when modelling stream flows in un-gauged locations. In such settings, it becomes necessary to use regionalisation methods and similarity measures based on common catchment characteristics, climatic regimes and locations, to estimate and transfer hydrological model parameters from parameterised gauged settings to the un-gauged catchment. This introduces model parameter uncertainty on regionalization result (Bastola *et al.*, 2008). Flow predication in ungauged basins is still an area of on-going international research (e.g. see International Association of Hydrological Sciences (IAHS) Decade on Prediction in Ungauged Basins (PUB)).

In a hydrological modelling approach, it is necessary to take these sources of uncertainty into account. For example, Bastola *et al.* (2011b) highlight the importance of accounting for a wide range of plausible uncertainties in a hydrological climate change impact assessment, when the outcomes of such an analysis are used to base decisions on. In the application of hydrological models to support decisions, the uncertainties are normally not separated into their individual sources but are aggregated and the model output represents the entire uncertainty ranges.

2.4.2.3 Uncertainties in Additional Modelling Steps

Once the future hydrological data is generated, these data can be used in other simulations produced by impact models such as water resources models. It is of importance that the wide ranges obtained from the previous modelling steps are incorporated into the additional modelling steps. In addition to the already existing uncertainty envelope, the water resource model itself introduces another layer of uncertain processes. To be able to simulate the water supply system, existing water infrastructure needs to be simplified and water abstractions, consumptions and return flows are taken from survey data or need to be approximated. To model future states of a water supply system, these variables need to be projected into the future with the help of socio-economic scenarios. This produces a wide range of possible future states of the water supply system, based on certain (often implicit) assumptions about the future.

However, it has to be noted that it is impossible to obtain a representation of the full range of possible uncertainties from all modelling steps involved. The range of possible future outcomes and their associated uncertainties are always highly conditional on the assumptions made, the models and parameters used throughout the modelling approach and computational constraints, which prevent full exploration of the uncertainty space. Therefore, the uncertainty envelope derived from each study will be unique and can only represent a fraction of the possible outcomes. Additionally, the uncertainties within these model projections increase with time, resulting in a wider spread of possible future outcomes when for example the projections for the 2020s (2010-2039) are compared with the outcomes for the 2080s (2070-2099). This is divergence is brought about by the propagation of modelling errors and the differences in the climate forcing due to different emission scenarios.

2.5 Traditional Approach to Adaptation Planning

To be able reduce vulnerabilities, water resources management and management needs to account for various potential future changes. However, to derive the best and cost effective adaptational response to future changes, high level of precise information on future supply and demands is traditionally required. However, the wider range uncertainties and the associated broad ranges of possible future outcomes, discussed above, represent a challenge for researchers and decision-makers alike, if it is aimed to provide this kind of information. For researchers there is an unrealistic pressure to reduce the uncertainties and provide 'better' future scenarios, so adaptation measures can be implemented. Moreover, it is difficult to cascade all the associated uncertainties through the entire modelling approach, as this is very computationally intensive. If this is attempted, even to a small degree, the presentation of future scenarios, including a wide range of possible future outcomes to decision makers becomes challenging.

Langsdale (2008) recommends explicitly displaying all equally possible outcomes (scenarios) and not the mean of all simulations, as this places too much confidence on the average condition. However, the decision-makers traditionally aim to optimise the performance of the water supply system. This requires a single or at least a small manageable number of future scenarios. Typically, for these scenarios adaptation options are considered and ranked according to predefined criteria to maximise the utility and therefore to information optimal (adaptation) decisions. This traditional workflow has been termed predict-then-act (Lempert *et al.*, 2004), top-down (Dessai & Hulme, 2004), predict-and-provide or scenario-led approach as the information is cascaded into the next modelling steps (Wilby & Dessai, 2010). However, in the face of adaptation to climate change, the wide range of uncertainties presented above challenge this traditional approach to decision-making, as no precise predictions are available using such a scenario led-approach. Although the top-down approach is widely applied, this methodology has only resulted in a few practical examples of anticipatory adaptation options being implemented (Wilby & Dessai, 2010).

The traditional predict-and-provide approach or top-down approach is rooted in the assumption that the future is predictable (Lempert *et al.*, 2004) and that it is possible to optimise a system accordingly. In the water resources sector, this means that probability distributions are used to characterise uncertainties against which different adaptation options are evaluated using a water resources model. Adaptation options are ranked based on their anticipated effectiveness and the vulnerability of the water resources systems is assessed using evaluation criteria to find the optimum solution or adaptation option to the identified problems under the given uncertainties. A schematic of the predict-then act approach is shown in Figure 2.6, with arrows indicating the possibilities of reverting to earlier assessment steps to update the process, resulting ultimately in a single or a set of optimum solutions.

However, in such a climate change vulnerability assessment, where uncertainties cannot be constraint, no subjective likelihood judgments should be assigned. In such situations, risk is not quantifiable and therefore, the predict-and-provide approach cannot longer be applied.

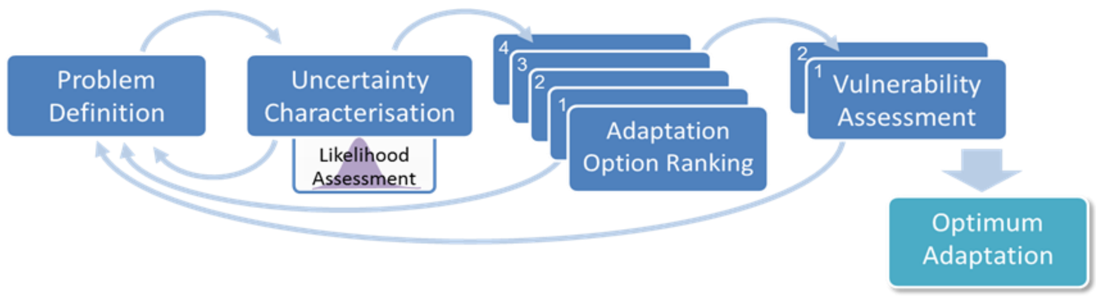


Figure 2.6 Schematic of the predict-and-provide approach.

Due to the lack of precise and clearly framed information about the state of future water resources, some researchers estimate the likelihood of future changes using probabilities associated with future impact projections (New *et al.*, 2007). However, probabilities associated with climate change are subjective (or Bayesian based on personal perception) (Dessai & Hulme, 2003) and different from classical probabilities (based on return frequencies) used by water managers. Dessai & Hulme (2004) highlight in their review article that any assessment of probabilities with the aim of providing information to climate adaptation can only be a provisional assessment that is highly subjective and conditional. Such an approach adds another layer of uncertainty, as based on the assumptions and statistical methods used to produce the probabilities the likelihood of outputs will differ, therefore facing the same difficulties as the traditional scenario approach, not being able to represent the full uncertainty space. For water managers and decision makers the use of probability functions in the context of climate change might present a misleading ‘true’ representation of possible future changes (Lempert *et al.*, 2004) and might be confused with the classical probabilities used in hydrology.

Brugnach *et al.* (2007) discuss different methods to assess uncertainties induced by the use of computer models. Such methods include model sensitivity analysis in which the variations of model output are assessed relative to the model input or scenario analysis to reflect different possible conditions or multi-model simulations. It is concluded that no single method can deal with all forms of uncertainties and that the goals of the analysis determine which method to use. However, independent of the method used, uncertainties need to be integrated into the modelling approach and clearly communicated if the output is to be used for decision making.

However, communication climate change uncertainties and the implications for planning to stakeholders and decision makers are difficult due to the complex modelling framework employed in climate change impact studies. Langsdale (2008) advocates that uncertainties must be included in any analysis and that the outcomes have to be communicated clearly to decision-makers. In pursuing this, the use of scenario-led approaches is recommended as this allows the exploration and analysis of possible futures and allows testing policy options within the range of simulated scenarios.

Additionally, Hallegatte (2009) states that uncertainties associated with future climate change impacts are so large, that traditional planning approaches, for designing or adapting infrastructure and other long-lived investments, are insufficient as they often seek an optimum solution. This insufficiency of providing information, which can be used to implement strategies using the traditional scenario-lead approaches, has also been identified by Wilby & Dessai (2010), who state that there is an abundance of top-down approach based assessments, however, the number of such studies that have resulted in the implementation of adaptation strategies has been rather limited. In the water resources sector this also becomes apparent in the fact that many climate change impact assessments end with the assessment of impacts of projected changes in river flow to inform water resources planning (e.g Christierson *et al.* (2012) or Sanderson *et al.* (2012)).

Overall, in a climate change vulnerability assessment, where uncertainties cannot be constraint, no subjective likelihood judgments should be assigned. In such situations, risk is not quantifiable and therefore, the predict-and-provide approach should longer be applied when deriving information to support decision making.

2.6 Alternative Approaches to Adaptation Planning

Recognising the limitations associated with the traditional scenario-led, predict-and-provide approach, alternative approaches for decision-making under uncertainty have been developed.

An alternative to the traditional prediction driven top-down approach, which starts the analysis with possible future emission scenarios derived from possible future states of the society, is the bottom-up approach (Dessai & Hulme, 2003). Bottom-up approaches begin with an assessment of the socio-economic system and identify climate change related vulnerabilities (Figure 2.7). If vulnerabilities can be identified, then future climate information can be used in a further assessment.

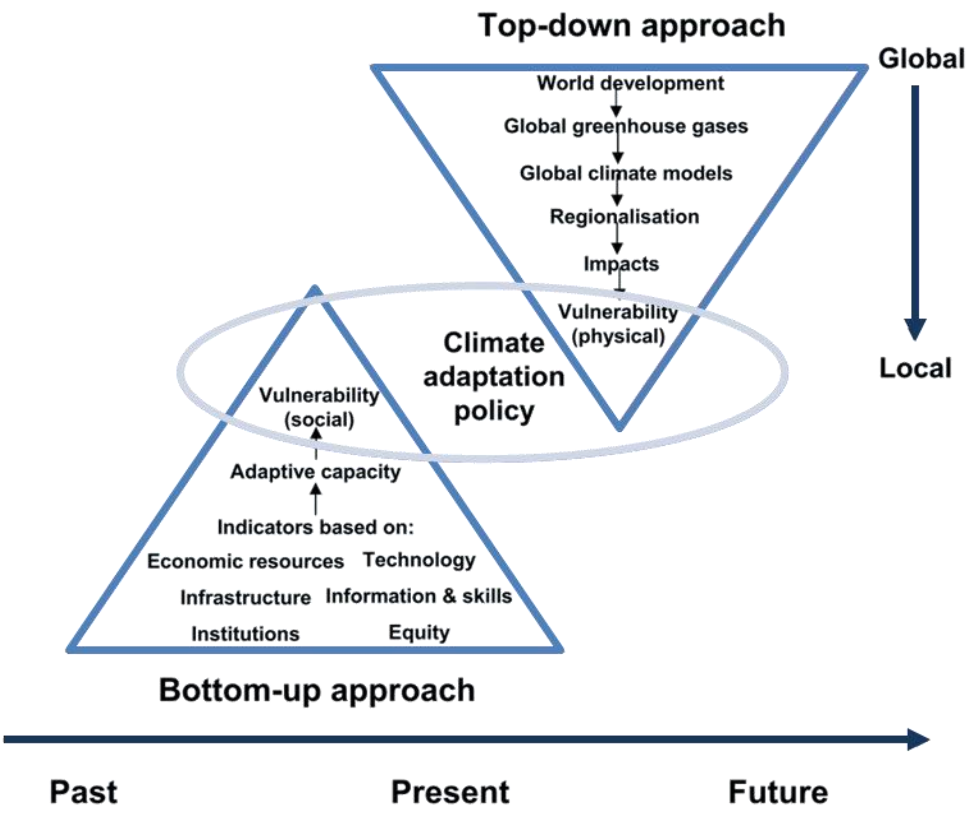


Figure 2.7 Bottom-up versus top-down approach to climate adaptation. Figure adapted from Dessai & Hulme (2003).

Within such an approach, exploratory modelling can be used to create ensembles of equally plausible but uncertain futures. Possible adaptation strategies targeting the identified vulnerabilities can be tested on their performance for each of the ensemble members. Such an assess-risk-of-policy framework aims to identify important uncertainties associated with selected decisions (scenarios) (Lempert *et al.*, 2004), to characterise and identify robust adaptation strategies (Figure 2.8).

Figure 2.8 Schematic of the assess-risk-of-policy approach.

Rather than optimising future strategies within a top-down framework, future anticipatory adaptation should be robust under a wide range of possible future scenarios (Langsdale, 2008). Robust decision-making can be applied in the context of uncertainty and decisions with the aim of identify the interaction between uncertainty and adaptation alternatives. Robustness can be used as a selection criterion for possible future strategies, aiming to identify adaptation options whose satisfactory performance is maximally insensitive to most significant uncertainties (Lempert *et al.*, 2004, 2006).

Robust decision-making, is an alternative to the traditional predict-then-act approach, which aims to identify the optimum strategy (maximum benefit) with an assessment that has the main objective to identify a single or multiple strategies that are least likely to fail and therefore robust to future climate change uncertainties.

2.6.1 Application of Alternative Approaches to Adaptation Planning

The overarching paradigm of the application of alternative adaptation and planning approaches to water resources systems is the acceptance of future uncertainties. In these approaches, uncertainty does not need to be exactly defined as a specific range. By accepting the presence of deep uncertainty and large uncertainty ranges, such approaches do not attempt to derive an optimal solution (such as the traditional top-down approaches). The new paradigm is rather based on the incorporation of climate change and system specific uncertainties to appraise the system performance and/or possible adaptation decision based on the uncertain but potentially useful information provided by future climate scenarios. Often the alternative approaches aim to derive robust future strategies, which help to reduce current and future vulnerabilities, by being the least likely one to fail, i.e. maximally insensitive to uncertainties (Lempert *et al.*, 2004), compared to the other strategies considered. Selected but non-exhaustive examples from the water resources sector applying alternative approaches, different to the traditional scenario-led approach, are provided below.

For example, Dessai & Hulme (2007) used a case study of future water resources management to apply a framework that allows the identification of adaptation options that indicate robustness to climate change uncertainties. The results indicated that the future water resources plans are robust to the sampled climate change uncertainties. However, the study also highlights that formulating a final adaptation strategy is complicated because of the number of possible measures available and stakeholders involved. Based on the setting, the definition of the criteria for success of an adaptation strategy is always context specific and final decisions can always be argued (Dessai & Hulme 2007).

Lopez *et al.* (2009) examined a water resources zone in southwest England to appraise the performance of different adaptation options under a large ensemble of climate change scenarios using a large perturbed physics GCM ensemble. Their analysis showed the benefits of using large numbers of future climate scenarios and different climate models, by increasing the range of climate model uncertainties, as obtained system failure rates differ depending on the climate scenarios analysed. The study indicated that within the investigated water resource zone, an increasing reservoir size might not be enough to ensure water supply during successive dry years and that additional adaptation measures might be needed.

Research conducted by Wilby & Dessai (2010) describes a conceptual framework for a scenario-neutral approach to adaptation planning. In applying the bottom-up framework, current and projected future climate variability is used to test the sensitivity of adaptation options across plausible ranges. Gober *et al.* (2010) also have advocated a departure from traditional water planning based on climate model output by arguing for the need of a new paradigm, which particularly accounts for uncertainty and the possibility of multiple future realisations. Based on the example of the Phoenix area in Arizona (Western United States), different future climate and policy decision scenarios are simulated. To facilitate the identification of robust policy decisions, *WaterSim*, a tool that allows the simulation of future water shortages based on climate scenarios, was developed. The results show an important outcome, in relation to the timing of specific decisions. They concluded that decision would not be successful if the aim is to produce a single optimum solution.

Brown *et al.* (2011) also presented a practical methodology that allows water resources planning and risk management under climate change. The alternative approach presented in their study of the water resources planning in the Upper Great Lakes of North America, is different to the bottom-up analysis described below which use climate information at an early stage of the decision appraisal process. Brown *et al.* (2011) identified future climate information considered to be relevant to determining the most favourable planning decision, to feedback into the process of climate information generation. The risk-managing tool developed focuses on the identification of vulnerabilities and climate risk managing through robust adaptation.

From the studies presented above it can be seen that within the water resources community new, alternative approaches are being developed and applied to various case studies. The methodologies and tools developed are important in dealing with the inherent uncertainties that future anticipatory planning is confronted with. To date, no widely accepted standard approach has emerged, on how to best deal with uncertain but potentially useful future climate information in the water resources sector.

2.7 Chapter Summary

The review of the scientific literature provided in this chapter commences with an overview of the potential effects of a changing climate on water resources. The potentials of and challenges associated with the analysis of hydrological observations to identify climate-driven trends are extracted from the literature.

The traditional chain of modelling steps within a top-down approach result in wide ranges of equally plausible futures for the water resource sector. For example, for some areas on the globe different signs of precipitation changes in the future can be obtained from different climate models (e.g. Figure 2.5), highlighting the uncertainties encountered.

These wide uncertainty ranges are problematic for anticipatory adaptation, particularly in the water resource sector, where infrastructure developments have long planning and implementation times. Using the traditional top-down approach is problematic in such situations and decision-making is at risk of delaying any adaptation response until a clear climate signal becomes apparent.

From the literature review various research objectives have been identified that can help to inform anticipatory decision-making and adaptation in the context of climate change and the water resource sector in a practical context as presented in Section 1.3. Hydrological observations and projected future scenarios have been identified as the key information sources for anticipatory planning in the water resources sector. However, in the context of a practical application of these information sources the review of the scientific literature identified the following research gaps in Ireland:

- Trend analysis of observational records is widely conducted to analyse changes in stream flow. In an Irish context, it is not known how low flows and other stream flow related indicators important to water resources management have changed due to climatic influences.

- The practical utility of the current state of trend analyses methods for informing adaptation decisions in the water resources sector has not been assessed.

- Future climate projections for Ireland have been shown to impact on stream flow; however, it has not been demonstrated how these changes might affect Irish water resources at the level of abstraction points.

- In Ireland, no methodology exists to incorporate uncertain future information in a decision appraisal framework for adapting water resources to future changes, particularly for un-gauged water abstraction points.

- Due to the wide ranges of uncertainties associated with multiple future realisations, the wide ranges of future scenarios need to be summarised and presented in a meaningful way to help inform anticipatory decision-making.

The next chapter addresses the first two research gaps and examines the utility of observed river flow records for informing anticipatory decision-making in the surface water resources sector. In chapter 4 to chapter 6, the remaining research gaps associated with future streamflow projections and uncertain scenarios will be addressed in relation to providing information to support future water resources planning and management.

3 Analysis of Observational Hydrological Records

3.1 Introduction

Observational hydrological records are used by water managers for long-term planning and management of water resources and water infrastructure design. Traditionally, historical flow records provide guidance for mean and extreme conditions that could be expected to occur, with some inter-annual and inter-decadal variability. This traditional planning approach is based on the assumption that the past observed records provide a reasonable planning guide for the future and that the expected future hydrological conditions will not be different to the ones experienced in the past observational data. However, under the assumption of a changing hydro-climatic system this paradigm might need to change.

By analysing historical flow data, it can be investigated if the records used to plan and manage water resources are still the same or whether hydrological conditions are changing. Any change in the envelope of hydrological conditions requires a reassessment of long-term planning and water infrastructure design and, if needed, an adaptive response. This is of particular importance with regard to climate change, where detection of possible hydrological changes might need to result in adaptation decisions, which can be both anticipatory and reactive.

This chapter addresses the first research aim of this thesis and examines whether observational records in Ireland can provide the information needed by decision makers to adapt to climate-induced changes that are important for water resources management. In this chapter, the research goals are to:

- Analyse observational river flow records for evidence of change in flow indicators relevant to water resource management.
- Investigate the challenges involved in extracting robust climate change signals from hydrological records.
- Identify whether a linear climate change signal will be statistically detectable in the timeframe required for adaptation with regard to both magnitude and timing.

In this chapter, the Irish Reference Network (IRN) for climate change monitoring and detection is presented in Section 3.2, followed by an introduction to the Irish hydrometric network (Section 3.2.1) and a review of commonly used trend analysis methods (Section 3.2.2). In Section 3.3, an overview on different types of low flow series are presented and succeeded by Section 3.4 to Section 3.5, in which different forms of trend analysis are performed on selected low flow indicators. Trend detection times and magnitudes for selected low flow indicators are analysed in Section 3.6. The chapter finishes with a discussion and conclusion (Section 3.7) and a chapter summary (Section 3.8).

3.2 The Irish Reference Network for Climate Change Monitoring and Detection

To increase confidence in the identification of climate-driven changes in hydrological records, the hydrometric data series analysed ideally need to be free from any other artificial influences. For the purpose of detecting and monitoring climate-driven change in Irish river flow records, Murphy *et al.* (2013) identified a selection of hydrometric stations that are representative of the Irish hydrological conditions and flow regimes.

The following key criteria, based on international best practice examples from other Hydrometric Reference Networks, were applied to identify stations for inclusion in the Irish Reference Network (IRN) (taken from Murphy *et al.* (2013)):

- Good and consistent hydrometric data quality (particularly at extreme flow ranges), as determined by hydraulic conditions at each site (stable control and accurate rating curves);
- Near-natural flow regime - zero or stable water abstractions and discharges (impact less than 10% of flow at or in excess of Q95);
- Long record length (minimum 25 years);

- Limited land-use influence (≤ 2.5% of catchment area developed). Stations subject to arterial drainage were excluded where possible, otherwise post-drainage records were used to improve spatial coverage;
- Stations must be representative of Irish hydrological conditions and climatic regions with good geographical coverage, ensuring that stations from each of the eight Water Framework Directive (WFD) River Basin Districts (RBDs) are included.

Based on the selection criteria described above, 35 hydrometric stations from the existing Irish river flow monitoring network, together with eight stations from Northern Ireland that are part of the UK Benchmark Network (Hannaford & Marsh, 2006, 2008) are included in the IRN. Through the selection process, these stations can be used to monitor and detect climate-driven trends in all ranges of the river flow regime.

For certain stations, some of these criteria (e.g. flow records affected by drainage) had to be applied less stringently in order to obtain an improved spatial coverage across Ireland. Particularly, the criterion for data quality ratings was relaxed for stations that had low quality ratings for either high or low river flows. These stations were included in the original Irish Reference Network, as defined Murphy *et al.* (2013); however, such stations with low quality need to be excluded from the analysis of the respective extreme indicator. Therefore, only subset of 34 stations of the IRN gauges are used here, selected as those that show the highest rating quality at low flows. Five stations with records commencing after 1979 were also excluded from the analysis due to their short record length. The sub-network of hydrometric stations shown in Figure 3.1, with sufficient good low flow quality provides the basis for further analysis of flow records in this chapter.

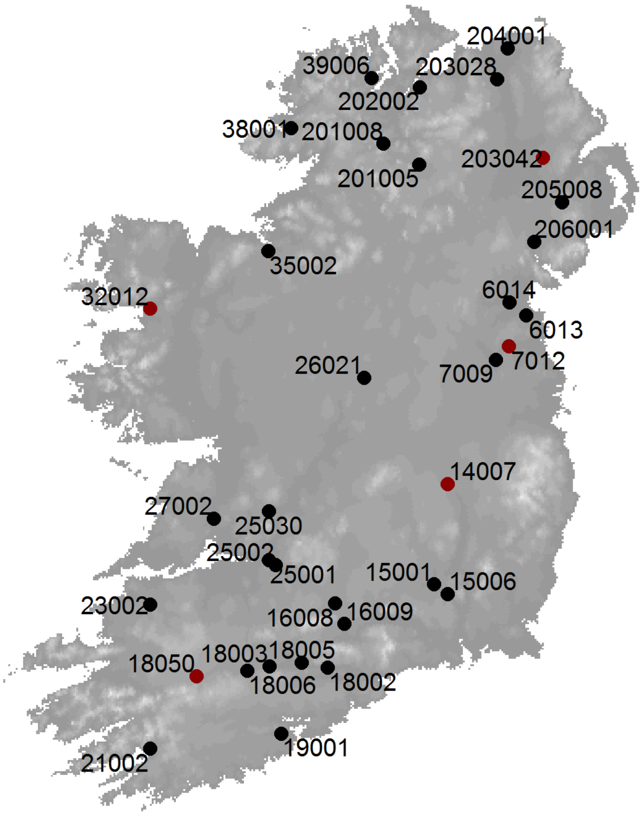


Figure 3.1 Sub-network of 34 stations of the Irish Reference Network and the UK Benchmark Network with good low flow quality rating. Stations shown in red are not analysed due to records commencing after 1979.

3.2.1 Hydrometric Stations and Hydrological Time Series

In Ireland, the Environmental Protection Agency (EPA) and the Office of Public Works (OPW) collect and provide the river flow data. The flow data available from the EPA is a collection of hydrometric data from Local Authorities, with the focus on water quality and low flows. This reflects the responsibilities of Local Authorities in the planning and provision of water supply. The key hydrometric objective of the OPW is the collection of flow data for the purpose of drainage monitoring and flood management.

Together with the different historical remit for data collection between the two hydrometric data providers, there are also two different quality ratings in use. The EPA uses four different data quality classes (Table 3.1 and Figure 3.2 (top)). The OPW uses eleven main data codes, which were aggregated here to five quality codes for plotting purposes (left column) (Table 3.2 and Figure 3.2 (middle and bottom)).

Table 3.1 EPA data quality codes (Source: http://hydronet.epa.ie).

Code	Description
Good	Highest quality of data
Estimated/Beyond Limit	Estimated data point edited data based on spot checks
Unchecked	Value has not been checked at this stage
Suspect	Suspected quality of data point

Table 3.2 OPW data quality codes (Source: http://www.opw.ie/hydro).

Aggregated Code	Code	Description
Good	31	Flow data estimated using a rating curve that it is considered to be of **good** quality and inspected water level data
Good	32	As per Code 31, but using water level data of Code 32
Fair	36	Flow data estimated using a rating curve that it is considered to be of **fair** quality and inspected or corrected water level data
Poor	46	Flow data estimated using a rating curve that it is considered to be of **poor** quality and inspected or corrected water level data
Caution	56	Flow data estimated using an extrapolated rating curve and inspected or corrected water level data – Reliability of data is unknown and it should therefore be treated with caution
Caution	99	Flow data that has been estimated using unchecked water level data – Data is provisional only and must be used with caution
Caution	101	Flow data that has been estimated using unreliable water level data – Suspected of being erroneous and must only be used with caution
Caution	145	Data is below data range and must only be used with caution
Caution	146	Data is above data range and must only be used with caution
Caution	150	Partial statistic – Data has been derived from records that are incomplete and do not necessarily represent the true value
Unacceptable	>150	Data is missing, erroneous or of unacceptable quality

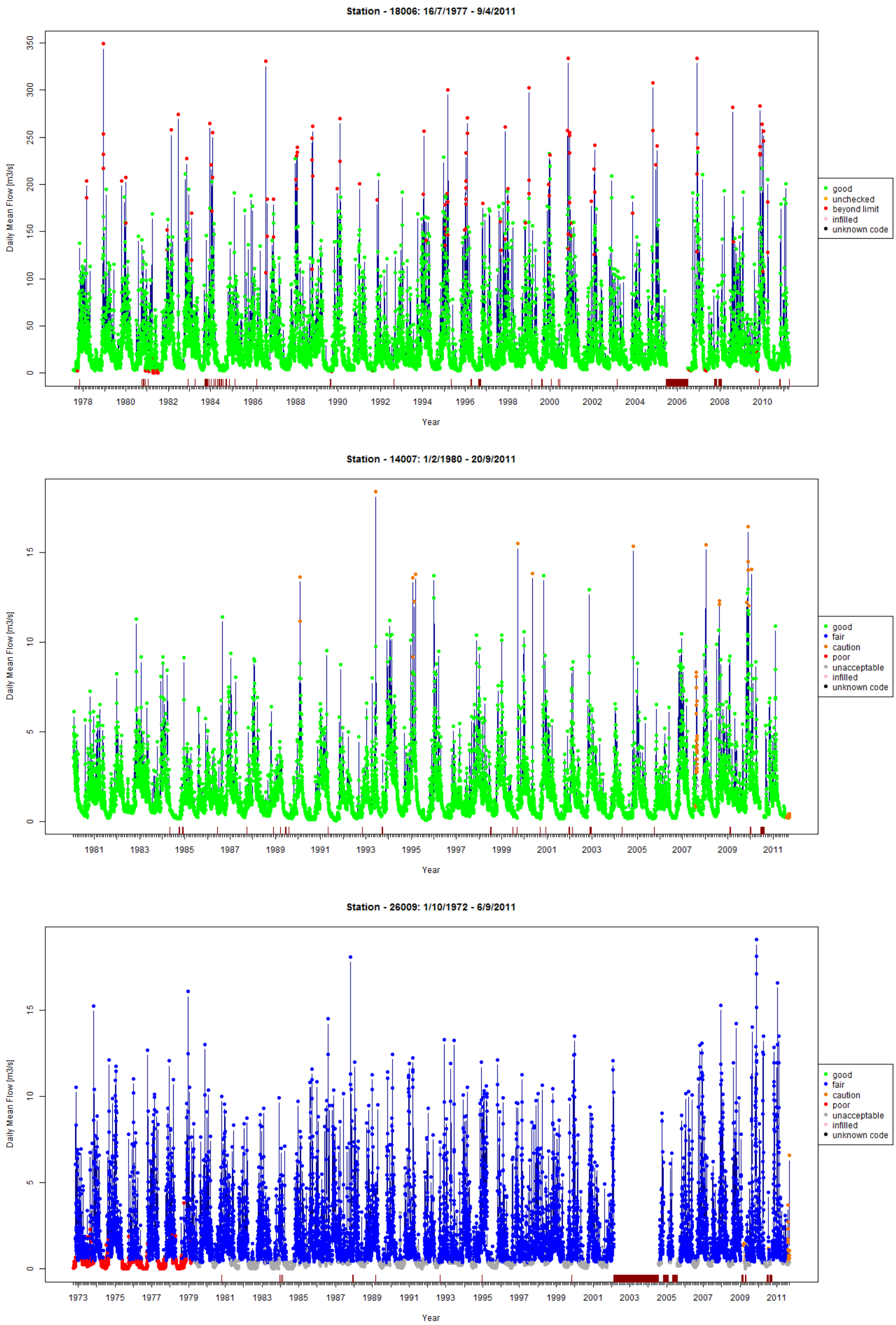


Figure 3.2 Example of hydrometric records and quality codes. From top to bottom EPA station, OPW station, (both stations used in analysis), OPW station (excluded due to poor and unacceptable low flow rating). Short dark brown vertical lines above the time axis indicate missing data points.

Table 3.3 34 Low flow stations from the Irish Reference Network and the UK Benchmark Network. The five stations shown in red are not analysed due to short record length (< 30 years).

Station	Station Name	River Name	RBD	Org.	Area [km^2]	Precip (61-90)	Start	End	Length [yrs]
6013	Charleville Weir	Dee	NB	OPW	309.1	873	1976	2009	34
6014	Tallanstown Weir	Glyde	NB	OPW	270.4	928	1976	2009	34
7009	Navan Weir	Boyne	E	OPW	1683.8	868	1977	2009	33
7012	Slane Castle	Boyne	E	OPW	2460.3	890	1982	2009	28
14007	Derrybrock	Stradbally	SE	OPW	94.9	814	1981	2009	29
15001	Annamult	Kings	SE	OPW	444.3	935	1973	2009	37
15006	Brownsbarn	Nore	SE	OPW	2418.3	942	1973	2009	37
16008	New Bridge	Suir	SE	OPW	1090.3	1030	1955	2009	55
16009	Caher Park	Suir	SE	OPW	1582.7	1079	1954	2009	56
18002	Ballyduff	Blackwater	SW	OPW	2333.7	1201	1956	2009	54
18003	Killavullen	Blackwater	SW	OPW	1256.7	1301	1973	2009	37
18005	Downing Bridge	Funshion	SW	OPW	378.5	1187	1973	2009	37
18006	Cset Mallow	Blackwater	SW	EPA	1054.8	1334	1978	2009	32
18050	Duarrigle	Blackwater	SW	EPA	248.8	1471	1982	2009	28
19001	Ballea	Owenboy	SW	OPW	103.3	1176	1973	2009	37
21002	Coomhola	Coomhola	SW	EPA	64.8	2580	1976	2009	34
23002	Listowel	Feale	SH	OPW	646.8	1346	1961	2009	49
25001	Annacotty	Mulkear	SH	OPW	647.6	1165	1974	2009	36
25002	Barrington's Br.	Newport	SH	OPW	221.6	1298	1954	2009	56
25030	Scarriff	Graney	SH	OPW	280	1185	1973	2009	37
26021	Ballymahon	Inny	SH	OPW	1098.8	945	1976	2009	34
27002	Ballycorey	Fergus	SH	OPW	511.4	1337	1955	2009	55
32012	Newport Weir	Newport	W	EPA	146.2	1784	1982	2009	28
35002	Billa Bridge	Ballysadare	W	OPW	81.1	1379	1973	2009	37
38001	Clonconwal Ford	Owenea	NW	OPW	111.2	1752	1973	2009	37
39006	Claragh	Leannan	NW	EPA	245.1	1527	1978	2009	32
201005	Camowen Terrace	Camowen	NW	NI	276.6	NA	1973	2009	37
201008	Derg	Castlederg	NW	NI	335.4	NA	1977	2009	33
202002	Faughan	Drumahoe	NW	NI	273.1	NA	1977	2009	33
203028	Agivey	Whitehill	NB	NI	100.5	NA	1973	2009	37
203042	Crumlin	Cidercourt Bridge	NB	NI	55.3	NA	1982	2009	28
204001	Bush	Seneirl Br.	NE	NI	299.2	NA	1973	2009	37
205008	Lagan	Drumiller	NE	NI	84.6	NA	1975	2009	35
206001	Clanrye	Mountmill Bridge	NB	NI	120.3	NA	1975	2009	35

The observational data analysed in this chapter is taken from the collection of stations forming the original IRN. As the analysis focuses on indicators relevant for water resources management, 26 Irish stations with good hydrometric performance at low flows are selected (E.g. Figure 3.2 (top and middle)). As the eight Northern Ireland stations have already been checked for their quality by Hannaford & Marsh (2006), no additional quality checks are performed on the data from these UK Benchmark network sites. Table 3.3 provides a summary of the 34 stations of the IRN with good low flow quality rating. Figure 3.1 shows the spatial distribution of the sub-network of stations with good low flow quality, stations shown in read were not included in the analysis due to short flow records of less than 30 years. The omission of stations in this study from the original IRN due to poor low flow rating (E.g. Figure 3.2 (bottom)) and short record length, gives rise to a spatial underrepresentation of some areas of the country (particularly in the East and the West of the country).

For the assessment of changes in the remaining 29 flow records, complete datasets are desirable, particularly if change detection methods are used that are based on the ranking of the data. However, for some stations, time periods with gaps (missing flow measurements) are present, indicated by brown vertical lines in Figure 3.2. To prepare the flow series of the IRN, Murphy *et al.* (2013) used HSYIM, a lumped conceptual rainfall runoff model, to generate stream flow time series to infill these gaps (for details see Murphy *et al.* (2013)). The influence of the infilled data on the flow records was investigated for each individual station in the IRN (for example see Figure 3.3). In addition to the overall visual coherence of flow pattern, linear regression and LOESS ((Local Polynomial Regression Fitting) line were obtained from the observed time series (with gaps) and the infilled data series resulting in similar trend directions and magnitudes. Murphy *et al.* (2013) concluded that the infilled observed flow data was suitable for trend analysis. As the overall regression and LOESS lines were coherent for the investigated indices used in this study, the infilled flow series from the IRN and the complete time series from the UK Benchmark are used.

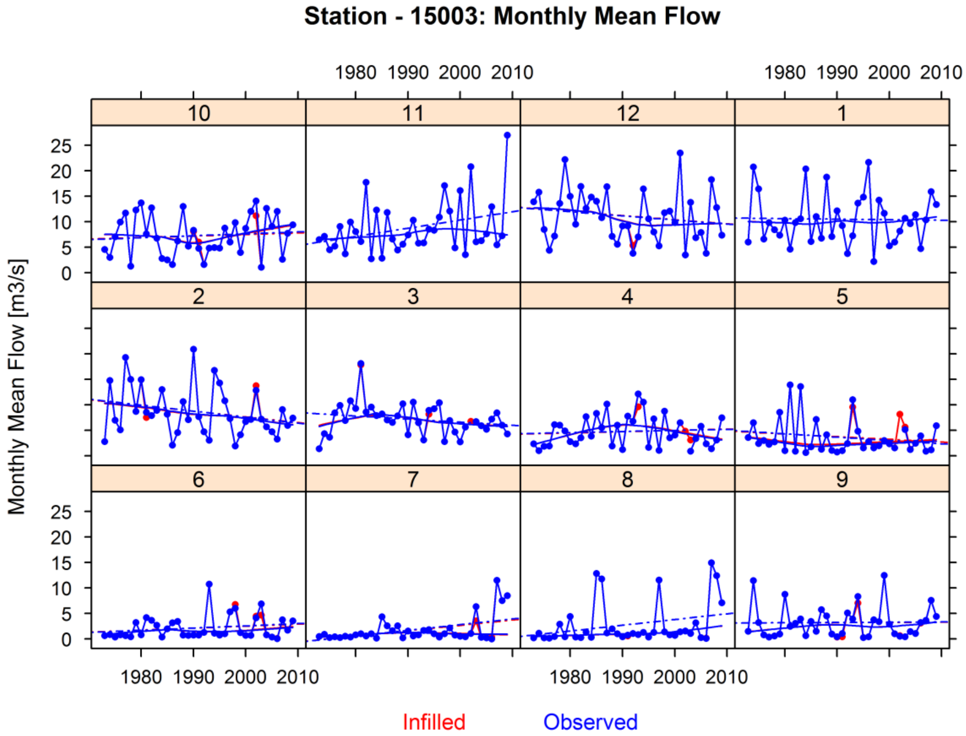


Figure 3.3 Comparison of infilled and observed series for monthly mean flows for station15003. Months are ordered for water year beginning October (10th month) from the top left to the bottom right. Solid and dashed lines represent the linear regression and LOESS line respectively (Murphy *et al.*, 2013).

3.2.2 Trend Analysis of River Flow Series - Methods

The hydrological records from the selected stations of the Irish Reference Network (IRN) are examined for long-term changes in low flow indicators. This section examines the methods commonly used to detect trends in hydrological records.

For any data analysis or change detection study, the methods and hypothesis tested should be chosen based on the data availability (time series) and objectives of the study, i.e. detection of step change vs. linear trend. Hypothesis testing is a statistical validation procedure meant to check whether the statistical hypothesis is true or not. For the statistical test used here, the null hypothesis H_o is '*no trend'*, which is tested against the alternative hypothesis H_1, '*trend*' detected by employing parametric or non-parametric tests (Önöz & Bayazit, 2003). Statistical tests are used to enable the comparison between the hypotheses H_o and H_1, with the help of significance levels which measure the probability of the H_o being mistakenly rejected (Kundzewicz & Robson, 2004).

If statistical tests are used to determine the significance of trends, two different types of statistical errors need to be considered, which are distinguished as Type I and Type II errors. A Type I error occurs when the null hypothesis (H_o=*no trend*) is falsely rejected, i.e. a trend is detected when no trend exists. To deal with Type I errors, the significance level (α) of the statistical test, which is the probability of a Type I error, is set to a predetermined level. For example, if the significance level is set at 5% (α=0.05), a 5% chance of mistaken trend detection is accepted. A Type II error occurs when the null hypothesis (H_o=*no trend*) is false, i.e. a trend is occurring, but is not detected by the statistical test. A Type II error can cause a trend not to be detected although a trend is happening. The probability of making a Type II error is called β, when the alternate hypothesis (H_1=*trend*) is true, at a specific significance level determined by α. The power of a statistical test is related to the Type II error and is expressed with the quantity 1-β.

When selecting a specific statistical test procedure or a set of tests for trend detection one needs to consider carefully the robustness of the tests to outliers, measurements below or above instrumental possibilities, missing data values, serial dependence and the distribution of the underlying data. Additionally, the power (probability of rejecting H_o) and the efficiency (estimation error) of the tests need to be considered (Hirsch *et al.*, 1991).

Non-parametric tests are widely employed for detection of trends in hydro-climatic indices. The advantage of distribution-free tests is that no assumption of normality or homogenous variance of the data is required compared to other linear trend detection tests like the Student's t-test to test for a linear relationship between two variables (which require data to be normally distributed). Generally, the decision on whether to use linear regression or a non-parametric test should be based on the distribution of the observed data. That is, whether the data is normally distributed or not. Non-normal distributions are for example skewed, spikier or flatter than normal.

For detecting linear trends a commonly used statistical test for hydrological data is the **Mann-Kendall** non-parametric **test** (Mann, 1945; Kendall, 1975), which is used to determine if a trend is monotonic over time and also allows the assessment of statistical significance at a predetermined level (e.g. 5% significance). The Mann-Kendal test is a rank based test were the data values are assigned ranks corresponding to the size of the data value (from rank 1 for the smallest value to highest possible rank for the largest value). This allows the comparison of the relative magnitudes using the ranks of the data without relying on the data values themselves.

The Mann-Kendall (MK) test statistic (S) for a time series of data (x_1, x_2, ..., x_n) with n being the number of observations is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i)$$ **Equation 3.1**

$$sign(x_j - x_i) = \begin{cases} +1 & x_j > x_i \\ 0 \quad if & x_j = x_i \\ -1 & x_j < x_i \end{cases}$$ **Equation 3.2**

For time series with n ≥ 8, the test statistic S is approximately normally distributed with a null mean and the variance (σ^2) of S is thus computed as follows:

$$\sigma^2 = \frac{n(n-1)(2n+5)}{18}$$ **Equation 3.3**

If a set of data points have the same data value the following correction needs to be subtracted from the calculated variance to account for tied groups:

$$\frac{\sum_{p=1}^{g} t_p(t_p - 1)(2t_p + 5)}{18}$$ **Equation 3.4**

Where g is the number of tied groups and t_p is the number of data points in the p^{th} group.

The normalised MK S test statistic (ZS) is then computed as below, resulting in a ZS statistic that follows the normal distribution with a mean of zero and a variance of one.

$$ZS = \frac{S}{\sigma} \quad \textbf{Equation 3.5}$$

The significance of a trend is tested by comparing the ZS with the computed probability. If ZS is negative, a trend is classified as decreasing and if the calculated probability is greater than the significance level α, the trend is classified as decreasing significantly. A trend is said to be statistically significant increasing if the ZS is positive and the computed probability is greater than the level of significance. In both cases if the determined probability is less than the level of significance, then H_o is accepted and the trend is said to be not statistically significant.

For linear trend detection, the non-parametric **Spearman's rho test** (ρ) can also be used. This test is based on ranks given to the data and used to test the correlation between time and the ranks of the data series (Kundzewicz & Robson, 2004).

$$\rho = 1 - \frac{6\sum_{i=1}^{n} {d_i}^2}{n(n^2-1)} \quad \textbf{Equation 3.6}$$

Where d_i is the distance between the ranks of the original and sorted series and i^{th} is the observation of the time series with length *n*.

It is recommended that several statistical tests are employed to detect changes (Radziejewski, 2009). Therefore, some studies still use both tests in conjunction to establish the presence of a monotonic trend (Villarini *et al.*, 2011). However, Yue *et al.* (2002) compared the results from the Mann-Kendall and Spearman's rho test and concluded that the outcomes are very similar; this finding is also supported recently by Shadmani *et al.* (2012). Therefore, in this research only the results obtained from the Mann-Kendall test are presented.

Another commonly used estimator for detecting trends is the **Theil-Sen slope estimator (β)** (Theil, 1950; Sen, 1968) which is calculated as the median (red line in Figure 3.4) of all possible pair wise slopes between all data points (X,Y) in a time series (blue lines in Figure 3.4), where Y is the stream flow variable and X is the time. The median slope estimator β is the summary statistic used to describe the magnitude and direction of trends over time. Compared to linear regression, the slope estimator β is more robust to outliers or single erroneous data points as their influence on β is minimised. Additionally, the data does not need to follow a particular distribution and missing values are allowed. The slope estimator β is expressed in the units of the time series and calculated as follows;

$$\beta = \text{median}\,\frac{(\mathrm{Y_j} - \mathrm{Y_i})}{(\mathrm{X_j} - \mathrm{X_i})}$$

$$\text{for all } 1 < i < j < n$$

Equation 3.7

where i is the data value and j the time. (Helsel & Hirsch, 2002)

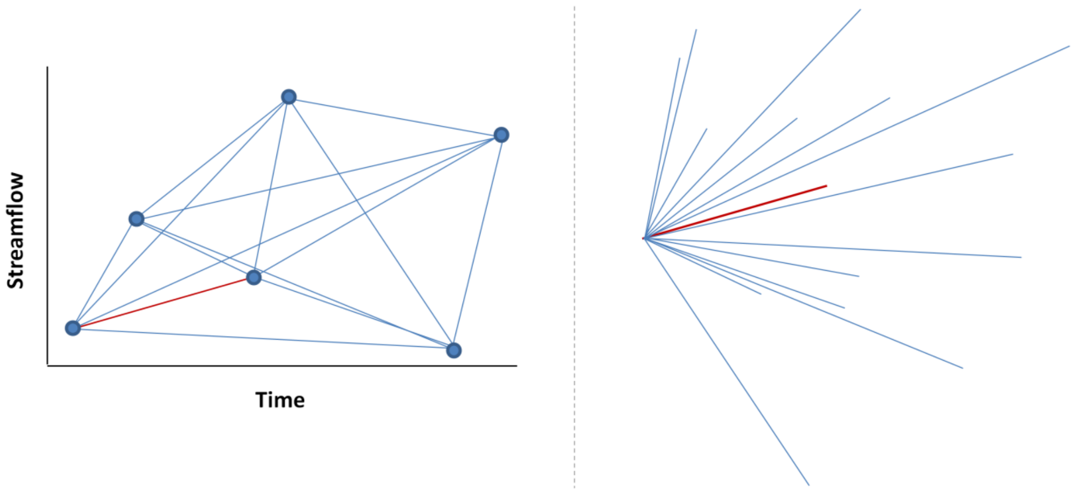


Figure 3.4 Graphical derivation of the median slope following the Theil-Sen-Approach. After Helsel & Hirsch (2002). Left: All possible pair wise slopes between six data points. Right: All possible slopes starting from a common origin to identify the median (red line) of the 15 slopes, which is the Theil-Sen slope estimator (β).

However, when using these statistical tests, one needs to consider the specific assumptions for each test, i.e. normality versus non-normal data distribution as discussed above, but also independence versus non-independence (positive or negative auto-correlation) of data. The analysed data can still be dependant even with zero auto-correlation, if the data is not-normally distributed. In the case of hydrological data, this means that statistical tests selected need to be designed for skewed distributed data that is often positively serially correlated over time and space; otherwise, the results of the tests can be misleading especially for significance testing (Type I error) (Kundzewicz & Robson, 2004). Ehsanzadeh & Adamowski (2010) note that even though negative autocorrelation can be present in a dataset, it may not have real physical importance and could be a result of sampling issues, measurement errors or other statistical artefacts.

Apart from selecting the appropriate trend analysis methods and tests, it is also important to consider the data structure itself. If the data exhibit a high degree of natural variability or oscillations, spurious trends for certain start or end years can be caused. Particularly, if the time scale of an oscillation in the series is longer than the observation period selected, oscillations can look like a trend (Chen & Grasby, 2009). Such trends can persist, disappear or change in sign depending on record length or observational window selected. Therefore, for trend analysis long time series in excess of 50 years are recommended (Kundzewicz & Robson, 2004; Yue *et al.*, 2012) to remove the influence of inter-decadal variability or outliers at the start or end of the analysed records.

If a statistical test cannot detect a trend, this does not necessarily mean that there is no trend. Radziejewski (2009) conclude from their study that this is due to two reasons; first due to a weak trend (low change signal to noise (natural variability) ratio) which cannot be detected by the test at a high significance level or second due to the reason that the trend only started recently. However, in the case of climate-induced trends in hydrological data, these trends can become detectable in future with an increasing trend magnitude and longer records. Therefore, even if trends cannot be found at this point in time, in future analysis with longer time series available, a trend might become detectable.

3.3 Analysis of Low Flow Series – An Overview

For water management the analysis of historical stream flow records can be a valuable source of information. For example, trends in the timing and magnitude of low flows are an important factor that needs to be taken into account when managing and planning for water resources (Ehsanzadeh & Adamowski, 2010). Therefore, this section analyses trends in various parts of the flow spectrum with specific focus on low flows.

Generally, there is no common definition for low flow indicators, and the term has been used in different contexts to describe the low-flow regime of rivers. Often low flows are analysed in terms of their magnitude and timing, and also with the help of a flow threshold, allowing for example to analyse the length of time, the accumulated volume or the number of events below such a threshold. Such thresholds can be a fixed discharge value or can be defined with the help of the flow duration curve (exceedance probability). The indicators analysed can look at instant events (e.g. a single data point) or examine low flows averaged over longer time periods (Gustard *et al.*, 1992).

In this study the analysis of the annual minimum flow (flow with the lowest volume) is considered to identify changes in the magnitude and timing of extreme low flows. However, this absolute indicator needs to be treated with care as a single point in the time series can be highly influenced by measurement errors, especially when the flow is at or below the measurement limit. To overcome this limitation, low flows can be averaged over different extended durations, to obtain a more representative description of low flows. For example, seven or thirty day periods can be used to calculate either the moving average flows or the sustained low , to indicate the magnitude and/or timing of low flow events. Additionally, time series of annual or seasonal low flow duration such as Q95 (the river flow that is equalled or exceeded 95% of that time) or Q90 can be analysed. For example, Q95 is one of the commonly used low flow indices in Ireland (Mandal & Cunnane, 2009).

In addition to the flow value analysis, which uses the magnitude and timing of low flows, threshold-based methods can be used to examine the frequency and duration of low flow spells. This methodology has particularly been used to investigate drought characteristics with regard to drought duration, severity and intensity (Mishra & Singh, 2010). According to the threshold principle, the start of a drought is identified when the river flow falls below the threshold level and the end is marked by the exceedance of the threshold.

The threshold level has to be selected carefully, as it is assumed to be constant over time for a given reference period. Depending on the threshold level, a certain stream flow magnitude will be classified as being a drought condition or not. Additionally, when selecting an excessively low threshold, small variations in stream flow can cause the flow to be above the threshold during an actual continuous drought period and the event is dissected into two independent periods (Tallaksen *et al.*, 1997). When deciding upon a threshold, often a certain stream flow level derived as a percentile from a flow duration curve is selected. For example, Hisdal *et al.* (2001; 2010) used the Q70 as a threshold level when examining trends in European stream flow droughts.

Richter *et al.* (1997), Smakhtin (2001) and Pyrce (2004) provide reviews on low flow and hydrological drought indices. Based on their recommendations the indicators discussed in the subsequent sections were selected for this study based on daily mean flow series, with the aim of covering a broad spectrum of hydrological low flow characteristics, including measures for magnitude, timing, duration and frequency of low flows and low flow spells in daily stream flow. Flow percentiles are analysed on a seasonal basis, as seasons are also often used as the basis for future flow studies under climate change. For all stations, each indicator is calculated for each year separately to derive annual time series.

3.4 Thresholds-Based Indicators

The analysis of low flow spell duration (maximum and cumulative duration) and frequency of daily time series is based on the method of hydrological drought analysis proposed by Tallaksen *et al.* (1997) and identified as the most suitable to examine trends in stream flow records (Hisdal *et al.*, 2001). The method employed uses a constant threshold below which the daily stream flow is considered to indicate low flow spells or drought conditions. If the flow is below the threshold, a low flow spell begins and is considered to continue until the specific threshold is again exceeded.

However, when employing such a method using daily stream flow series Tallaksen *et al.* (1997) highlight the need to eliminate mutually dependent minor drought periods, caused by short time periods above the threshold level, by employing a pooling procedure of the original time series. Based on results from Tallaksen *et al.* (1997) and the recommendations by Hisdal *et al.* (2001) an 11-day moving average of the original stream flow series was obtained before analysing the low flow spell indices. The threshold based indices derived are used to analyse the characteristics of low flow spells and are not to be confused with extremes of absolute low flow values.

Three threshold-based low flow spell indicators were calculated on an annual basis, based on the smoothed daily series of 11-day moving average flows (see Figure 3.5).

- Annual Maximum Low Flow Spell Duration (AMD) – No. Days
- Annual Cumulative Duration of all Low Flow Spells (ACD) – No. Days
- Number of Low Flow Spells (NLFS)

The selection of the constant threshold level ultimately determines what is considered as being a low flow spell. Depending on the flow regime of a region, Hisdal *et al.* (2001) recommend thresholds of Q70, Q80 and Q90 (flow exceeded 70%, 80% or 90% of the time respectively) as appropriate for European perennial rivers. To determine the appropriate threshold level for Irish rivers, the smoothed time series was analysed for each selected station, for the threshold levels Q70, Q80 and Q90 determined from the time period 1976-2009.

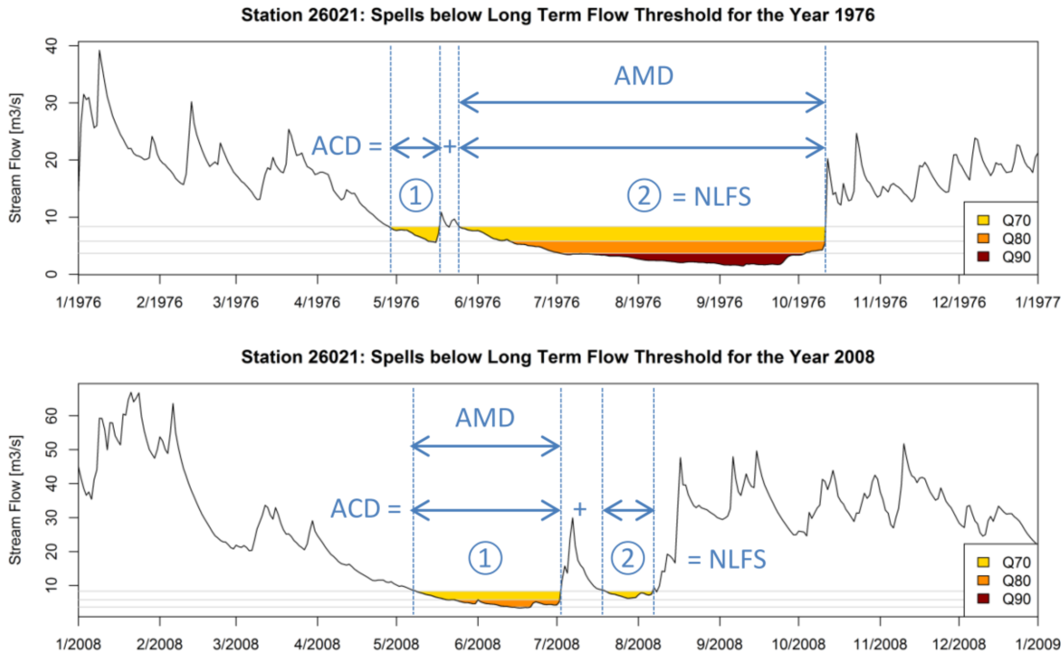


Figure 3.5 Example calculations of the three low flow spell indices (AMD, ACD & NLFS) below the Q70 long-term flow threshold derived from the period 1976-2009, using a 11-day moving average flow.

The long-term thresholds of *Qn* (with n= 70, 80 and 90) are calculated as the average value of the flow percentile (flow exceeded n% of the time):

$$Qn = \frac{1}{y}\sum_{i=1}^{y} Q_{n_i}$$ **Equation 3.8**

In Figure 3.6 four illustrative examples of the analysis of threshold levels are shown. In the figure, colour coding is used to indicate the lowest threshold below which the daily mean flow is falling. Flows falling below Q90, Q80 or Q70 are shown in red, orange and yellow respectively; flows > Q70 (above the highest threshold) are shown in white. Each day of each year is shown, except the 29th of February during leap years.

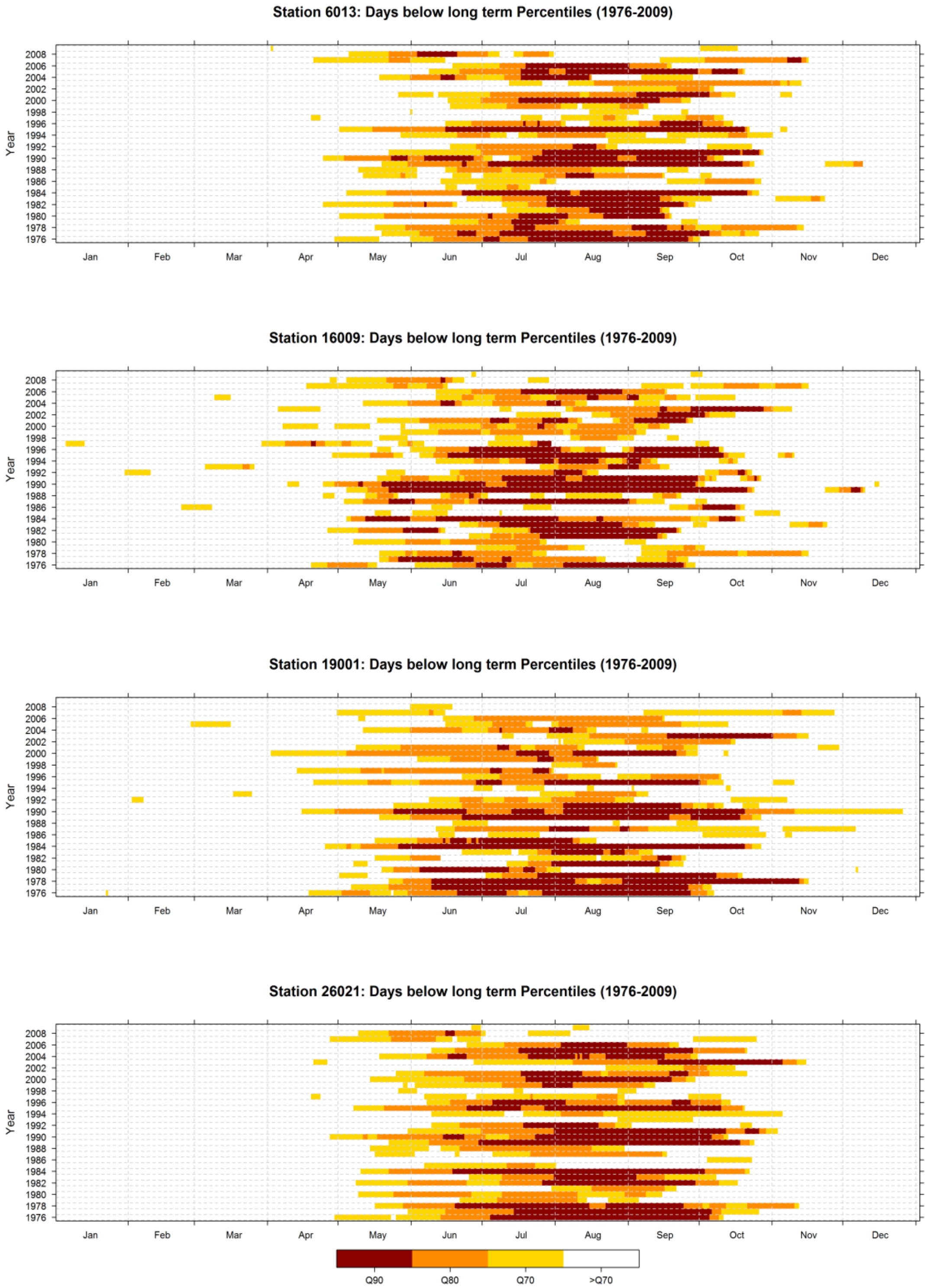


Figure 3.6 Illustrative example stations. Flow below long-term percentiles over the period (1976-2009). Flows below Q90, Q80 or Q70 are shown in red, orange and yellow respectively. Daily flows above these thresholds are shown in white.

After analysing the effects of different long-term flow thresholds for all stations (not shown), Q70 is chosen as appropriate threshold for Irish rivers. A threshold level using Q70 allows obtaining separate low flow spells, to perform the analysis on and across different Irish stream flow regimes, but also allows having a least one low flow spell occurrence per year. If a lower level threshold (i.e. Q80 or Q90) had been selected, many dependent minor low flow spells per year or no low flow events at all (for certain years would) have been obtained. The analysis of three low flow spells indicators (AMD, ACD and NLFS) is based on the Q70 threshold for each individual flow station as shown in Figure 3.5.

Figure 3.7 shows the annual time series of the threshold-based indicators for each station analysed. Flows of the individual stations are shown in grey, the 50th percentile in black and the 5^{th} and 95^{th} percentile of all stations in red. The time series of AMD and the ACD show a high inter-annual variability. The selected period 1976 to 2009 aims to incorporate as many stations as possible and represents the best spatial coverage. For the selected analysis period from, higher AMD and AMC values are present at the start and lower values towards the end of the record. These high values are caused by the commencement of most of the monitoring sites due to a drought period in the early 1970s. Low AMD and AMC values at the end of the record are due to the unusually wet summers experienced recently. For NLFS a high degree of inter-site variability is evident with many of the stations show no change. To quantify these changes, a trend analysis is performed in the next section.

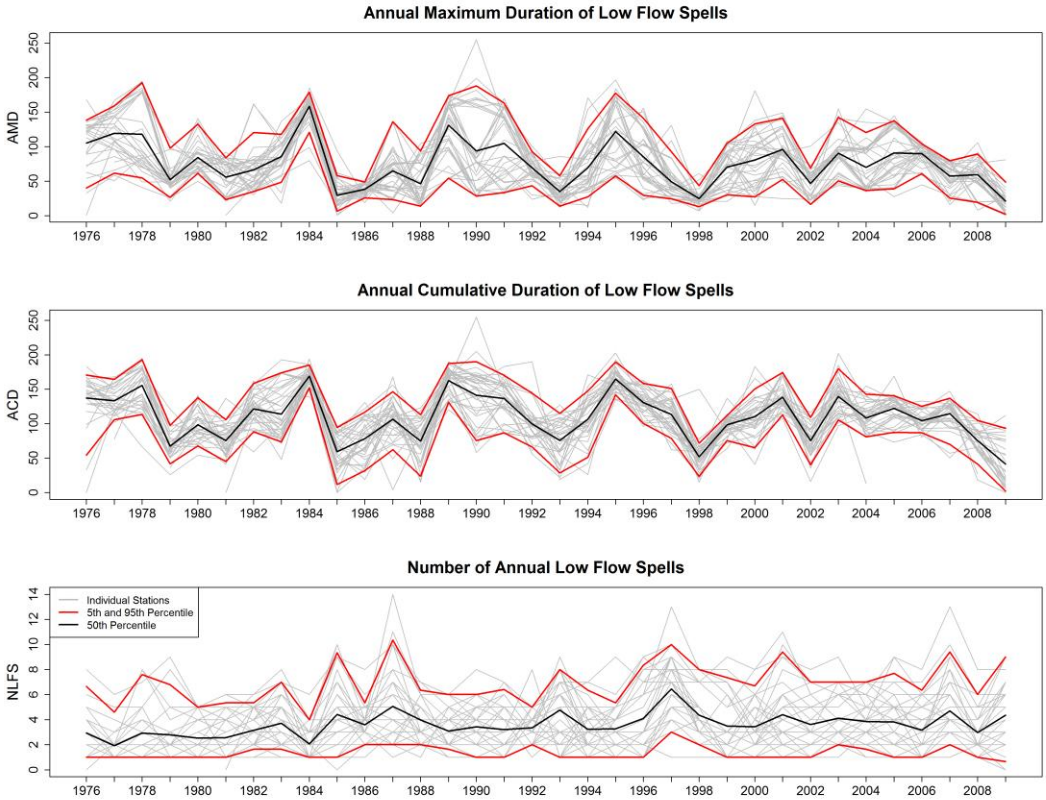


Figure 3.7 Annual time series of threshold-based indicators. Grey lines show each analysed station. Red lines indicate the 5th and 95th percentiles and the black line is the median of all stations.

3.4.1 Trend Analysis of Threshold-Based Indicators

The threshold-based indicators are calculated to derive an annual time series as described in the previous section and are then assessed for trend in this section. The magnitude of change over the fixed period (1976-2009) is assessed using the Theil-Sen Approach (TSA) to derive the median slope estimator β, which represents the magnitude of change per year (in the units of the index) (see section 3.2.2). To facilitate comparison between stations, the trend slope β is expressed as a percentage over the record length in relation to the indicator mean (μ) over that time period (long-term average) (Stahl *et al.*, 2012). The relative magnitude of the TSA Slope is shown on the maps as a percentage.

$$Relative\ TSA\ Slope\ \% = \frac{\beta * n}{\mu} x\ 100 \qquad \textbf{Equation 3.9}$$

This relative slope allows comparison between stations in the network, which have high differences in their indicator mean. The approach used in this study is found to be preferable to the standardised flow anomaly (SFA) used by Murphy *et al.* (2013) for comparing the TSA slope over time periods with different length. Using the relative TSA slope avoids uncharacteristic inflation of the magnitude of slopes for shorter periods, particularly if extreme values (high or low compared to the mean) are present at the start or end of the record. To determine the spatial characteristics of the obtained slopes, a map for Ireland depicting these trends for each indicator is produced. The significance of trends (5% level) was obtained using the Mann-Kendall (MK) Z Statistic. On the maps, significant changes in the threshold-based indices are indicated by a white triangle.

As significance of trends is tested, the serial correlation structure of each indicator is assessed using autocorrelation function (ACF) correlograms of the residuals of a linear regression model fitted to the time series. Figure 3.8 shows an example of the correlograms derived to access autocorrelation. If at any time lag (> 0) the estimates of the autocorrelation function are above the dashed line representing the significance level (5%), then there is a significant autocorrelation for that time lag. The three threshold-based indicators did not show any statistically significant serial correlation for any of the stations.

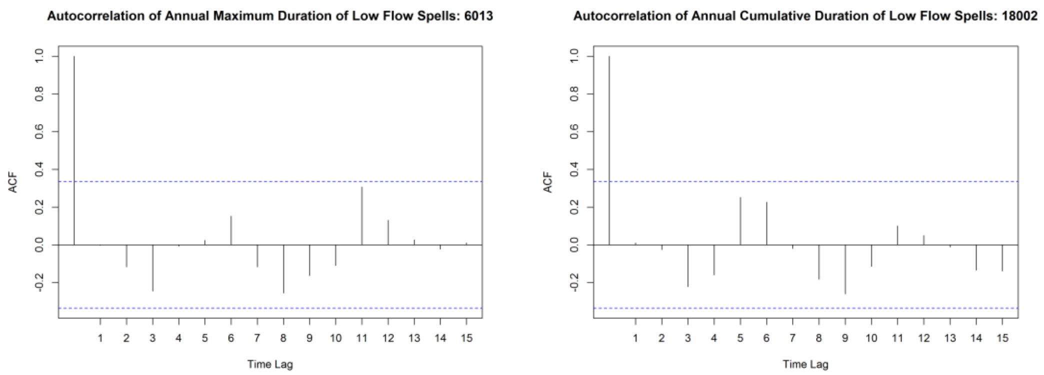


Figure 3.8 Example of ACF correlogram of the residuals of a linear regression model for Annual Maximum Duration (left) and Annual Cumulative Duration (right) of Low flow spells for Station 6013 (left) and 18002 (right). The statistical significance level (5%) in shown in blue dashed lines.

As most of the hydrometric monitoring stations in the IRN commence during/after a drought period in the early 1970s and end with unusually wet years, it is necessary to set the obtained trends for the fixed period (1976-2009) in context. A second period with three years removed from the start and the end of the record (1979-2006) is therefore analysed for all three threshold-based low flow spell indicators (Figure 3.9 to Figure 3.11). The second period from 1979-2006 has been selected to investigate the influence of the first three years of the selected fixed period record (1976-2009) which show high AMD and ACD values (dryer conditions) and the last three years of that fixed period show very low AMD and ACD values caused by flow conditions highly above the Q70 long-term threshold.

Although the selected periods vary only by a few years, the trends obtained are very different when the extreme high start and the low end are removed. This is particularly evident for the two indicators AMD and ACD, where negative trends cease to be significant and the majority of trends even change the sign between the two periods. For NLFS, the results are mixed for both time periods, showing either no trend (black data point) or mostly significant positive trend. This indicates that the number of independent low flow spells below the Q70 threshold increases over time for at specific locations. For the five stations this increase in the number of low flow spells seems to be independent of the selected period. Whereas for the other four stations the time period selected is of importance, as the trends cease to be significant or no trend is indicated for the period 1979-2006 (Figure 3.11).

The differences in trends obtained for AMD and ACD highlights the influence of the start and end of record analysed on the trends obtained from fixed periods. However, the shortcoming of the threshold-based analysis is that the thresholds are defined by the entire data from the fixed period of analysis, which results in different thresholds when different time frames are analysed. This makes the results from two different periods of analysis not directly comparable, which inhibits a detailed analysis of the influence of the analysed period.

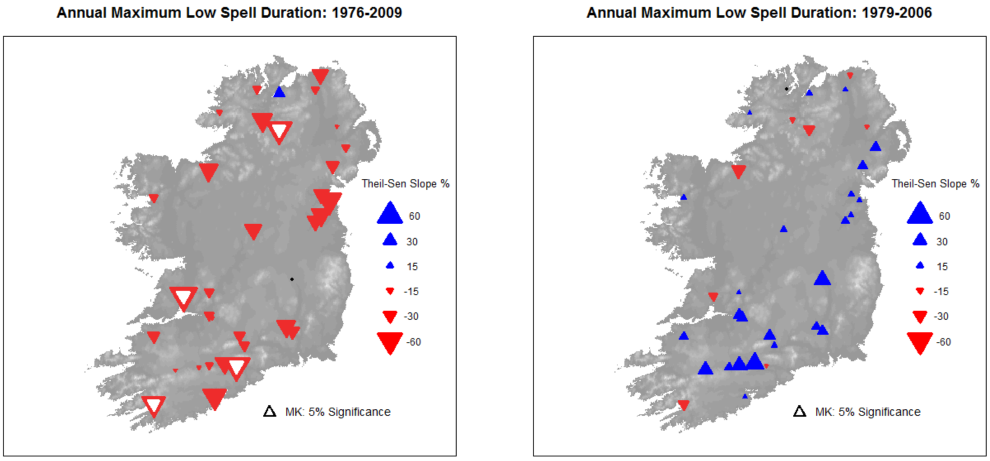


Figure 3.9 Trends in Annual Maximum Duration of low flow spells below Q70 for 1976-2009 (left) and 1979-2006 (right). Increasing (decreasing) trends are shown in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles. No trends are marked by black points.

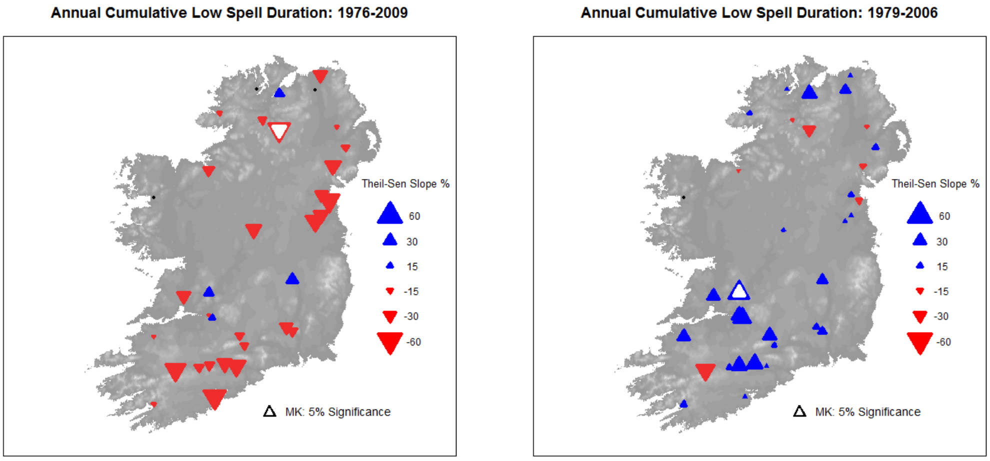


Figure 3.10 Trends in Annual Cumulative Duration of low flow spells below Q70 for 1976-2009 (left) and 1979-2006 (right). Increasing (decreasing) trends are shown in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles. No trends are marked by black points.

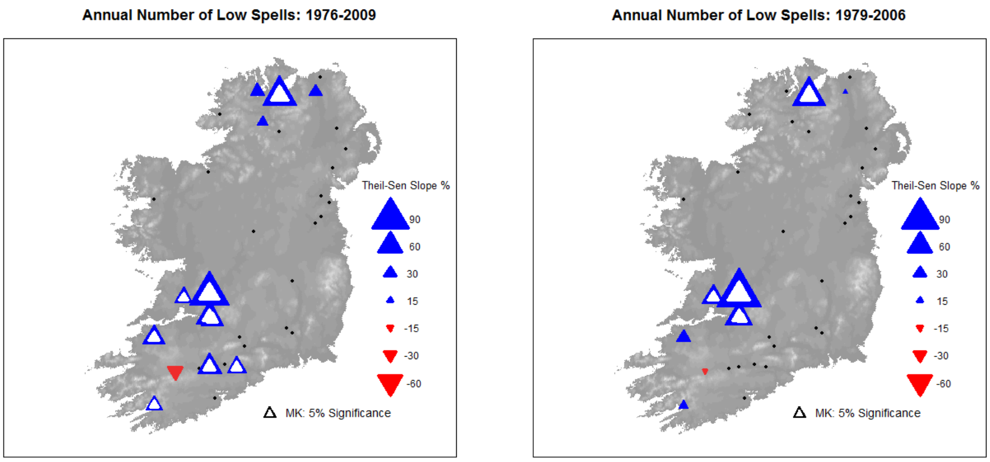


Figure 3.11 Trends in Annual Number of low flow spells below Q70 for 1976-2009 (left) and 1979-2006 (right). Increasing (decreasing) trends are shown in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles. No trends are marked by black points.

This non uniqueness of thresholds, is in general a major drawback of data analysis based on long-term thresholds defined by the data characteristics/values themselves. When employing threshold-based analysis, the data requirements are high as all sites analysed need to have complete data series of not only of the same length but also over the same time periods. Such requirements limit the possible forms of application and analysis that can be performed with such indicators.

Therefore, the analysis of the long-term threshold based low flow spell indicators in this thesis is limited compared to the extended possibilities of analysis of low stream flow based indicators in the following sections.

3.5 Low Flow Indicators

Apart from the information provided by analysing low flow spells, possible changes in seasonal low flows are also of importance to water managers. Seasonal changes are of particular importance as future changes in hydro-climatological variables are also projected to change seasonally. While the main interest of analysis focuses on summer and autumn, for completeness possible changes in different flow indicators are investigated on a seasonal basis for the four seasons spring defined as; (March to May), summer (June to August), autumn (September to November), and winter (December to February). For each of the seasons, annual time series of indices were computed. These seasonal indices include seasonal mean flow and series obtained from flow duration curves (FDCs) which include ranges from median flows to low flow conditions (e.g. Q95, the flow exceeded 95% of the time), resulting in six time series of indicators for each season. Where the Q*n* flows are daily mean flows in a specific season exceeded n% of the time. Changes in some seasonal low flow indicators (e.g winter *Qn* flows) might not directly effect in stream water abstractions, but can have implications for aquifer and reservoir recharge.

In addition to seasonal low flow ranges, the magnitude and timing of low flows are analysed. In Ireland there are commonly two types of statistically defined low flow categories, the annual m-day moving average flow (MAF) and the annual m-day sustained low flow (SLF) (for both categories, m= 1,7,10,15 or 30 days) (Brogan &

Cunnane, 2005). The sustained low flow represents the lowest daily mean flow that is not exceeded for the next m-consecutive days per year. For example for m=7, the timing (Julian Day of the year) of such a flow represents the start of the driest week in each year and the maximum flow during this week is the 7-day sustained low flow for that year (MacCarthaigh, 1989). The 7-day moving average flow (MAF) is the average of the daily mean flows of the seven lowest consecutive flows, where the Julian Day indicates the start of that period.

Absolute low flows (e.g. annual daily minimum flows) were excluded from the analysis in this study as time series of extreme low flows are often affected over time by factors such as modified cross sections, weed growth and changes in datum causing erroneous measurement and also generally difficult to measure.

The following indicators are derived from daily mean flow time series:

- Seasonal Mean
- Seasonal Q50 (Median)
- Seasonal Q70
- Seasonal Q75
- Seasonal Q90
- Seasonal Q95
- Annual minimum 7-day sustained low flows (SLF) (Magnitude and Timing)
- Annual minimum 7-day moving average flow (MAF) (Magnitude and Timing)
- Annual minimum 30-day sustained low flows (SLF) (Magnitude and Timing)
- Annual minimum 30-day moving average flow (MAF)(Magnitude and Timing)

All of the above indicators are analysed, but only the results for the analysis of the Q50, Q75, Q95, 7-day SLF (Flow Magnitude & Timing), and 30-day SLF (Flow Magnitude & Timing) are shown in detail as the results turned out to be similar to the other indicators with similar exceedance values. Although the mean flow is a widely used indicator in water resources management, it was found to be influenced by the contribution of high flows and is therefore less representative than the median of the flow regime.

3.5.1 Temporal Variability of Low Flow Indicators

This section examines the long-term variability of the annual time series of low flow indicators over the available record length up to 2009 before analysing trends for the fixed period in the next section. The annual indicator scores shown in Figure 3.12 to Figure 3.15 are the indicator values standardised to the indicator mean (μ) and its standard deviation (σ), to allow changes in Q*n* and low flows of different magnitude to be plotted and analysed together.

$$Standardised\ Indicator\ Score\ = \frac{Indicator - \mu}{\sigma} \qquad \textbf{Equation 3.10}$$

Figure 3.12 to Figure 3.15 show the flows of the individual stations in grey, the 50th percentile in black and the 5th and 95th percentile of all stations in red. At the start of the time series analysed (1957) only 5 stations (or 15% of all stations) have observed records, by 1979 all stations have records. This increase in stations number over time results in an increasing spread of the standardised scores obtained. However, the graphs can be used to set the recent records for which numerous stations are available into a longer-term context.

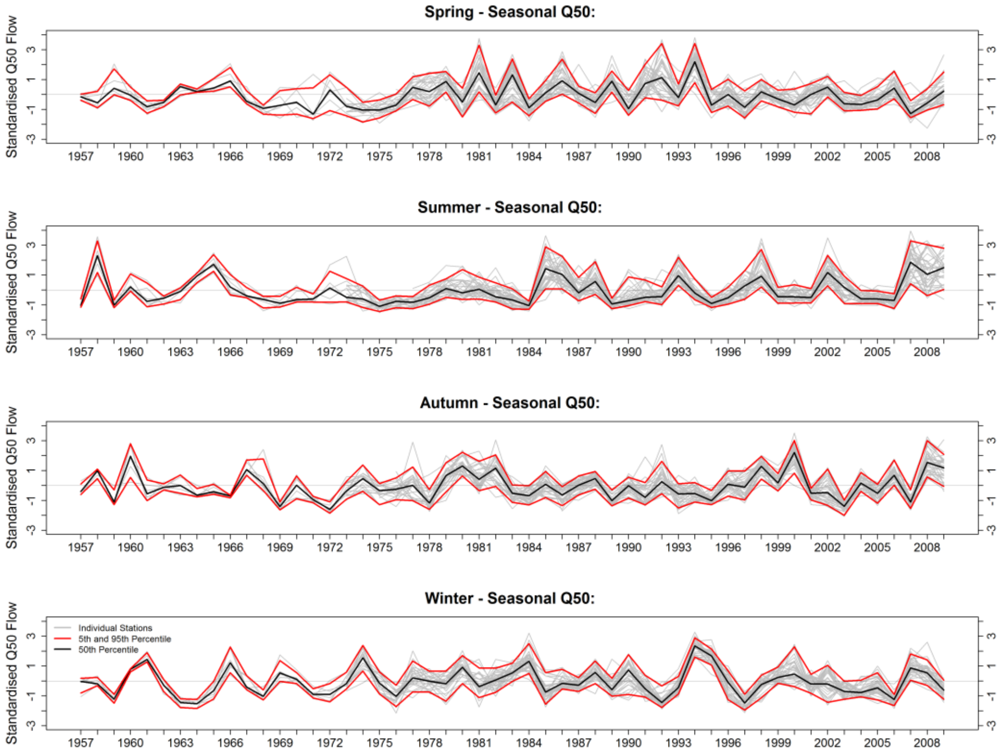


Figure 3.12 Annual time series of seasonal Q50 flows. Grey lines show each analysed station. Red lines indicate the 5th and 95th percentiles and the black line is the median of all stations.

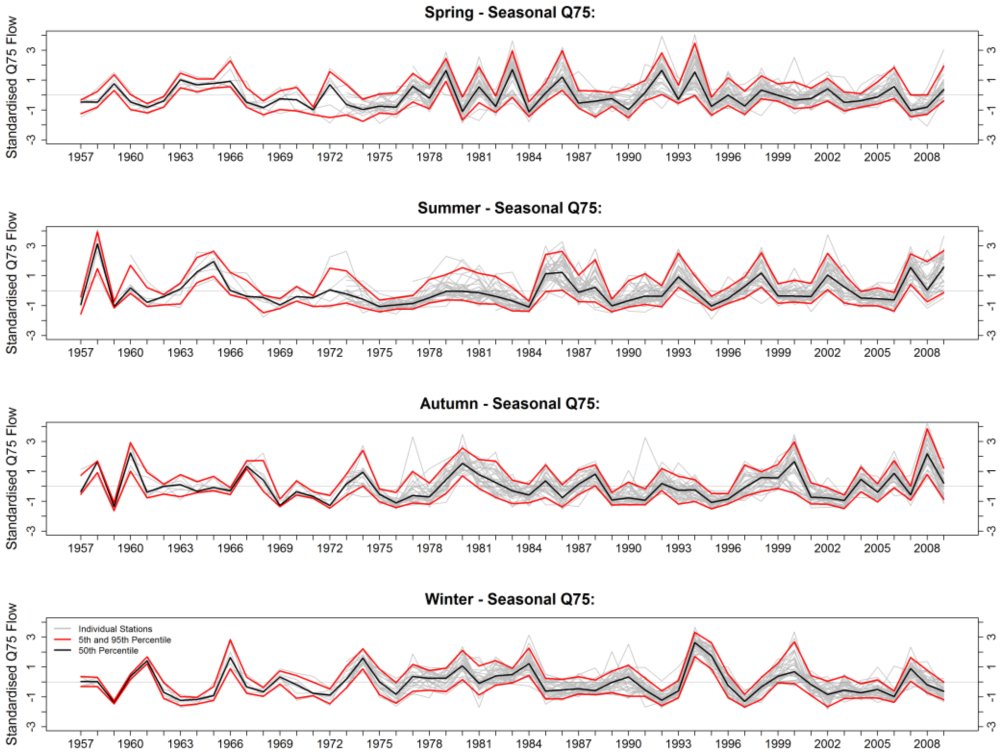


Figure 3.13 Annual time series of seasonal Q75 flows. Grey lines show each analysed station. Red lines indicate the 5th and 95th percentiles and the black line is the median of all stations.

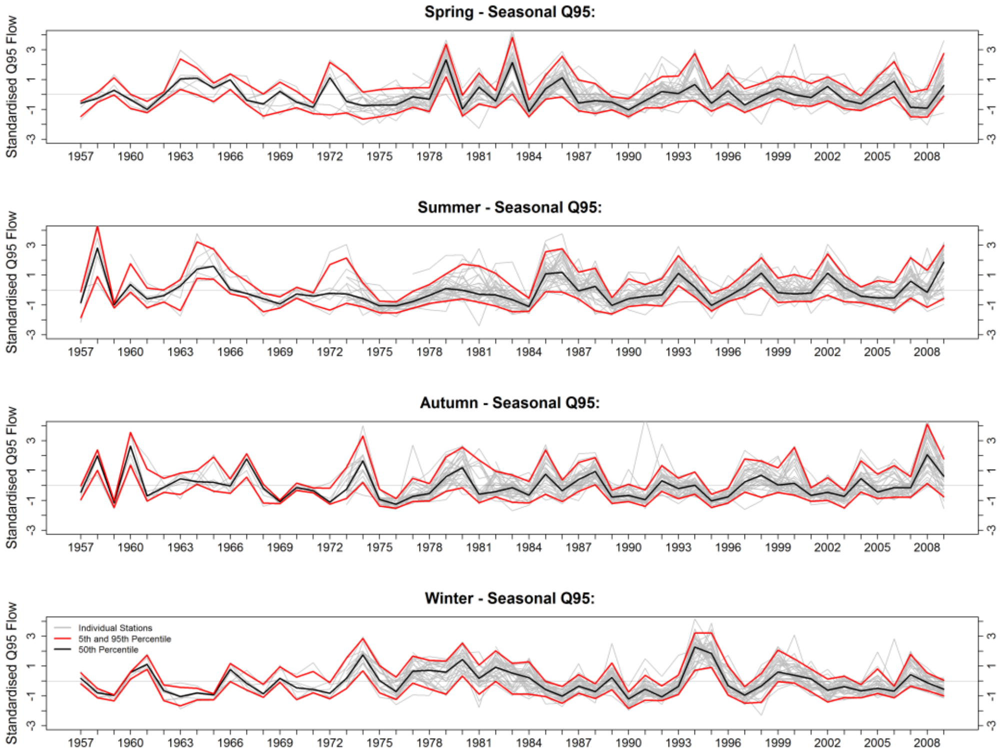


Figure 3.14 Annual time series of seasonal Q95 flows. Grey lines show each analysed station. Red lines indicate the 5th and 95th percentiles and the black line is the median of all stations.

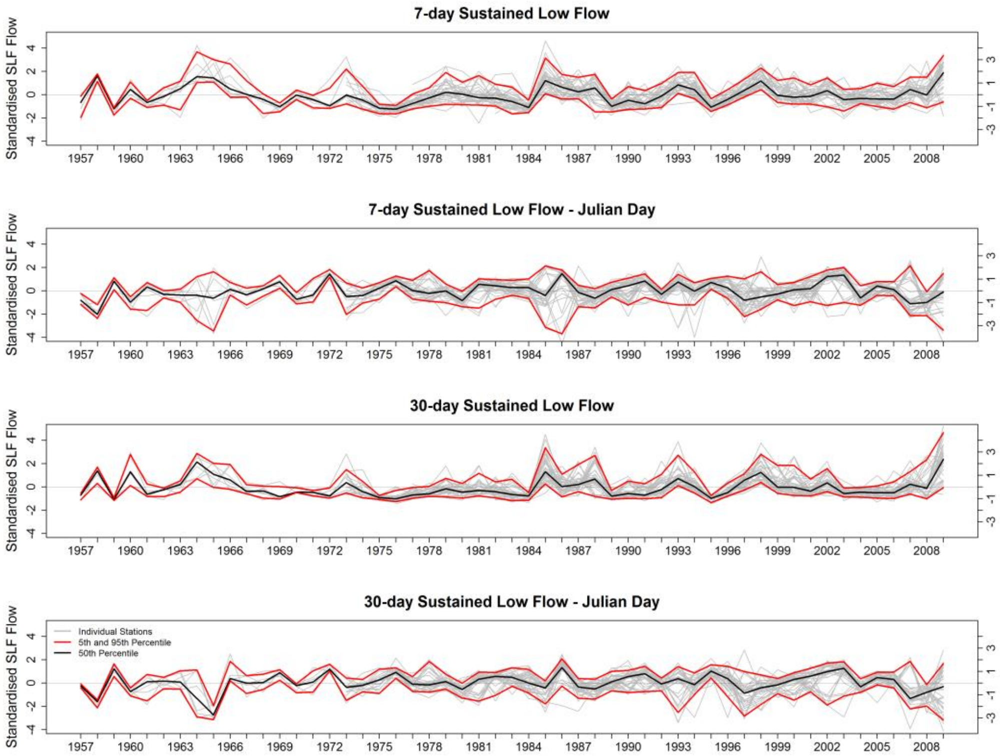


Figure 3.15 Annual time series of 7-day and 30-day standardised sustained low flows (magnitude and timing). Grey lines show each analysed station. Red lines indicate the 5th and 95th percentiles and the black line is the median of all stations.

In Figure 3.12 to Figure 3.14, all the Seasonal Q*n* flows (flow exceeded n% of the time) show a high degree of inter-site and inter-annual variability with similar overall patterns for each season. The seasons themselves show different distinct patterns. However, the magnitudes of standardised scores for individual years are different. For example for summer flows, Q50 shows the last three years of the record have the highest standardised flows, whereas Q75 only shows two out of the three years as high. When examining Q95, only the last year of record is very high relative to the median of all stations. This indicates that different parts of the flow regime respond differently to the wetter summers at the record end.

The standardised n-day sustained low flows scores have a higher maximum variability compared to the seasonal *Qn* flows (larger y axis values in Figure 3.15). Magnitude and timing of SLF flows follow a different pattern over time and appear to be independent on an annual basis. Over the entire record, the median of all stations indicates the highest flow values of the SLF for 2009.

3.5.2 Analysis of Low Flow Indicators - Fixed Periods

Having examined the temporal variability, the extracted indices for each station are analysed for trends over the fixed study period 1976-2009, which allows for comparison between hydrometric stations. Similar to the fixed period analysis for the threshold-based low flow indicators the seasonal Q*n* flows and the n-day SLF indicators are analysed for trends. In Figure 3.16 to Figure 3.19, the trend magnitude is shown as the Relative TSA Slope (%) of the Theil-Sen-Approach derived using Equation 3.9. The Mann-Kendal test is used to determine the significance of trends at a 5% significance level, following the same approach as the analysis of the low flow spell indicators

The time series of low flow indicators are also assessed with regard to autocorrelation. Some individual stations showed positive serial correlation, which can increase the probability of detecting a statistically significant trend when no trend exists (Type I error). Serial correlation can cause the estimated errors to be smaller than the ‘true’ errors, which can lead to the false conclusion that parameter estimates are more precise than they are. This increases the tendency to reject the null hypothesis (H_0=*no trend*) and spurious trends can be detected in the data.

Therefore, where significant serial autocorrelation (5% level) is evident in the data block-bootstrapping is employed to preserve the internal temporal correlation structure within a time series. This bootstrap re-sampling procedure is employed to estimate the distribution of the test statistic. When performing block-bootstrapping, the selected block length should reflect the temporal dependency (autocorrelation) of the time series (Kundzewicz & Robson, 2004). A block length of four is used to allow for serial correlation as suggested by Önöz & Bayazit (2012) for small samples ($25 \leq n \geq 50$), to obtain a rejection rate close to 5% level (α=0.05). With an H_0=*no trend* any ordering of the data is equally likely (Khaliq *et al.*, 2008). The distribution of the test statistic is estimated using 10,000 re-sample blocks. If the MK Z statistic o f the original series is found to be in the tail of the distribution (10,000$*$(α/2)), then the original ZS can be considered as being significant and it is likely that a temporal trend exists (Khaliq *et al.*, 2008).

Consequently, to account for serial correlation when indicating the significance of the results on the figures, the procedure described above is applied. For stations showing serial correlation for a specific index, the significance level plotted on the map for that indicator, are determined from a distribution of 10,000 block-bootstrapped samples of the Mann-Kendall Z statistic. The null hypothesis (*no trend*) is rejected and the trend is marked as being significant on the map, when the MK ZS of the original series is located in the tails of the distribution. This means, when the data is ranked from the lowest to the highest value of the MK statistic, H_0 is rejected if the original MK Zs is higher than the 9,750th highest or lower than the 250th MK statistic of the 10,000 block bootstrapped samples at a significance level of α=0.05.

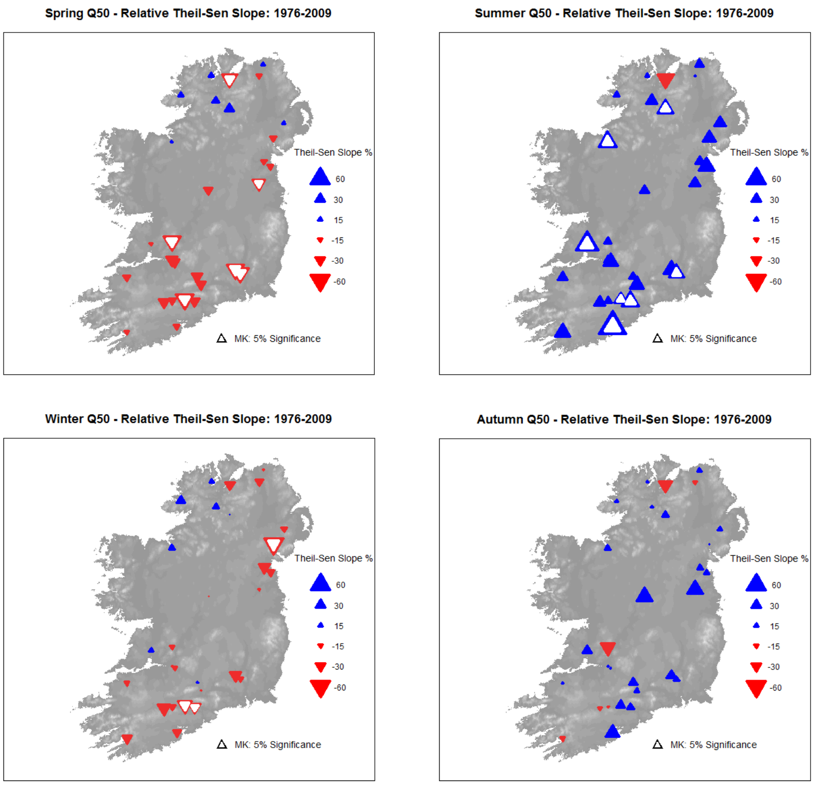


Figure 3.16 Trends seasonal Q50 flow for 1976-2009. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

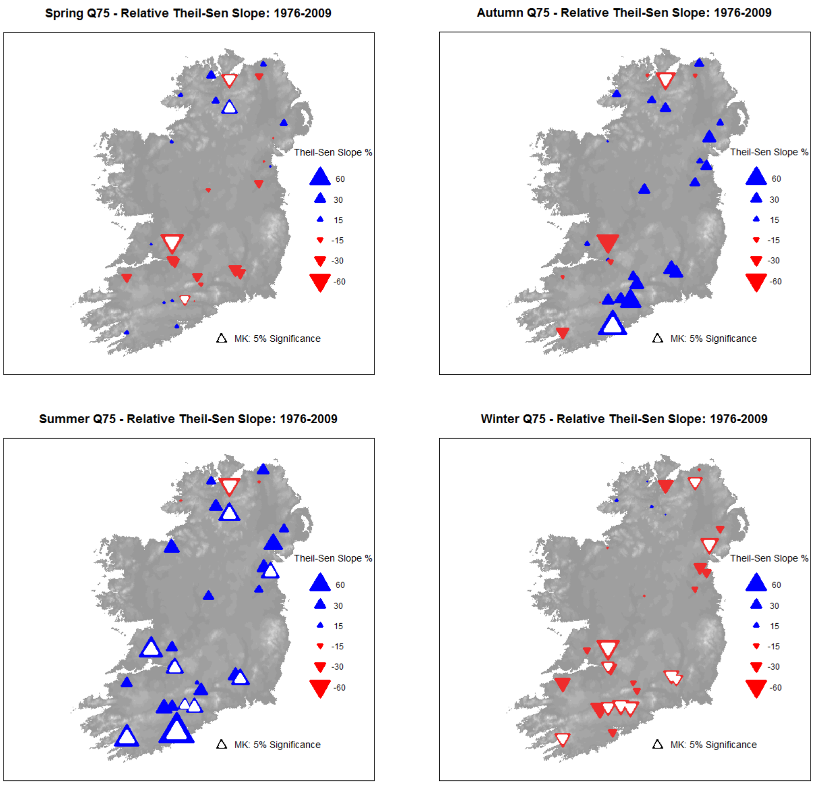


Figure 3.17 Trends in seasonal Q75 flow for 1976-2009. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

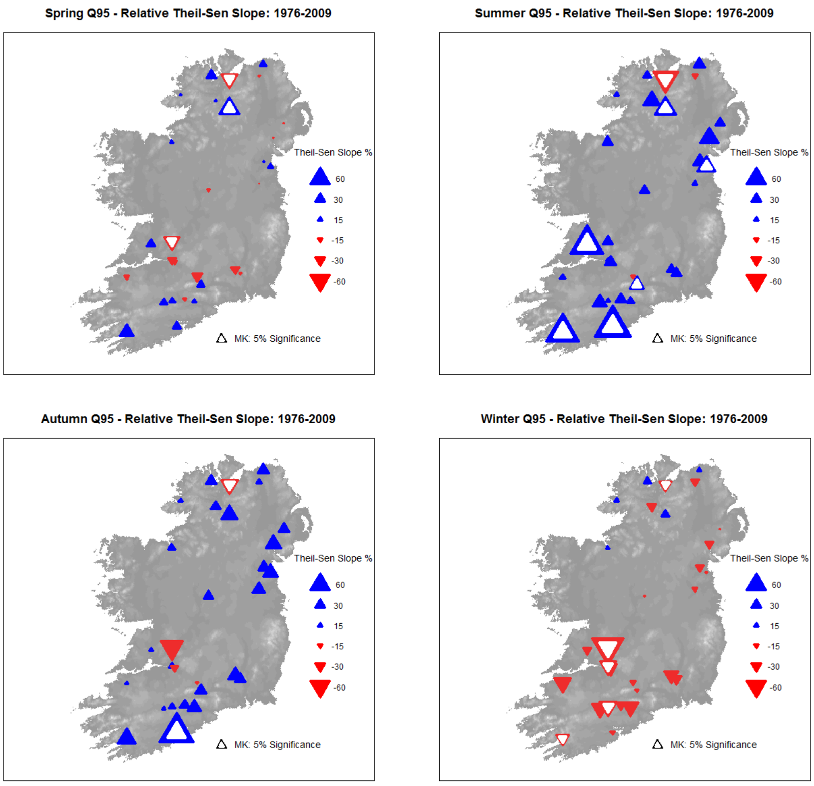


Figure 3.18 Trends in seasonal Q95 flow for 1976-2009. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

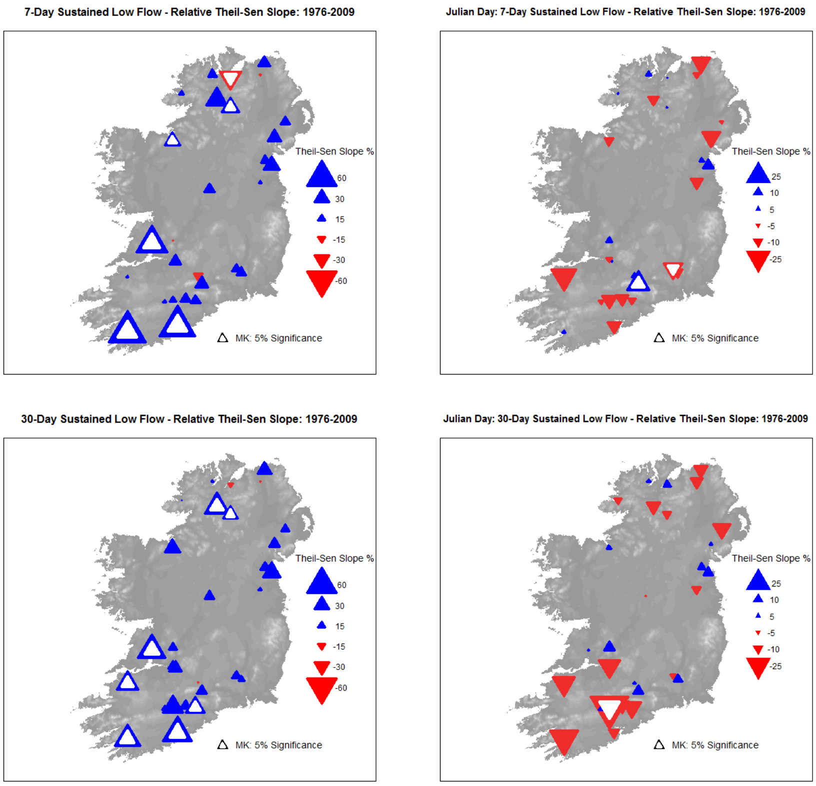


Figure 3.19 Trends in 7-day (top) and 30-day (bottom) sustained low flows for 1976-2009. Magnitude (left) and Julian Day/Timing (right). Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

The seasonal *Qn*s for the fixed period 1976-2009 are shown in Figure 3.16 to Figure 3.18. The results are described together below by season (n=50, 75 or 95). Later the SLF results shown in Figure 3.19 are discussed separately. In spring, Q50 shows a high number of negative trends using the Theil-Sen Approach, six of the trends are significant at the 5% significance level for the Mann-Kendall statistic. For spring Q75 the magnitude of negative trends decreases while small positive trends are found for spring Q95.

Summer and autumn *Qn* flows are mainly positive. Trends in summer *Qn* have a higher magnitude compared with autumn and also have a much higher number of significant trends, particularly for Q75 which has the highest number of significant positive trends for that period.

Winter *Qn* flows for the fixed period are dominated by negative trends, some of which are significant. Again, Q75 has the highest number of significant trends at the 5 % level for the MK statistic.

The 7-day and 30-day sustained low flows both show mainly positive trends in magnitude, whereas the timing indicates negative trend magnitudes (few significant). Negative trends in the TSA slope for the Julian day of the start of the sustained low flow periods indicate that these low flow periods happen earlier in the year.

Overall, for all low flow indicators there is no clear spatial pattern observable for Ireland for *Qn* and n-day sustained low flows for the period 1976-2009. An interesting outcome is the fact that the positive trends derived here for summer tend to oppose the commonly held expectation of drier summers and/or more extensive drought conditions under projected future climates. To better understand the spatial and seasonal variability of trends for a specific region an analysis of a single time period can only provide limited information (i.e. a snapshot in time). Particularly if the indicators analysed are highly variable on a year-to-year basis, a change of a couple of years in the analysed time period can result in different trends magnitudes and directions (as evident in the threshold-based low flow analysis). To provide a better understanding of possible effects of climate variability and change in hydro-climatic indicators, multiple time periods need to be analysed.

3.5.3 Analysis of Low Flow Indicators - Varying Start Year

Trend studies are often used to place the most recent records (end of record) in the context of long-term trends. However, the choice of the start year of the analysis can possibly influence the outcome of the overall trend obtained. Therefore, a trend analysis is performed by changing the start year of the analysis. For each start year between 1973 and 1987, trends up to 2009 (relative TSA Slope (%) and MK Z statistic) are calculated and plotted on the map. The same approach is used for the end year of 2006 so that recent wet extremes can be isolated. For the ease of visual interpretation, special animations of the changing trends over time with varying start years were produced (see supplementary files). Here, for ease of presentation the individual sequences from 1973 to 1987 are shown as maps for Q50 in Figure 3.20 (ending 2009) and Figure 3.21 (ending 2006) and in Figure 3.22 and Figure 3.23 for the timing of 7-day sustained low flow as illustrative cases.

In all four figures, the number of stations on the map increases with time, as stations with varying record length (earlier start years) are included. Figure 3.20 shows the trends in summer Q50 ending in 2009 for 15 different start years in sequence, with the majority of trends being positive. With regard to the trend magnitudes, there is no clear, spatial pattern. Some negative trends appear to emerge predominantly in the north. The number of significant trends (MK) changes considerably over the 15 start years examined with a maximum of 10 positive trends for the first couple of start years examined (although not for all stations continuous) to no significant tends for analysis starting in 1985. From one year to the next, some stations with trends can become significant or stations can lose their significant trend result. These findings highlight the dependency of statistical significance on the time period analysed.

For summer Q50, trends ending in 2006 show a different pattern (Figure 3.21). Positive trends are only found for tests starting in 1973, 1974 and 1975. Trends starting from 1976 and ending in 2006 show mixed signs for relative TSA slope, although positive trends still have a higher magnitude compared to the negative trends, which tend to be weak. Trends starting from 1977 onwards are dominated by stations showing negative trends. Most of these negative trends are non-significant at a 5% level, with the exception of trend analysis starting in 1985.

For both end years investigated, the drought conditions in the early 1970s are evident, resulting in positive trends for analysis starting in that period, independent of the end years. The extreme wet summers at the end of the record cause Q50 flows to be higher, causing significant trend when starting in the early 1970s. For trend analysis ending in 2006, few are significant at a 5% level. These overall differences in sign, magnitude and significance shown for the two periods, highlights the influence of the start year and end year of analysis when analysing trends particularly when extremes are present.

The timing of the 7-day Sustained Low Flow (Julian Day of the start of the driest week in a year), shows mixed trends when varying the start year of analysis for trends ending in 2009 (Figure 3.22). For all start years, the majority of trends are negative, which indicates that the week of the lowest flows is happening earlier in a year. Station 16009 in the southeast is an exception showing a significant increasing trend for the first couple of start years. For some start years, the number of stations showing an increasing trend in the TS Slope increases (e.g. 1978 or 1987) compared to the other start years, but with lower magnitudes. Overall, there is a lack of significant trends and no apparent spatial pattern.

When analysing trend ending in 2006, the sign of the majority of trends in the timing of the 7-day Sustained Low Flow change direction (Figure 3.23). The majority of trends are positive which does suggest that the driest week of the year is happening later. Trends in the southwest show a distinct pattern of predominately weak decreasing trends for the majority of start years. Overall, there are no significant trends for the period ending in 2006, apart from station 16009.

For the illustrative case studies (summer Q50 and the timing of 7-Day SLF) and the other indicators analysed (not shown) the start and end year have a strong influence on the trend obtained. Depending of the start and end year, particularly when extremes are present, the sign, magnitude and significance of trends found for individual stations vary considerably and can change from one year to the next. This analysis of the spatial evolution of trends observed with varying start years can provide water managers with a better understanding of climate variability and change.

Trends obtained from fixed period studies are often used to provide insights into changes in future hydrological characteristics (here focus on low flows), or even to extrapolate the observed trends into the future for entire regions. However, the results presented here from the analysis of trends in Irish low flow indices have shown extreme care is needed in doing so. For example, the two illustrative case studies have shown that the regional trends obtained from two different end years can become contradictory when shifting the period by as little as three years. Any future planning based on trends ending in 2006 will result in different plans compared to trends obtained three years later.

Figure 3.20 Summer Q50; Trends over varying start years ending in 2009. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

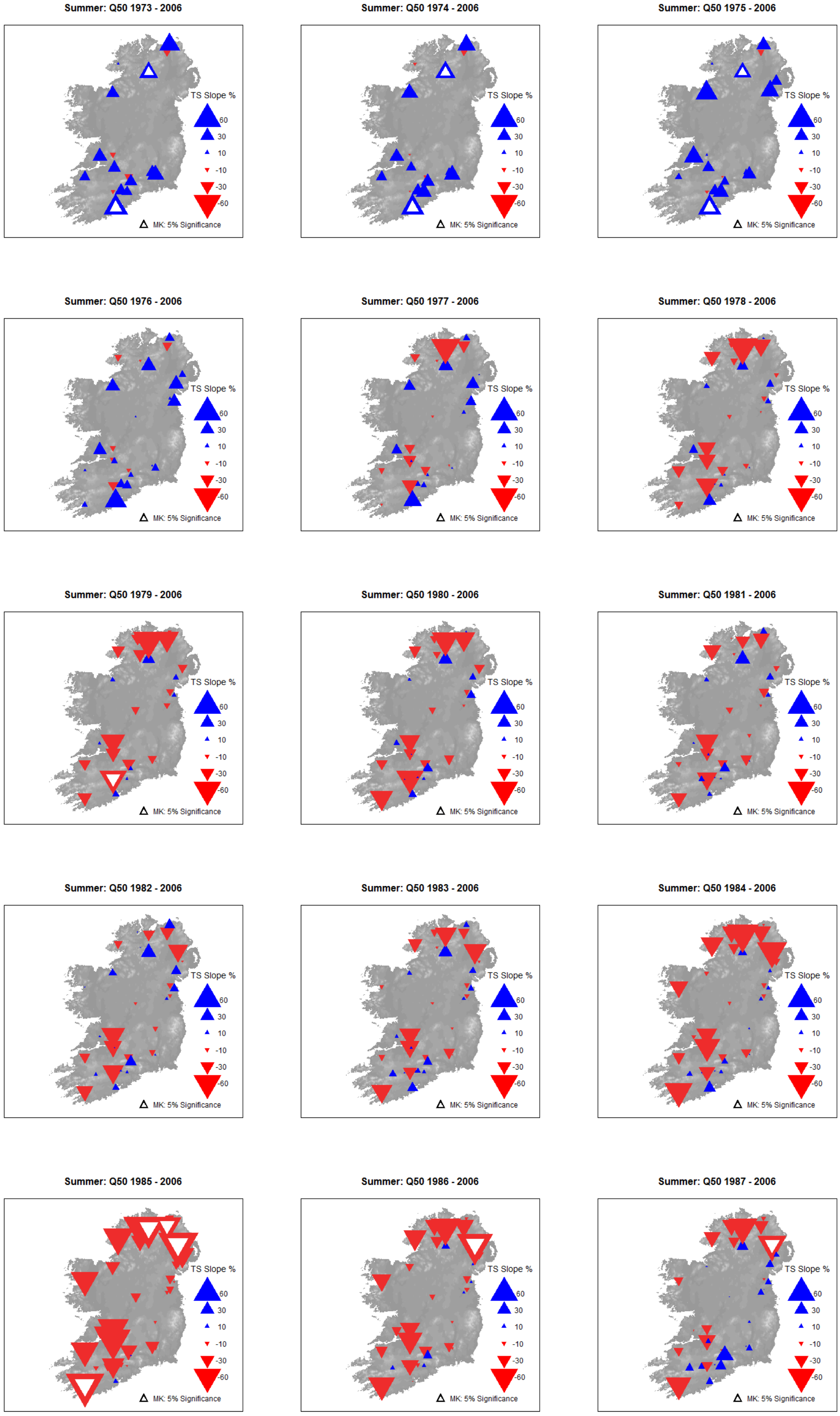


Figure 3.21 Summer Q50; Trends over varying start years ending in 2006. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

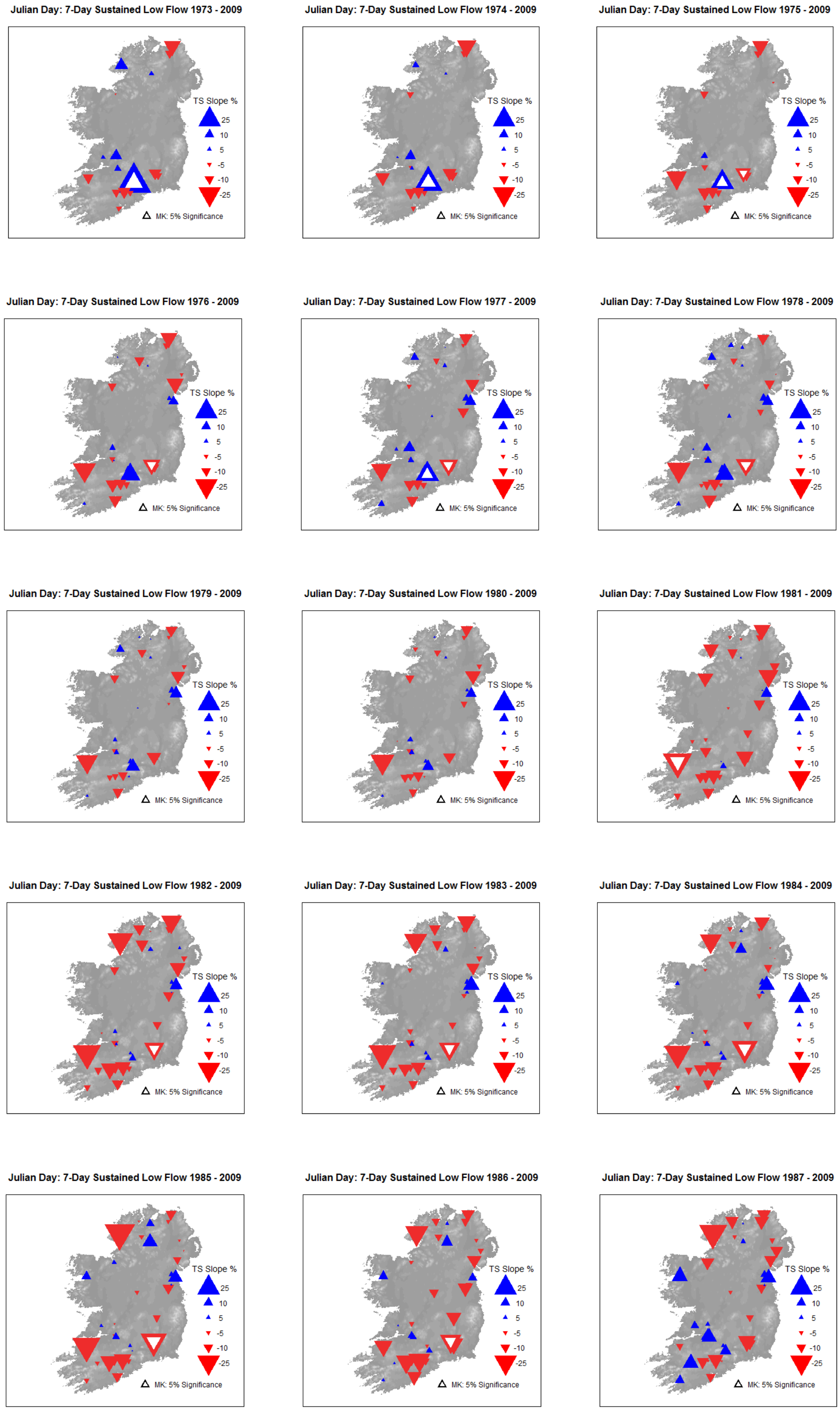


Figure 3.22 Timing of 7-Day Sustained Low Flow; Trends over varying start years ending in 2009. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

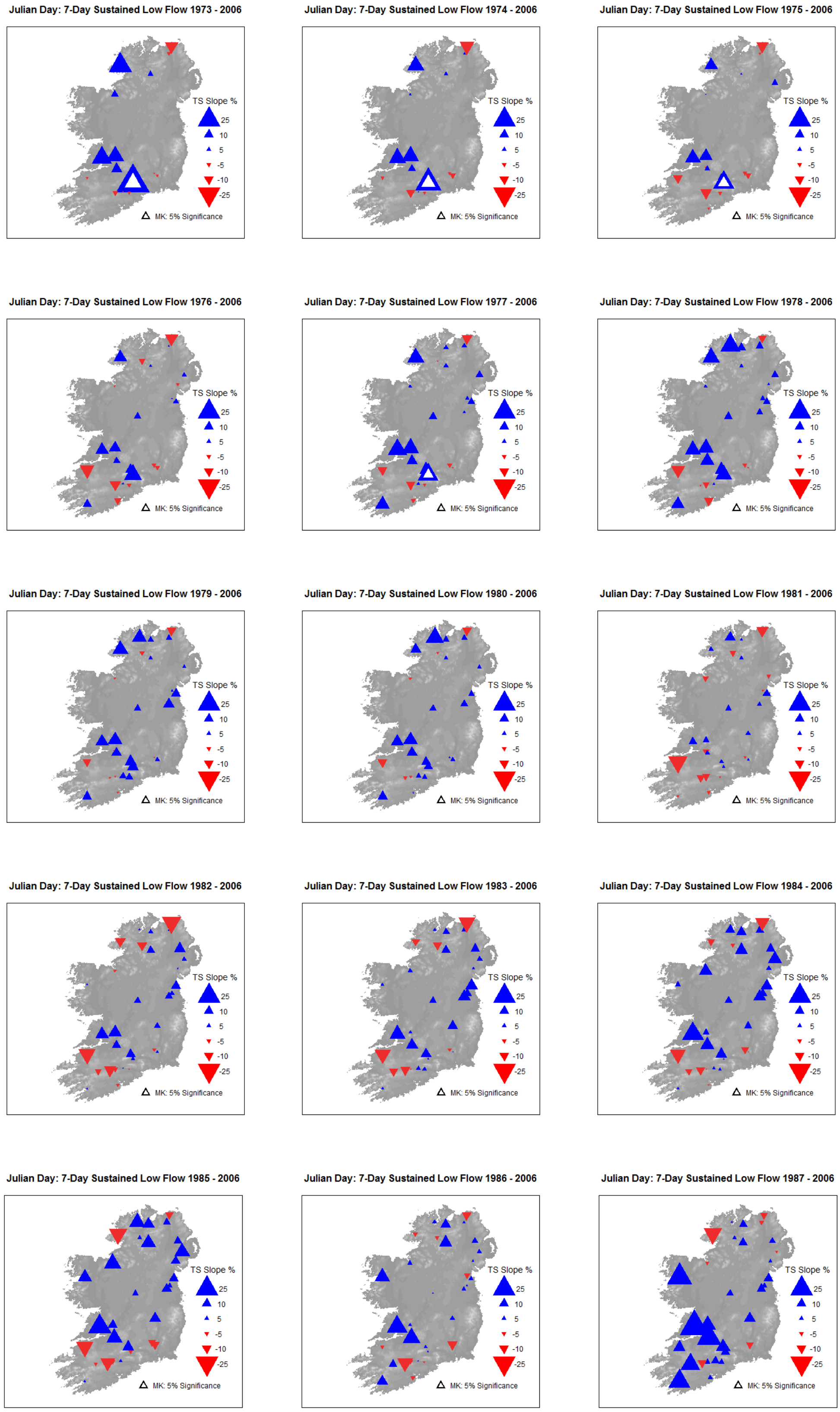


Figure 3.23 Timing of 7-Day Sustained Low Flow; Trends over varying start years ending in 2006. Increasing (decreasing) trends in blue (red). Significant trends for the Mann-Kendall ZS (5% significance level) are marked by white triangles.

3.5.4 Analysis of Low Flow Indicators - Varying Start Year & End Year

To further understand the variability of trend direction and significance an analysis of varying both start and end year of analysis is performed. This allows a low flow indicator analysis to establish the effects of extremes in a long-term context.

For the long-term analysis the five stations with the longest records (1957-2009) available are used (16008, 16009, 18002, 25002, and 27002). Although this approach limits the spatial coverage, it allows the identification of combinations of start and end years that are influential in producing negative/positive trends. In Figure 3.25 to Figure 3.28 all possible combinations of start and end years resulting in a minimum record length of 10 years are analysed for trends using the Mann-Kendall (MK) Z statistic.

Figure 3.24 is provided to illustrate how Figure 3.25 to Figure 3.28 can be interpreted. The x-axis represents all possible start years and the y-axis shows all end years used to calculate MK ZS with a minimum record length of 10 years. In the three panels, each grid cell shows the number of trends derived from the respective combination of start and end years of the period analysed. In the left panel the number of positive trends is shown, out of the n number of stations (here n=25) and the middle panel shows the number of negative trends. The right panel shows the number of positive/negative trends significant at the 5% level. The grid cells in the left panel show either positive or negative significant trends, depending which sign is dominant. If for example one positive and one negative significant trend occur for the same cell, no trend is shown. The darker the blue or red colour, the more stations show positive or negative trends respectively. If extreme low or high periods for a specific indicator are present, which are influential to the overall trend derived from the MK statistic, this period results in darker coloured clusters/bands in the panels. Vertical dark coloured bands show an influential start period (e.g. 1985 for negative trends in Figure 3.24), whereas horizontal bands indicate a strongly influential end date (e.g. 2009 for positive trends).

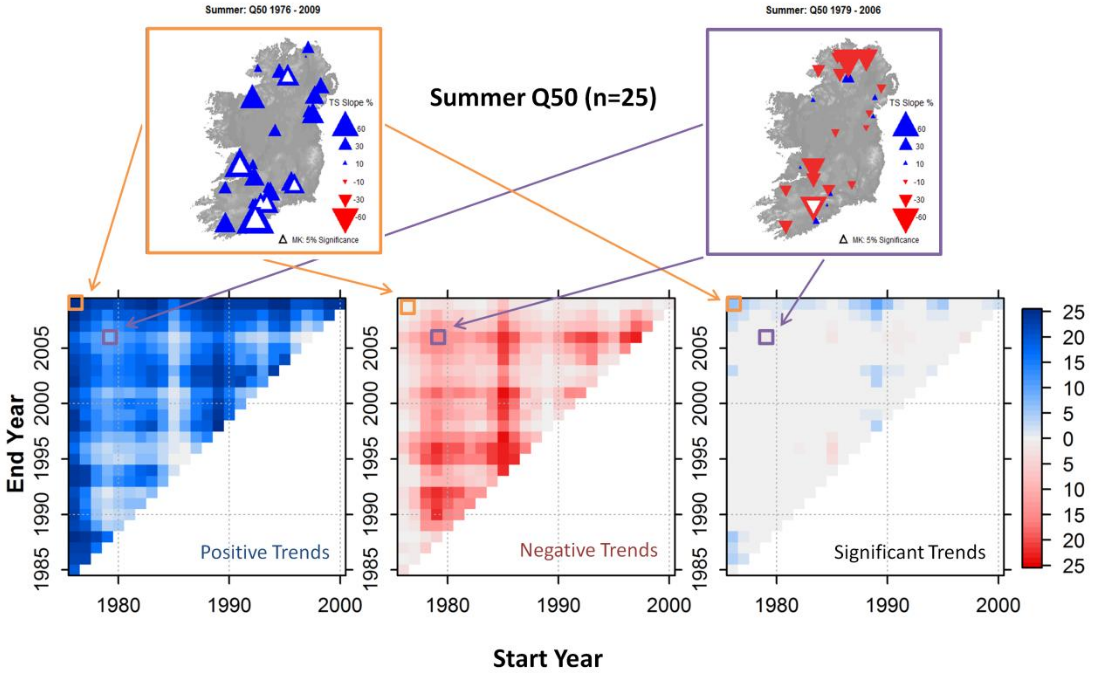


Figure 3.24 Illustrative interpretation of Figure 3.25 to Figure 3.28 using summer Q50 (orange: 1976-2009, purple: 1979-2006) as an example. Positive (negative) trends are shown in blue (red). Trends are significant at a 5% slevel. Each grid cell summarises the spatial trends obtained from the maps.

All indicators are analysed for trends using the Mann-Kendall statistic with varying start and end years. Only seasonal Q50, Q75 and Q95 and for the m-day low flows only magnitude and timing of the 7-day and 30-day Sustained Low Flow are shown. Seasonal mean flows, Q70 and Q90 as well as 7-day and 30-day moving average flow for the five stations with long records are provided in Appendix I. *Qn* flows for all seasons are analysed to present the changes in the seasonal low flow regime. Changes in some seasonal low flow indicators (e.g. winter *Qn* flows) might not directly effect in-stream water abstractions, but have implications for aquifer and reservoir recharge can have substantial implications for water resources management. Additionally, drought events have been shown to be associated with clusters of dry winters or low winter flows (Marsh *et al.*, 2007).

In the next section, the results for the *Qn* flows are presented, and then the results from the sustained low flow analysis are examined.

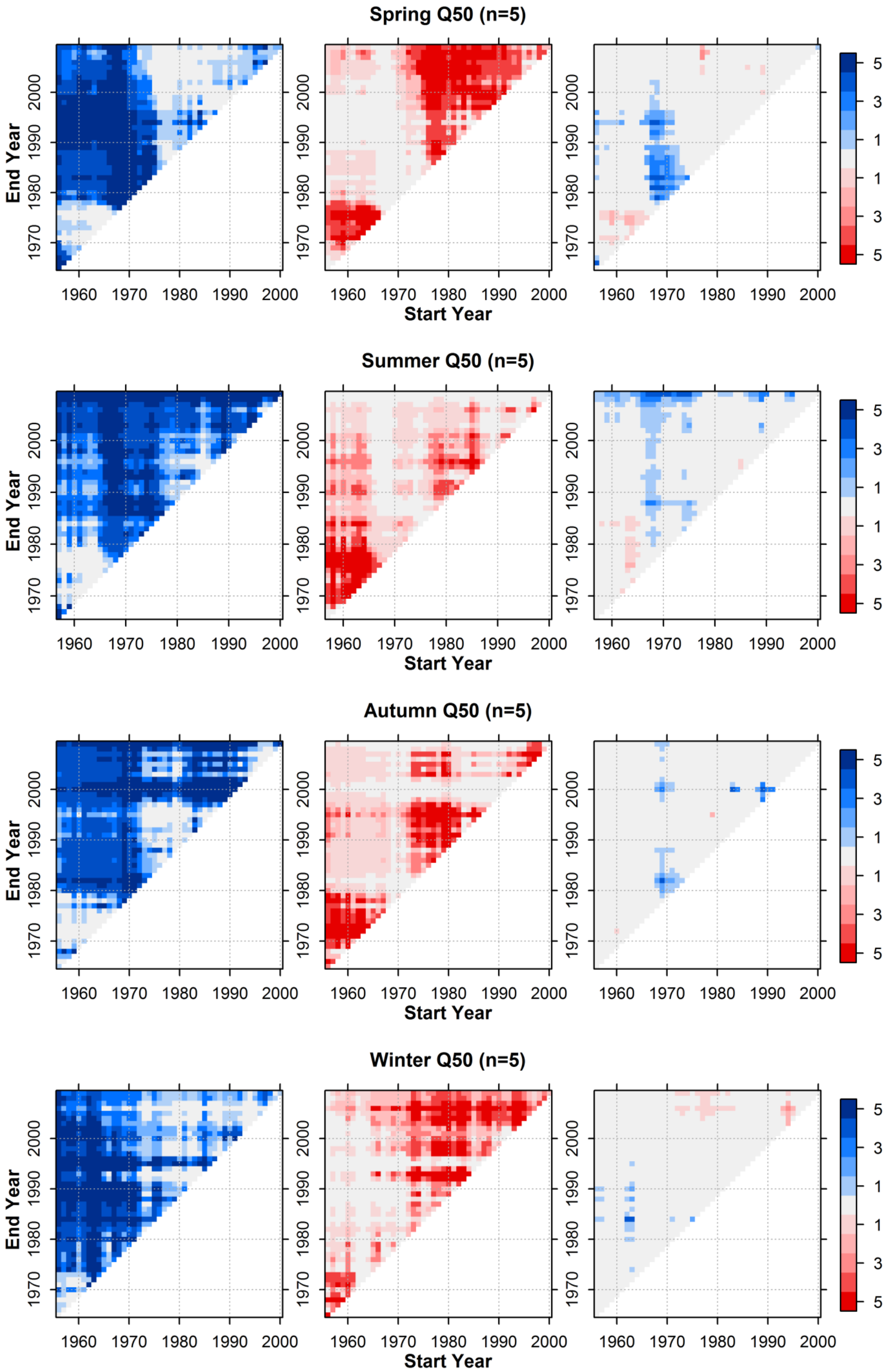


Figure 3.25 Trends in seasonal Q50 Flows for five stations with long records, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

Figure 3.25 shows the trends in seasonal median flows (Q50). For spring Q50 flows, there is a clear change in direction of trend with start years around the mid-1970s. The significant positive trends (5% level) that were apparent for analysis starting around 1980 then disappear for end years around 2000.

Summer Q50 flows for trend tests ending from 1980 onwards are predominately positive. High numbers of significant positive trends are found for most of the start years for trend analysis ending in 2008 and 2009. Additionally the influence of the drought conditions in the late 1960s/early 1970s are apparent in producing significant positive trends for trend tests starting around that period, for most of the long-term records.

This long-term information allows setting the results from the previous analysis in the long-term context. With this analysis, it can be shown that these trends are caused by the end year(s) of analysis. As these trends are only a recent phenomenon time will show if the trends continue, i.e. if this is an emerging signal, or if this is only caused by the extremes.

From the autumn Q50 flow in Figure 3.25, there is a change from increasing to decreasing trends starting around the mid-1970s. For trends starting after the mid-1980s, there is no clear persisting positive or negative trend signal. Winter Q50 shows positive trends for all tests starting before the early 1970s, thereafter trends are predominantly negative. This characteristic is evident for all end years.

Mean Flows show similar patterns of clusters of increasing and decreasing trends as Q50 flows in spring and autumn (Figure shown in Appendix I). However, trends beginning around the mid-1960s to mid-1970s show a tendency of becoming significant, particularly for trends ending around and after 2000. This tendency is not apparent in Q50 autumn flows and might be caused by a strong contribution of high flows on the mean flows.

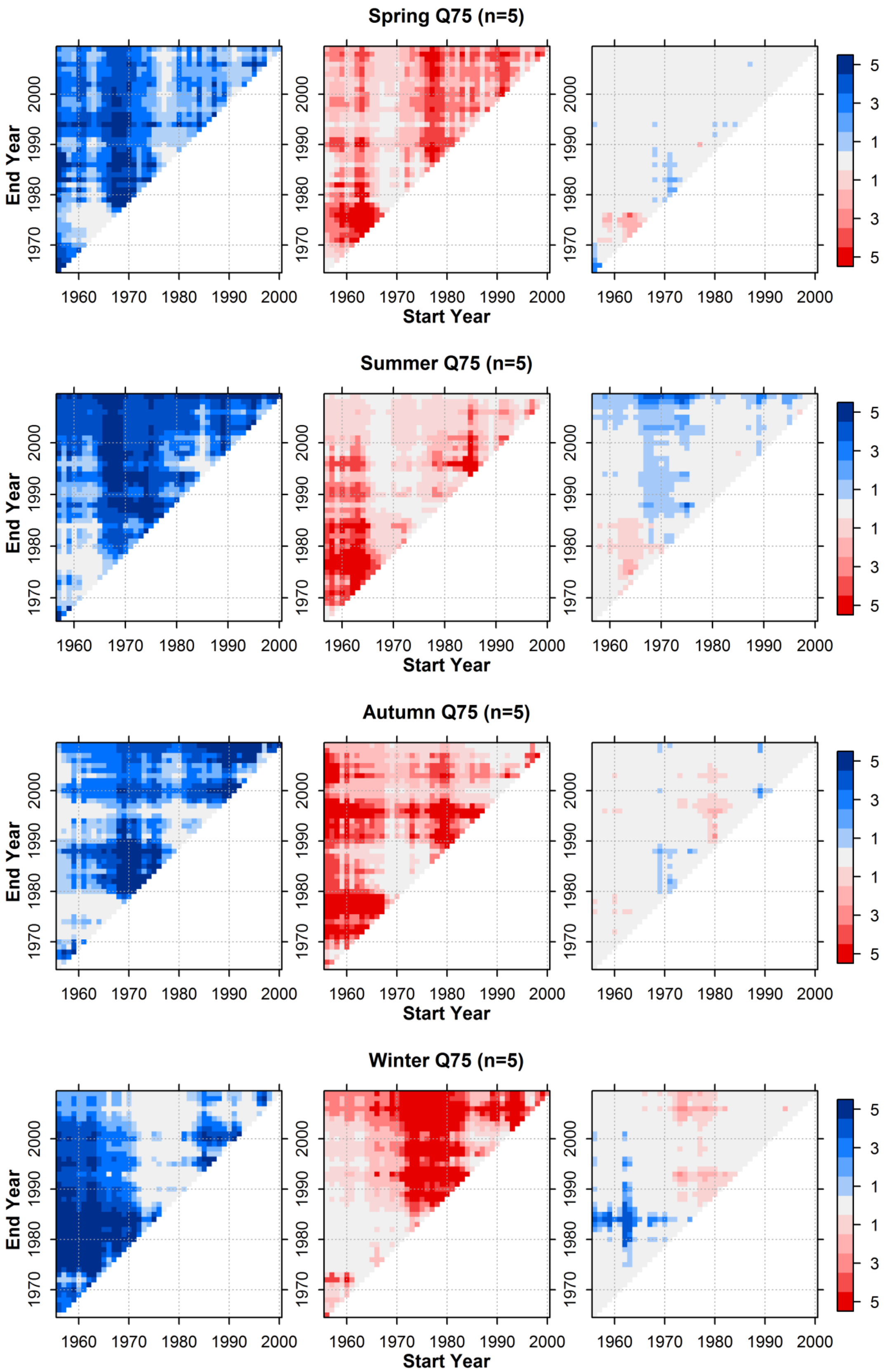


Figure 3.26 Trends in seasonal Q75 Flows for five stations with long records, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

From Figure 3.26, spring Q75 shows a mixed pattern of increasing and decreasing trends depending on the combination of start and end years. The change in trend direction for analysis starting around the mid-1970s seen in Q50 flows is less pronounced for trend tests staring from the 1980s onwards. Overall, few significant trends are evident in spring Q75, particularly for longer records analysed.

Summer Q75 and Q50 flows have a similar temporal pattern of trends, with predominately positive sign for trend tests starting from the mid-1960s onwards. Tends derived from records ending after mid-1980s become positive for tests starting in the 1970s. For analysis ending from 2000, the prevailing trends are positive, with higher numbers of significant trends compared to Q50.

The change from positive to negative trends around the 1970s that is apparent in autumn Q50 flows in Figure 3.25 is not apparent in Figure 3.26 for Q75 flows. Generally, the trends show mixed clusters, and trend sign changes within years.

The signal of change in trend results for analysis starting pre and post 1970s is more pronounced for winter Q75 flows compared to Q50 flows. The same divide is also apparent for the high number of the trends in Q75 that are significant at a 5% level. The trends derived for Q70 (shown in Appendix I) show a very similar pattern to Q75.

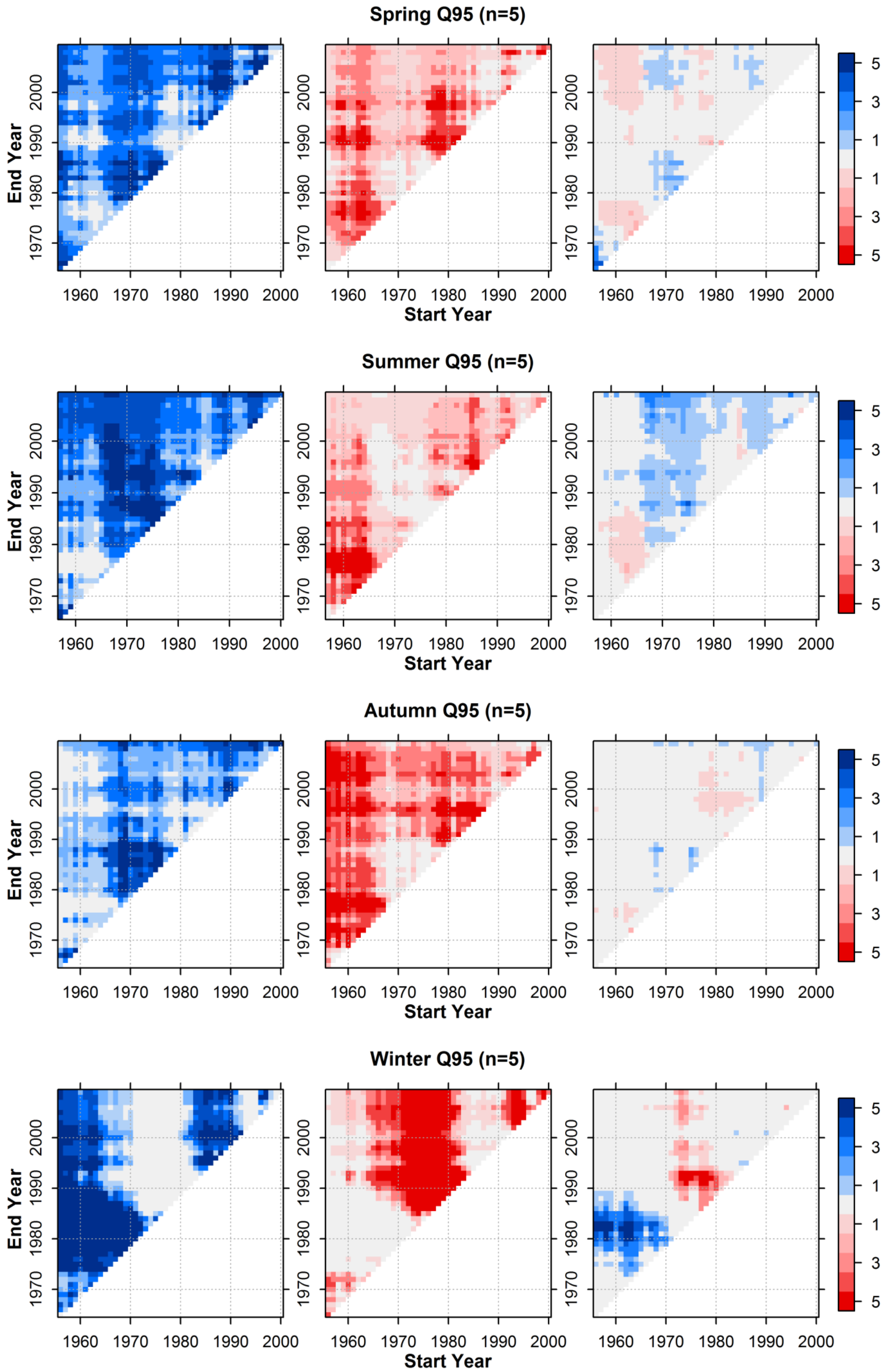


Figure 3.27 Trends in seasonal Q95; Flows for five stations with long records, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

In Figure 3.27, the trends in seasonal Q95 are shown. The trends obtained for all seasons are similar to Q90 flows, shown in the appendix. Spring Q95 flows show a mixed pattern of increasing and decreasing trends similar to Q75. From 2000 onwards, long records show a single dominant significant negative or a positive trend.

Summer Q95 flows show a change from negative to positive trends for tests starting from mid 1960s onwards. This also becomes apparent in the high number of significant positive trends after that period. This is also evident in summer Q90 flows (shown in Appendix I).

Autumn Q95 flows with early start years show the opposite trends that were apparent in Q50. For Q95 and Q90 flows, trends starting pre 1970s are predominantly negative, compared to predominantly positive Q50 (Figure 3.25) flows for the same start years.

From Figure 3.27, winter Q95 flows show distinct phases of positive MK Z statistics for trends starting around pre 1970s and post the 1980s. A discrete phase of negative trends is found between these positive phases. These phases can also be found in winter Q90 flows. Trends starting from the mid-1950s up to the 1970s and ending between the mid-1970s and 1990 show a cluster with a high number of positive trends. A cluster of high number of negative trends for tests starting between 1970 and 1980 and ending in the early 1990s is also evident.

These patterns of distinct phases for winter Q95 and summer Q95 are on line with the finding by Marsh *et al.* (2007), indicating that clusters of low winter flow can cause clusters of low flows in the subsequent summer.

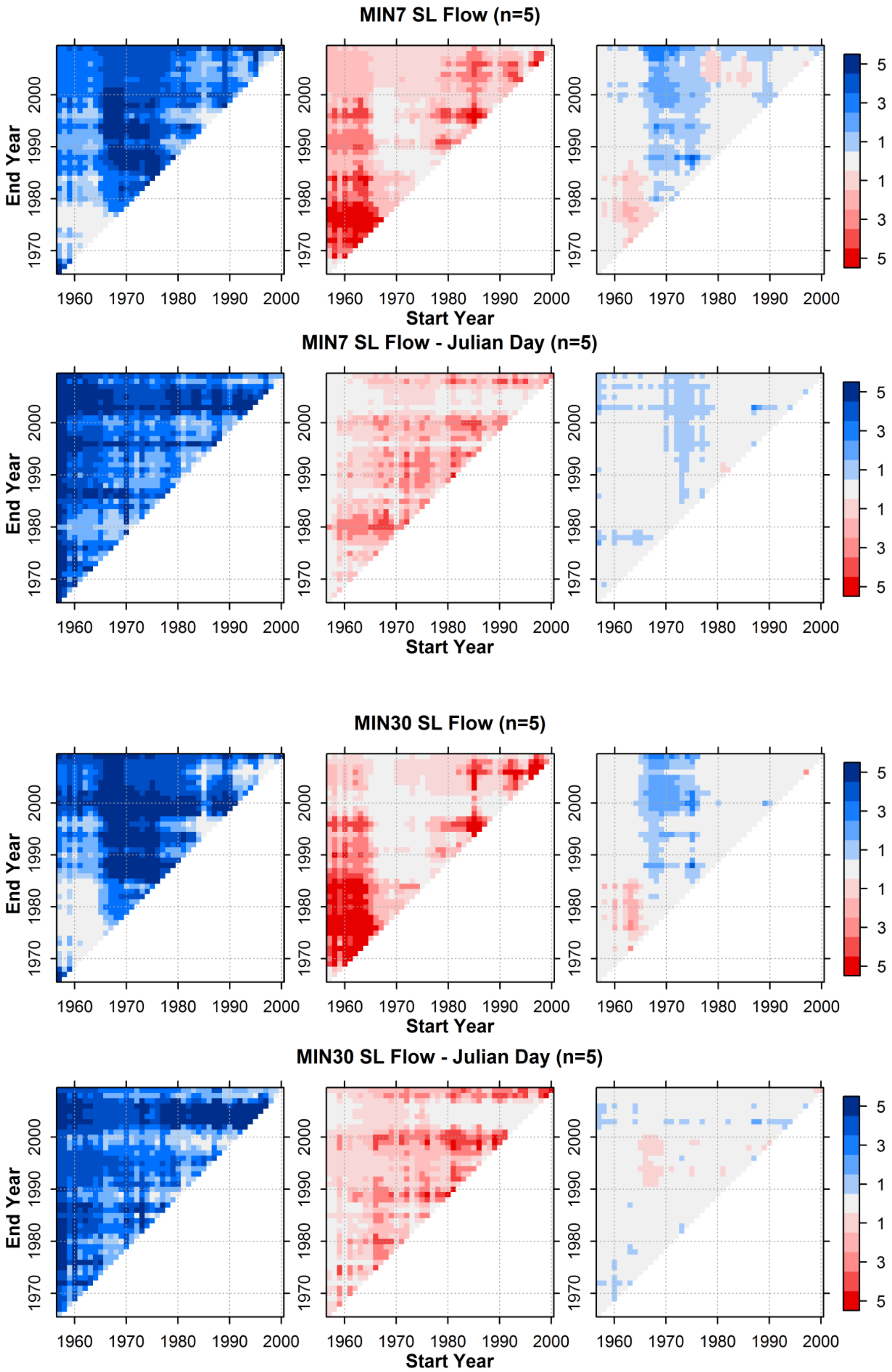


Figure 3.28 Trends in Magnitude and Timing for 7-day and 30-day Sustained Lows, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

In Figure 3.28, the trends obtained for the magnitude and timing (Julian Day) of the 7-day and 30-day sustained low flow are shown. The patterns obtained for the trends in magnitude are similar for both sustained low flow periods. Trend tests starting before mid-1960s show a negative tendency, which becomes increasingly positive the longer the investigated record becomes. Trends analysed with start years before mid-1960s result in predominately positive trends, with a strong cluster of significant trends starting through the 1970s. The long term drought condition is apparent for both the 7-day and the 30-day sustained low flow, indicated by the dominance of significant positive trend

The trends obtained for the timing of the 7 and 30-day sustained low flows shows that there is no clear pattern of these prolonged low flow periods occurring earlier or later in a year. For the 7-day sustained low flow there is one dominant station that shows significant positive trend results, whereas in the timing of the sustained 30-day flows, there is also one dominant station with both significant positive and negative trends.

It can be seen from the results derived from the analysis of low flow indicators with varying start and end years of analysis that the trends obtained are highly dependent on the time window analysed, even when analysing longer time periods. Although some indicators show similar seasonal and temporal patterns, there is no clear, persistent positive or negative trend signal emerging across seasons. However, across certain indicators similar patterns can be found.

All of the low flow indicators investigated here show high degree of natural variability, with clusters of high and low indicator values compared to the long-term mean value (inter-decadal variability). In addition, periods of extremes in the indicators appear to be present for the end of the analysis period, even for the longest records in excess of 50 years (found in the upper left corner of the graphs). This indicates that the suggestion by Kundzewicz & Robson (2004) and Yue *et al.* (2012) of a minimum length of 50 years to confidently detect temporal trends might not be enough to lessen the influence of extremes, particularly at the start and end of record.

For the low flow indicators analysed, the signal of change obtained from the trend analysis is low compared to the noise (variability and outliers) in the time series analysed. A lack of dominant significant persisting trends does not mean that there is not a long-term signal in the hydrological time series analysed. No significant trends can also be cause by a positive and a negative trend obtained from different stations cancelling each other out. However, it is difficult to estimate from these time series when a change in signal (of long-term climate change with or without human causes) might become detectable.

Because of such a low change signal to noise ratio, apparent trends derived from fixed-period analysis cannot be used as confident guides to inform future water resources planning and decision-making, as change in study design can change the outcomes to a high degree. Therefore it is important not only to evaluate the magnitude of trends (i.e. Theil-Sen Slope) in observed records or their significance, but also when a trend of a certain magnitude in a given indicator will be detectable to inform decision-making or what changes might be required to produce and detect trends for a certain significance level.

3.6 Detection Times & Magnitudes of Trends in Low Flow Indicators

The time required to statistically detect any trend is dependent on the variability in the records, the trend magnitude and the setup of the statistical test. As described in Section 3.2.2, the null hypothesis H_0 for the statistical test here is 'no trend' with the alternate hypothesis H_1 being 'trend'. Whether a trend is detected depends on the two types of statistical errors (Type I and Type II). Before conducting a statistical trend analysis the setup of the statistical test, i.e. the levels of α (confidence level of a test) and β (power of a test) need to be predetermined. Based on the assumption that the population trend magnitude (τ) and the standard deviation (σ) are known (for samples > 20) (Lettenmaier, 1976), Ziegler *et al.* (2005) provided an equation that relates the time needed (in years) to detect an observed linear trend of a certain magnitude (τ) to a specific α and β and the variance (σ^2) of the time series. Wilby (2006) solved the equation to obtain the detection time y_{detect} (in years) (Equation

3.11), where $W_{\left(1-\frac{\alpha}{2}\right)}$ and W_{β} are the standardised normal deviates at cumulative probabilities $\left(1-\frac{\alpha}{2}\right)$ and β respectively (Ziegler *et al.*, 2005).

$$y_{detect} = \left[\frac{12\sigma^2}{\tau^2}\left(W_{\left(1-\frac{\alpha}{2}\right)} - W_{\beta}\right)^2\right]^{\frac{1}{3}} \qquad \textbf{Equation 3.11}$$

Additionally, this equation can be rearranged to obtain the minimum trend magnitude (τ_{min}) (per year) needed to be statistically detectable by a given time period (Wilby, 2006) with a specific α and β and the variance (σ^2) of the time series (Equation 3.12).

$$\tau_{min} = \left[\frac{12\sigma^2}{{y_{detect}}^3}\left(W_{\left(1-\frac{\alpha}{2}\right)} - W_{\beta}\right)^2\right]^{\frac{1}{2}} \qquad \textbf{Equation 3.12}$$

Here estimates of detection times and minimum trend magnitude are derived using the statistical criteria of $\alpha = 0.05$ and $\beta = 0.10$, which give a low probability of detecting a trend when it is not occurring (Type I error) and not detecting a trend when it is occurring (Type II error) (Ziegler *et al.*, 2005; Wilby, 2006; Harrigan, 2010). In line with these authors, the minimum number of years (y_{detect}) or the minimum trend magnitude (τ_{min}) needed to detect a trend from the year 1990 is calculated. The year 1990 has been chosen as reference year as this is the end of the reference climate period (1961-1990). For brevity, only the results of two illustrative indicators, Q50 and Q95 are presented.

3.6.1 Estimates of Detection Times for specific Trend Magnitudes

As the sample variance (σ^2) is a key variable of both equations, the influence of the sample variance derived from a specific fixed period of observations on detection times is explored. y_{detect} is calculated with variance calculated from alternating start years of analysis for each station. This means for each station *n* estimates of the sample variance are derived firstly using the period 1976-2009, and then sequentially dropping the start year (e.g. 1977-2009) to a minimum of 20 years (1990-2009). This variance is then used to calculate y_{detect} for three hypothetical trend magnitudes (5%, 20% and 40% change) that represent uncertainties in the ranges of potential future changes. These trend magnitudes are selected to represent a linear anthropogenic climate change signal in river flow as simulated for mean monthly flows by impacts assessments from catchment based studies in Ireland (e.g. Steele-Dunne *et al.* (2008)). By plotting the y_{detect} for each start year iteration the influence of the selected period can be evaluated.

Figure 3.29 shows the detection times derived for summer Q50 (left) and summer Q95 (right) for different magnitudes of assumed change. Following the method employed by Wilby (2006) the percent changes in the indicator are assumed to be linearly distributed over the period from 1990 to the mid-2020s (2025).

For both, Q50 and Q95, depending on the sampled variance, large differences in detection times are obtained. y_{detect} obtained for summer Q50 is less influenced by the change in the start year, with the exception of station 205008 and station 206001 (North Eastern and Neagh Bann RBD respectively), which show a particularly strong reduction of detection times when variance is calculated after 1986, which represents a lower variance relative to the full record. For summer Q95, the influence of individual years on the detection times is more pronounced. For example for a 5% change by the 2020s, station 27002 (Shannon RBD) shows a detection time of 344 years when the variance of the period 1958-2009 is used, whereas y_{detect} drops by 40 years when the variance of the period 1959-2009 is used.

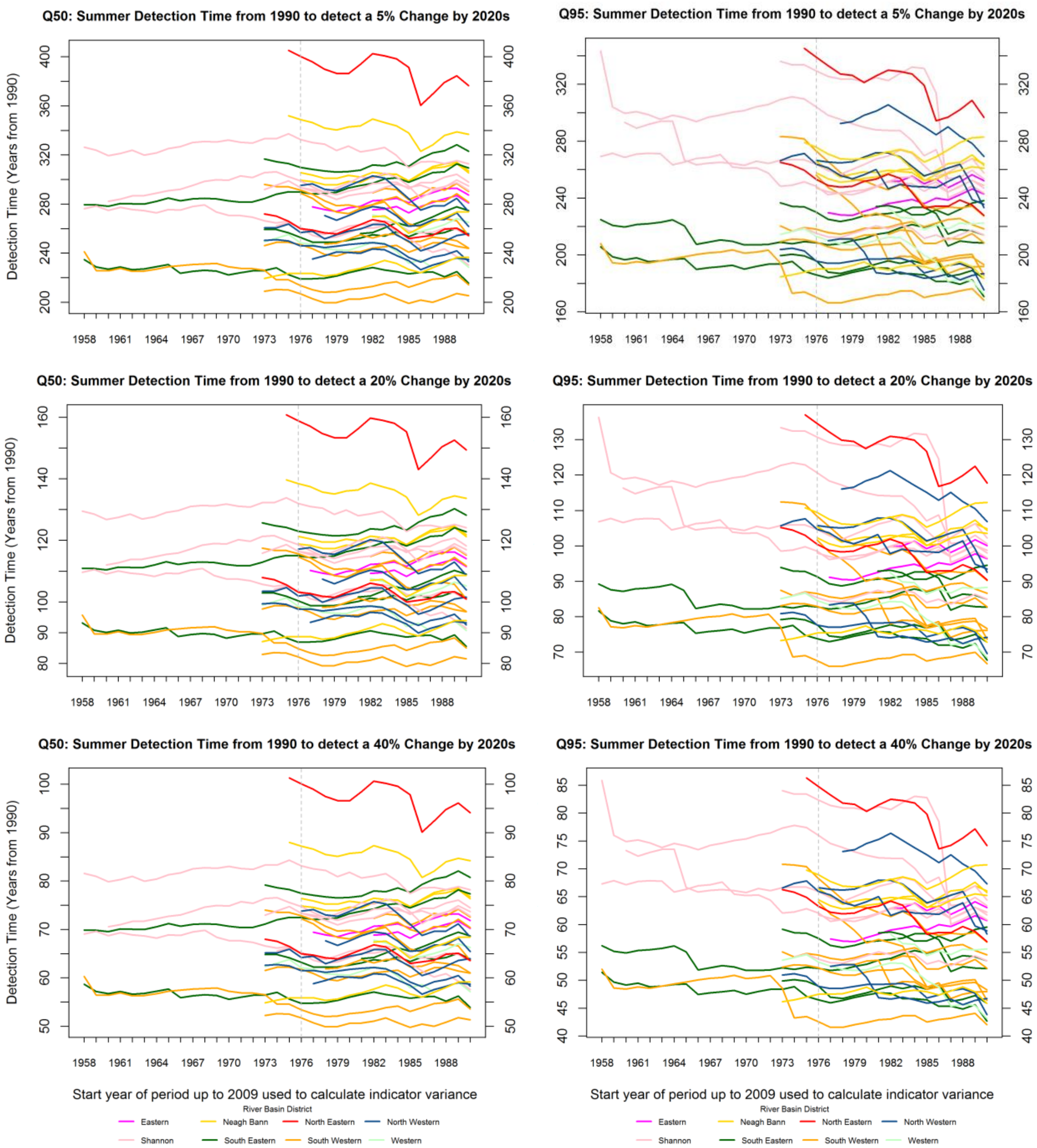


Figure 3.29 Dependence of detection times on sample variance determined from start year of period for each station (from 1990). Left summer Q50, right summer Q95. From top to bottom; 5%, 20% and 40% change by 2020s. The vertical grey line marks the start year (1976) of the fixed period.

For summer Q95 there are several such drops for several stations, highlighting the influence that extremes in individual years can have on the increase in detection time. A particularly strong increase in detection time is apparent for station Scarriff located at the River Graney (25030, Shannon RBD). If the variance is calculated post 1987, the detection times are around 240 years, whereas if the period used to calculate the variances include 1986 and earlier start years, the detection times are around 320 to 330 years. This strong increase in detection times (80 to 90 years longer) is caused by two extreme years (see Figure 3.30), where Q95 flows were over three times larger than the long-term average for station 25030. These years with unusually high Q95 flows, result in a strong increase in the variability of the time series, thereby lowering the signal to noise ratio, which decreases the detectability of any change signal present in the data.

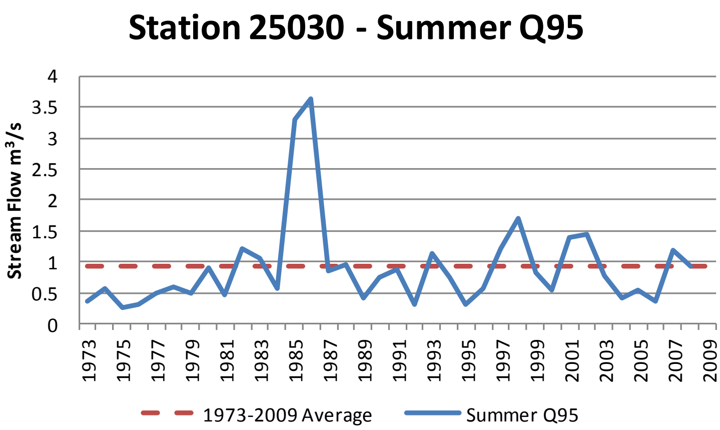


Figure 3.30 Summer Q95 Flow for Scarriff (Station 25030) at the Graney River (blue) and long-term average Summer Q95 (1973-2009) in red.

For both indicators, independent of the hypothetical magnitude of change employed, the relative differences in the detection times between the individual stations depend on the level of variance in the period of observations sampled. This finding is also true for individual indicators where those that show a higher variance reveal longer detection times for climate change signals to emerge. From Figure 3.29 it can be seen that changes of the same magnitude in summer Q50 might take longer to be detectable compared to changes in Q95. For example for a 5% change in the indicator with the variance derived from 1976 to 2009 (indicated by dashed vertical grey line), the detection times (from 1990) range from 210-400 years for summer Q50, whereas the ranges for summer Q95 are around 170-340 years. Therefore, the climate change signals in key indicators for water resource management will not be statistically detectable in the timeframe necessary for anticipatory adaptation.

Additionally, the results in Figure 3.29 show that the higher the magnitude of change or the greater the climate change signal (displayed here as the percent change) the lower the detection times. For a 20% change in summer Q95 the detection times range between 65 and 135 years and for a 40% change between 43 and 86 years. Therefore, even with the magnitude of change at the limits of the extremes from climate change impact assessments, climate change signals will not be detected in the time frame required for planning and implementing anticipatory adaptation, if action is taken only after the signal emerges from the noise.

Even when the indicator and station is selected to enhance the magnitude of the climate change signal or minimise the variance respectively, it is unlikely that trends will be statistically detectable using traditional tests at commonly used significance levels (i.e. 5% or 10% significance levels). For the two indicators analysed the lowest detection time of ~45 years is obtained by station 18002 (at Ballyduff, River Blackwater, South Western RBD), for a 40% change in Q95 by mid 2020s. This means that in such a setting even in the best case of such a strong trend, trends might not be detectable until ~2035. This result is obtained with a relatively low sample variance estimated from observation over the period 1976-2009. With longer records, it is likely that the variance of the sample would increase and therefore increase detection times. Additionally, if there is a future increase in the variance of the indicators analysed, the trends will take longer to be detectable under the statistical framework employed.

Overall, there are no spatial patterns for specific River Basin Districts or for specific time periods to produce shorter or longer detection time across all different start years used to calculate variance estimates. Therefore, it is concluded that the period 1976-2009 is representative of the average variations in y_{detect} for most of the stations investigated and also allows benefiting from the highest sample variance. This period will be used to estimate the sample variance from observations for the next steps of analysis. It is acknowledged that the longer periods used to estimate the variance will result in longer detection times. However, the period 1976-2009 is selected to include as many stations as possible in the analysis.

An illustrative example of estimated detection times for the IRN is provided. The focus of the analysis is not on individual stations but on the y_{detect} derived from all low flow stations used in this chapter. Estimates of how long it might take for a certain percentage of stations (e.g. 50%) to show a statistically significant trend are derived. Such an approach can have practical implications for water resources planning, as for example decision-making could be delayed until a certain number or percentage of stations show significant trends.

Employing the sample variance from the period 1976-2009, possible detection times (y_{detect}) for both seasonal Q50 and Q95 are calculated for all stations. From Figure 3.29 it can be assumed that the sample variance of the selected period is representative of the variance derived from periods starting within the next three years. Therefore, stations commencing their record within the next three years of the selected period are also included in the analysis (with the sample variance derived from the longest possible record). Stations with shorter records are omitted from the following analysis resulting in 29 stations being analysed for detection times and trend magnitudes.

The calculations of y_{detect} are based on two hypothetical change magnitudes (20% and 40%) linearly interpolated from 1990 up to the mid-2020s (2025) and mid-2050s (2055). Hypothetical estimates of percent changes per indicator have to be applied as future stream flow simulations have only been conducted for a small number of flow series, most of which are not part of the IRN network.

Figure 3.31 and Figure 3.32 show estimated detection times from 1990 for all seasons for Q50 and Q95 respectively. A 20% change in the indicator is shown as solid lines, whereas bold lines indicate a 40% change. Detection times based on these changes happening by mid-2020s and mid-2050s are plotted in red and blue respectively. The horizontal dashed lines show 25% (8 stations), 50% (14 stations) and 75% (21stations) of the stations.

Overall, for each station, the stronger trend (40% change) has a lower y_{detect} to be detectable at the 5% significance level, compared to a 20% change. The detectability increases and therefore the detection times decrease due to an increased signal to noise ratio. If the same change magnitudes are used over different timeframes (i.e. 2020s and 2050s), lower detection times are estimated for the 2020s, as the same trend magnitude is experienced over a shorter time period.

For both indicators, the lowest values for y_{detect} are shown in winter. For example, for winter Q50 the shortest detection times indicated by a station for a 40% change by the mid 2020s is 31 years ranging up to longest detection times of 125 years for a 20% change by mid 2050s. For summer Q50 the detection times for the same scenarios range from 50 up to 258 years. These differences in detection times of each indicator are due the difference in variances in each specific indicator. Lower variances in winter Q50 result in lower detection times.

Additionally, for both winter indicators the differences in y_{detect} between 25%, 50% and 75% of the stations are smaller compared to other seasons. For example in winter Q95 (20% change by 2050s) the mid-range of stations shows a range between approximately 115 to 130 years, whereas for summer Q95 the mid 50% of the data indicate detection times between 130 and 180 years. This means for winter Qn that there is a closer agreement in the mid-range of stations on the detection times required, compared to the other seasons. However, this close agreement only applied to the mid-range of detection times. Individual stations can cause the maximum detection times for specific indicators to increase considerably (e.g winter Q95).

For water managers summer Q50 and summer Q95 are important indicators of water availability. However, these indicators show the highest detection times of the investigated indicators. For example a 40% change by 2020s is estimated to be detectable for at least 50% of the stations for summer Q50 by 2055 (65years from 1990) or for Q95 around 2050 (y_{detect}=62 years). Therefore, it is not only important to determine when such changes might become detected but also what magnitude of change might be required to detect a change by the 2020s or 2050s at a certain significance level.

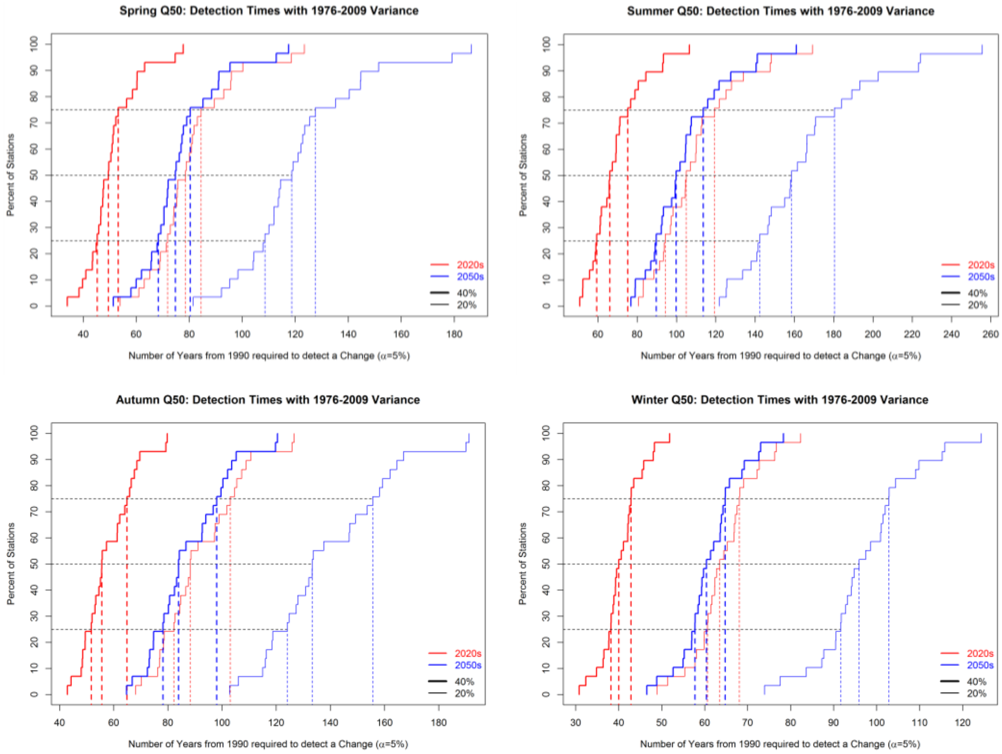


Figure 3.31 Detection Times of Seasonal Q 50. 20% (40%) changes are shown solid (bold) lines. Changes occurring by mid 2020s (2050s) are plotted in red (blue). Dashed horizontal lines show from bottom to top 25%, 50% and 75% of the investigated stations.

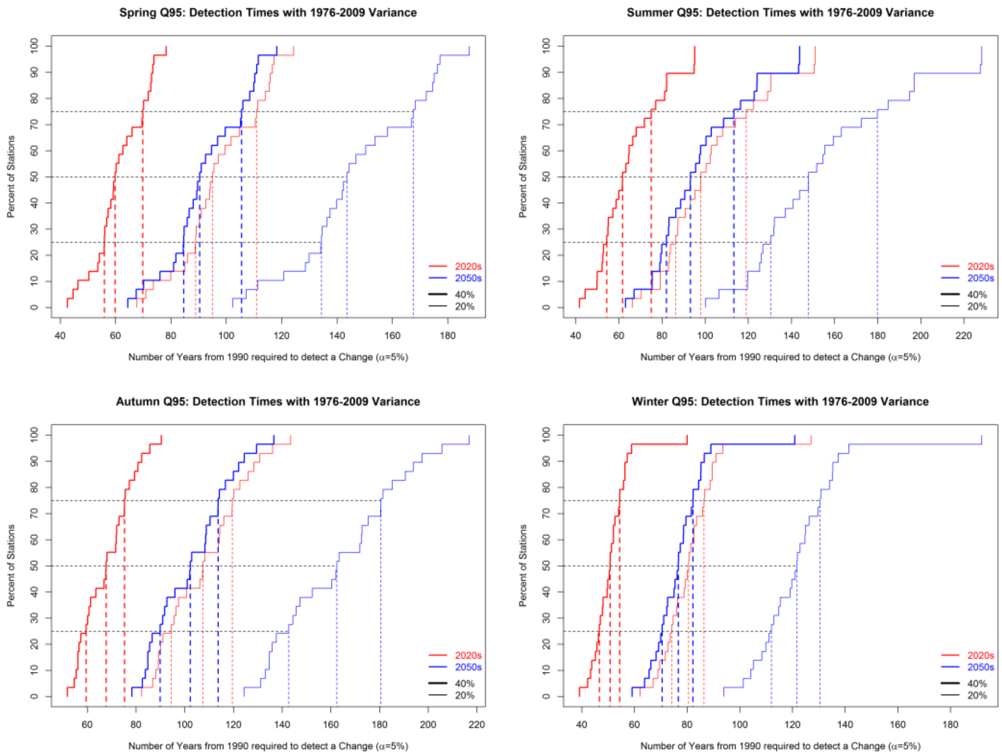


Figure 3.32 Detection Times of Seasonal Q 95. 20% (40%) changes are shown solid (bold) lines. Changes occurring by mid 2020s (2050s) are plotted in red (blue). Dashed horizontal lines show from bottom to top 25%, 50% and 75% of the investigated stations.

3.6.2 Estimates of Magnitude of Change required for Detection

With a conservative significance level of $\alpha=0.05$, the detection times obtained in the previous section show that future changes might not be detectable in the majority of stations in the timeframe required for preparing for and adapting to these assumed linear changes. However, the detectability of changes not only controlled by the strength of the change signal and the natural background variability, but also by the significance level employed. By selecting a less stringent significance level, the detectability of trends increases, however, at the same time the risk of falsely statistically detecting a change, when no change is occurring, also increases.

This section therefore investigates the minimum magnitudes of change required for linear trends to be statistically detectable at specific significance levels for two time periods. Two different significance levels, $\alpha=0.05$ as previously employed and a less strict criteria for a Type I error of $\alpha=0.1$ are analysed. For both indicators the magnitudes of change required for detection by 2025 (mid-2020s) and 2055 (mid-2050s) are estimated, again assuming monotonic trend.

Figure 3.33 shows the minimum magnitude of change required for summer Q50 (left) and Q95 (right). Changes occurring by the mid-2020s and mid-2050s are plotted in red and blue respectively. Light colours represent a significance level of $\alpha=0.05$ whereas darker colours represent a lower significance criteria of $\alpha=0.1$. Dashed horizontal lines show from bottom to top 25%, 50% and 75% of the investigated stations.

Both investigated indicators show shorter detection times when the significance criteria are less strict reducing the required magnitudes of change on average by about 10%. However, the magnitudes for change required to be detectable by 2020s in Q50 are very high ranging from 63% ($\alpha=0.1$) to 213% ($\alpha=0.05$). The lowest change required is indicated by the station Agivey located on the Whitehill (203028) (NB RBD) with a magnitude of 63% ($\alpha=0.1$) or 70% ($\alpha=0.05$) with a maximum of change required 212% ($\alpha=0.05$) for station 205008 (Lagan) located on the Drumiller (NE RBD).

For 50% of stations to have a detectable trend in summer Q50 by the 2020s a 95% change (α=0.1) or 105% change (α=0.05) in the indicator is required. Similarly for summer Q95 if a change is sought to be detected in at least 50% of the stations, a change of 85% (α=0.1) or ~95% (α=0.05) is required. Although a less strict statistical criterion is used, the changes in magnitude required for linear changes to become statistically significant are very high and very unlikely to be experienced.

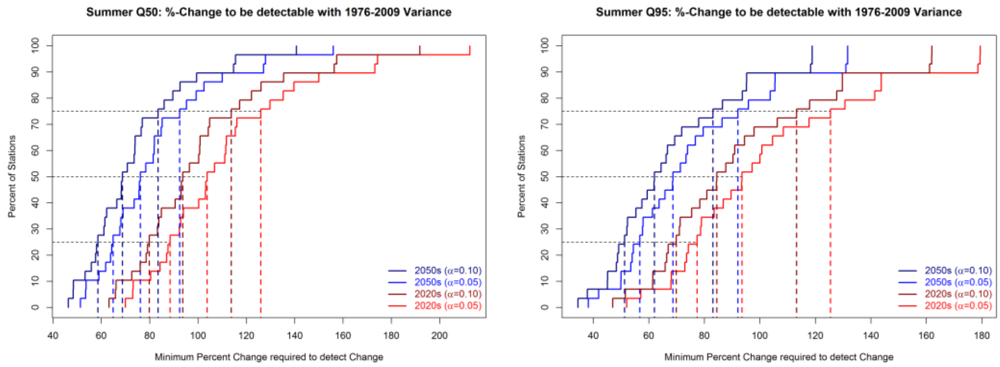


Figure 3.33. Minimum change magnitude required for summer Q50 (left), Q95 (right). Changes occurring by mid 2020s (2050s) are plotted in red (blue). Light (dark) colours represent a significance level of α=0.05 (α=0.1).Dashed horizontal lines show from bottom to top 25%, 50% and 75% of the investigated stations.

Depending on the indicator and site selected, the sample variance of the indicator, and the magnitude of trend, different detection time estimates are obtained. Overall, changes are unlikely to be statistically detectable for many years and in most cases not within the time required for informing anticipatory adaptation in the water resources sector.

Additionally, the minimum changes required to be detectable are large, and well beyond any simulated impacts to date. This means that water management and planning for anticipated future changes will be required to take place without these changes being formally statistically detectable. This presents a challenge for local scale adaptation where expensive investment may be required where evidence, based on traditional statistical frameworks and standards may not be available. When this is coupled with the uncertainties associated with future projections of climate change impacts at local scales it shows that new tools and approaches are required for effective adaptation.

3.7 Discussion and Conclusion

In this chapter, the first research aim and supporting objectives have been addressed by deriving selected flow indicators from Irish river flow records and by analysing these for evidence of climate-driven changes.

The time series of 34 flow records analysed, have been taken from an Irish Reference Network (IRN) consisting of near-natural reference stations. By analysing flow indicators derived from the IRN, the prime confounding factors such as poor data quality and artificial influences are substantially reduced. However, any analysis will always be dependent on the historical legacy of such a network. Within the Irish Reference Network, only five hydrometric stations with long good quality records (particularly in the lower flow regime) are present. Most of the flow records in the network begin around the mid-70s, a time period heavily influenced by the prevailing drought conditions. Additionally, exceptionally wet years, which are also reflected in river flows, occurred at the end of the available flow records. The presence of these extremes at the start and the end of record makes the extraction of robust trends and the detection of a climate change signal difficult.

A wide range of stream flow indicators covering the lower part of the flow regime and of direct relevance to water management have been analysed for trends. The results obtained from the analysis showed that different parts of the flow regime respond differently to changes in the precipitation inputs. For the set period of analysis (1976-2009), the seasonal trends obtained (increases in summer low flow indicators), are contradicting the projected changes in Ireland of drier summers for both precipitation and mean river flows. However, when the extremes at the start and particularly end of the record are removed by using shorter time periods this contradiction remains but is not as strong. Nonetheless, there is little evidence of persistent significant trends that can be associated with an anthropogenic climate change signal. Time will tell if the recent wet summers are part of the natural variability found in the hydrological system or are an indication of a long-term climate driven trend.

Natural variability of river flow can occur in relation to changes in regional large-scale atmospheric circulation, which are influenced by large-scale climatic processes (Sen, 2009). The most important driver of natural climate variability in Ireland and the UK is the North Atlantic Oscillation (NAO) (Murphy & Washington, 2001; Hurrell & Deser, 2009). Fluctuations in the pressure gradients between northern and southern parts of the Northern Atlantic are used to define the NAO indices, depending on the location of pressure measurements at the earth surface (i.e. the pressure difference between the Icelandic low and Azores high). Changes in the mean circulation patterns related to the NAO are associated with changes in the number and intensity of storms and in storm tracks (Hurrell & Deser, 2009).

A positive NAO index indicates stronger than-average and northward shifted mid latitude storm tracks (Westerlies) and enhanced rainfall activities, particularly in winter, over the British Isles. With regard to low flows and drought, Wedgbrow *et al.* (2002) found that positive winter anomalies of NAO index are correlated with drought across eastern parts of the British Isles in summer. They also showed that below-average summer flows in northwest and southwest of England and Wales were preceded by positive seas surface temperature anomalies in the North Atlantic. Therefore, it is likely that the high variability apparent in low flows in Irish rivers can be attributed to changes in the NAO index. However, to which extend the recent wet years are influenced by physical drivers such as the North Atlantic Oscillation or sea surface temperatures still needs to be further researched.

A pattern similar to Ireland, of increasing summer flows has also been identified in the UK (Hannaford & Buys, 2012). The evidence from the UK together with similar observation from Irish rivers indicates that large-scale drivers are influencing the observed pattern. However, Hannaford & Buys (2012) also conclude that this contrast between observed summer flow increases and projected summer flow decreases needs further research. Recent work by Sutton & Dong (2012) indicates that warmer sea surface temperatures in the North Atlantic are associated with wetter recent summers, which could explain the contradictions of projected changes due to anthropogenic climate change. Another study on changes in stream flow in Nordic countries, also reported discrepancies between observed seasonal trends and future projections (Wilson *et al.*, 2010). Further research on the causes of the differences between recent observations and future projections is needed; as such conflicting information presents a significant obstacle to anticipatory adaptation, particularly for evidence-based decision-making processes.

The analysis of varying start and end years in trend analysis in Section 3.5.3 and Section 3.5.4 has shown that due to large inter-annual variability it is difficult to decipher a robust climate change signal. This high natural variability results in a low ratio between any anthropogenic climate change signal and natural indicator variability. The difficulties posed by a low signal-to-noise ratio on statistical trend detection have also been pointed out by previous studies (Wilby, 2006; Fowler & Wilby, 2010; Hannaford & Buys, 2012).

A key finding from this chapter is that long-term anticipatory adaptation and planning in water resources management cannot be based on trends derived from relatively short fixed periods. As such trends are mainly dominated by inter-annual and inter-decadal variability, resulting in an ambiguous trend signal. Even though the analysis of five long-term stations (with over 50 years of data) with varying start and end year of analysis provides a better understanding of the evolution of trends, compared to the shorter periods, these long records are not enough. Although the analysis can provide some insights into trend persistence and variability, the trends derived from long stations are still strongly influenced by the extremes at the record end. Additionally, even with trends derived from records with a length of over 50 years, the observational data cannot provide the information as to whether the derived trends are 'real' trends, oscillations, regime shifts or caused by natural variability due to their short observational record compared to the timescale of natural changes. Longer records can play an important role in resolving this shortcoming.

The findings from this chapter show that depending on the study design (e.g. different start, end years or significance level and power of the statistical test selected) different trend magnitudes or even conflicting trend signs can be obtained. Trend studies need to clearly communicate these implications as otherwise misleading information can be derived from such results. Additionally, based on these findings caution is required when comparing trends from multiple studies that do not use identical methods or time series particularly when the selected period contains extremes at or near start or end dates. Overall the analysis of fixed periods can be problematic for flow indicators where the direction, magnitude and statistical significance varies considerably with the chosen period, as for low flow indicators analysed in this study.

Given these difficulties in deciphering a clear trend signal from observable records, an estimation of possible detection times and magnitudes of change needed for a trend to become formally statistically detectable has been conducted. The main factors influencing the detectability of trends, at a predefined significance level, are the magnitude of the change signal and the natural variability (noise). Depending on the time periods selected the variability and/or the trend magnitude vary, which in turn influence the detectability.

Using observational records, the detection times derived for specific magnitudes of change are large. The same applies to the change signal needed for trends to become detectable, at a specific significance level, due to a high natural variability of the investigated indicators. The estimates derived assume that change occurs linearly over time. Additionally such calculations are based on a constant sample variance. However, if the variance in the indictors increases with time, the time that will be required to detect changes will also increase.

The magnitudes of linear changes required for detection are larger than those projected. This means that water management and planning for anticipated future changes will be required to take place without these changes being formally statistically detectable. Waiting for these trends to become formally detectable might not be an option for water resources management. Trend analysis can be used as a tool for exploring the data; however, adaptation cannot wait until such changes can formally be detected with low significance levels. Additionally it is uncertain if the detected trends will continue into the future, or if the nature of expected future changes will change.

The lack of statistically significant trends and the difficulties with the future extrapolation of trends derived from observed data poses a problem for the traditional approach of evidence based policy making. This is particularly the case if a low risk approach is taken, and decisions on adaptation are based on specific statistical significance levels (small α) before action is taken. Additional methods to provide information for future water resources management are required if this traditional approach is to be continued.

In Ireland, the water supply mainly comes from local surface water sources. Therefore, local information on trends at the water abstraction sites would be important for water resources planning and adaptation. However, in Ireland most of the water abstractions sites are un-gauged. The only sources of information for decision-making based on trend analysis are therefore based on close by gauging stations or regional studies, which can be utilised to inform planning decisions. By relying on trend analysis results obtained from nearby stations there is the risk that these stations do not show trends and therefore it could be concluded that there is no trend at the water abstraction site considered. The same risk is also applied by inferring regionally derived trends to an un-gauged location, as adaptation always needs to be considered at a local scale.

The analysis of the long-term flow records available in Ireland, has shown that depending on the period of record analysed, the statistical significance of trends is short-lived. This is coupled with a strong influence of extremes at the start and end of the record when using traditional statistical techniques. However, just because a trend loses its statistical significance from one year to another, does not mean it will lose its practical significance, which means the effects of the changes (although not statistically significant) may still be important to inform practical decisions.

Overall, the analysis of trends in this chapter has shown that the detection of statistically significant and consistent trends at the local scale (site specific) is difficult. By analysing multiple sites for similar trend test results coherent regional patterns of trends and their statistical significance can be identified. However, it is difficult to conclude whether, the stations with significant trends or without significant trends represent the true trends. Therefore, local adaptation decisions in the water resources sector should not be based solely on whether a trend is significant or not.

Nevertheless, observational data is and will be the single most important source of information to understand how anthropogenic climate change translates into hydrological changes. Good quality observational records from networks such as the IRN can also be used in future to analyse changes, and over time or with the development of new techniques in time series analysis human induced change in flow might become identifiable. Additionally, observational records are also important to calibrate and validate hydrological model outputs, which in turn then also become important in informing water resources decision-making. However, if such observational data can be used always depends on the purpose and the data requirements for such a study, i.e. time series, record length, data quality, location among others.

3.8 Chapter Summary

This chapter has examined the utility of trend analysis on indices derived from river flow records in informing anticipatory climate change adaptation in the water sector. The chapter can be summarised as follows:

- The observed trends for the relatively short fixed periods can only provide a snapshot in time and are therefore highly dependent on the selected period.
- Long flow records are important to provide context for trends derived from shorter flow records, but appear still too short to represent long-term changes in an Irish context
- To date, due to high inter-annual variability and low signal-to-noise ratios, no robust anthropogenic induced climate change signals can be deciphered in low flow indicators derived from the river flows taken from the Irish Reference Network.

- The trends that are found in the data do not agree with future climate scenarios and expectations of reductions in summer flows and more severe droughts. Further research is needed to understand the differences between recent wet summers and projected summer flow reductions. Flow observations can play an important role in improving reconciliation.
- Adaptation to anticipated changes cannot wait until trends in low river flow regimes become formally statistically detectable, with traditional statistical techniques and low levels of acceptable risk, due to the high indicator variance, resulting in estimated detection times longer than required for anticipatory water resources adaptation.

The examination of the utility of hydrological time series to inform adaptation planning in the Irish water sector has highlighted, that observational records alone cannot provide sufficient information for anticipatory adaptation. Therefore, anticipatory adaptation will also need to be based on assessment of future projected changes. The following chapter describes the framework, tools and methods employed to use uncertain future climate projections in informing anticipatory adaptation decisions.

4 Framework and Tool Development for Anticipatory Adaptation

4.1 Introduction

While climate change is expected to change water resources, observational evidence from stream flow records in Ireland cannot, to date, provide the information needed for the development of planned anticipatory adaptation strategies. In this chapter, the second research aim is addressed by developing a modelling framework and tool to provide information to adaptation planning and decision-making when faced with large ranges of future outcomes and future climate uncertainties. The tool developed here is specifically designed within an Irish context to use the information on climate change scenarios, water resource systems and catchment/socio-economic data available and currently in use by national agencies in Ireland. The decision-making/ support tool developed in this chapter aims to fulfil the following research objectives:

- Incorporate national climate change scenarios that are currently used in impacts and adaptation assessment in Ireland. In addition, provide the flexibility in the model setup to allow future incorporation of larger ensembles of climate change scenarios.
- Integrate uncertainties derived from the application of hydrological models. In particular, in a real world application where many points of interest for water management are without observed flow records, the tool shall incorporate uncertainties associated with deriving stream flow in un-gauged settings - particularly model parameter uncertainty.
- Include non-climatic drivers that affect water resources, such as population growth and supply network characteristics.
- Provide a framework for model output analysis and result presentation of equally possible multiple future outcomes of the water resource model, in a practical context.

In this chapter, a framework and methods are presented which will be used in the following two chapters, to assess the vulnerability of surface water abstractions to projected future changes and to appraise the effectiveness of adaptation options to assist planning and decision-making when faced with large ranges of future climate uncertainties, in an Irish context (Section 4.2.). In Section 4.3, the hydrological model and the data required for the hydrological modelling approach are presented. Given that many surface water abstraction points have no river flow data in close proximity, a modelling approach for un-gauged catchments is described in Section 4.4. The water resource modelling tool (WEAP) is introduced in Section 4.5. For the future simulations, the different regional climate projections currently used in the Irish the water sector for impacts and adaptation planning are presented in Section 4.6., together with the future water resource system scenarios in Section 4.7. Section 4.8 and Section 4.9 deal with the thresholds and performance metrics used to investigate the water resource system performances under the ranges of future water availability and water resource scenarios. The chapter concludes with a discussion (Section 4.10) and a summary in Section 4.11.

4.2 Framework for Planned Anticipatory Adaptation

As observational data in Ireland cannot solely provide the information required for planned anticipatory adaptation, additional information is needed to allow planning and prioritising adaptation action. Scenario planning provides a range of possible future outcomes on to inform decision-making. Additionally, results of vulnerability assessments help to further refine the possible impacts and help to provide a base for adaptation measures. However, it is important that the planned adaptation measures, which are anticipating a certain change, are still kept flexible to allow for further adaptation and to avoid being locked into a specific adaptation path. Stakhiv (1998) advocates a ‘learning by doing’ approach because adaptation to climate change is still a relatively new concept and no past experience is available to draw upon and guide such decisions. Learning by doing is the basic idea for adaptive responses, where policies and regulations are adjusted in response to new information and gained experiences.

Recognising that adaptation to climate change cannot be a linear one-directional step or measure, but rather a process that needs to account for flexibility and have procedures in place that allow for adjustments, an appropriate framework is required. The core of the framework developed here consists of three iterative processes, with linkages between the individual process pathways (as shown Figure 4.1). A key feature of the framework is that the processes are circular, allowing for decisions and modelling steps taken to be reviewed over time, in the light of new challenges or new information.

The first iterative process for anticipatory adaptation or planning for an uncertain future (blue cycle) requires a sequence of actions that define the problem, a tool for anticipatory decision-support, decision-making and the implementation of these decisions. Then the effects/effectiveness of these measures need to be monitored and evaluated. Within this key step observational evidence from monitoring networks (e.g. hydrometric reference networks) plays an important role: providing a source for feedback, which can then be used for an iteration of the process or to change the problem definition if necessary. Iterative frameworks also allow for adjustments and refinements, through additional iterations, before a decision is implemented (Connell *et al.*, 2005). Similar iterative frameworks have been proposed for the UK by Willows & Connell (2003) and Ranger *et al.* (2010).

The key component that provides the information to the anticipatory adaptation cycle is the decision-support cycle (green cycle). It is within this loop that climate information/scenarios can be used with a new focus. The two main components of the decision-support loop are the vulnerability assessment and the iterative process of robust adaptation option appraisal (light green cycle) (Figure 4.1). All three iterative processes presented here are framed and influenced by climatic influences (observed climate and uncertain climate projections) and non-climatic pressures such as ecological and socio-economic pressures.

However, it needs to be highlighted that there will be no single framework and no single tool for planned anticipatory adaptation in general. Due to the differences in framing conditions, such as state of the system, legislative frameworks or funding, frameworks and tools will always be context specific. In this work, the decision-support tool for the Irish water resource sector is represented by the green loop of vulnerability assessment and robust adaptation option identification to support decisions for planned anticipatory robust adaptation. The main focus of this work is the loop on decision-support for adaptation and the development of a tool that can be used for more effectively informing robust adaptation. Section 4.2.2 to Section 4.2.4 will expand on the decision support loop in more detail.

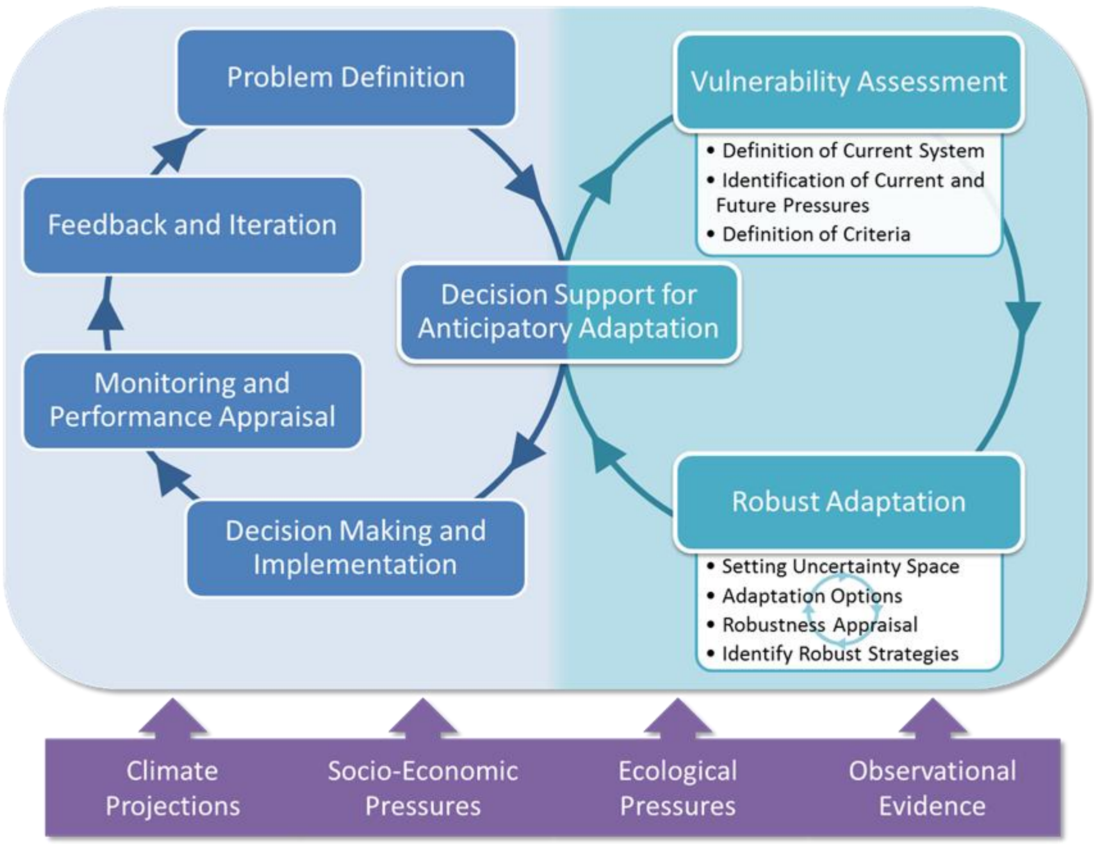


Figure 4.1 Adaptation framework for planned anticipatory adaptation showing the influence of climatic and non-climatic pressures (purple boxes) on the iterative processes of anticipatory adaptation (blue loop) and decision-support (green loop) in conjunction with robust adaptation option appraisal (light green loop).

4.2.1 Application of the framework for anticipatory adaptation in the water resources sector

The sample application of the framework shown in Figure 4.1 to water resources management under climatic change will be presented below. The application starts with the identification of the problem (at the top of blue circle), which in this illustrative application is the desire to implement anticipatory adaptation measures to the anticipated changes in future water availability if needed. In the second step information is required to support anticipatory adaptation. This is the step where the decision support loop (green) intersects with the decision anticipatory decision making loop (blue) and where the application of the decision support tool is situated (for details of the tool see Section 4.2.2 to Section 4.2.4).

To support decision making, the vulnerability of the water resources system needs to be assessed through establishing key characteristics and pressures of the system such as water abstractions and population growth (see Section 4.2.3). Additionally in this step, decision making criteria need to be established that allow identifying critical thresholds that should be avoided or determining criteria of adaptation success. Examples of such thresholds are minimum flow requirements that would not allow further water abstraction or maximum number of days in which water demand cannot be met. The next step in the green loop involves the robust adaptation option assessment, indicated by the small light-green coloured loop in Figure 4.1 and explained further in Section 4.2.4.

After conducting the adaptation option assessment, with regard to their robustness to the uncertainties considered, either robust adaptation options emerge that are considered to be satisfactory according to the criteria defined in the previous step, or another iteration of the green loop might be required until satisfactory options are identified. The robust adaptation options identified can then feed back into the adaptation decision-making process (blue loop). If several equally desirable adaptation options were identified the decision maker has to decide according to additional decision criteria such as costs or other priorities. After making the decision of a specific or a set of measures, they need to be implemented.

Once the anticipatory adaptation measures are implemented it is important that the effects of these measures are monitored and the performance of the measures is assessed in regular intervals. For example, if the implemented measure is the introduction of water charges to reduce water demand, monitoring would involve metering domestic water demand together with an evaluation if water charges are resulting in the expected reductions in water demand.

The last step in the anticipatory decision making loop, involves taking into account the results obtained from the performance appraisal und using the information to feedback into the next iteration if the selected options are not performing as anticipated or if new information such as new climate projections, new population growth rates or water demand figures become available.

As the decision support loop is central to support robust adaptation decision making, the next sections will focus on the details associated with that process.

4.2.2 Decision-Support Tool

Facing the uncertainties associated with future water resources planning and management under climate change, a tool supporting decision-making under such uncertainties is needed. In the context of Ireland with a lack of a coherent national water resources planning approach incorporating future climate uncertainties, the following tool to support decision-making is developed in this study.

The core of the tool is the coupling of a water-accounting model (Water Evaluation and Planning System (WEAP)) with a hydrological model (HYSIM; HYdrological SImulation Model) which has been widely used for Irish catchments. The schematic of the tool is provided in Figure 4.2.

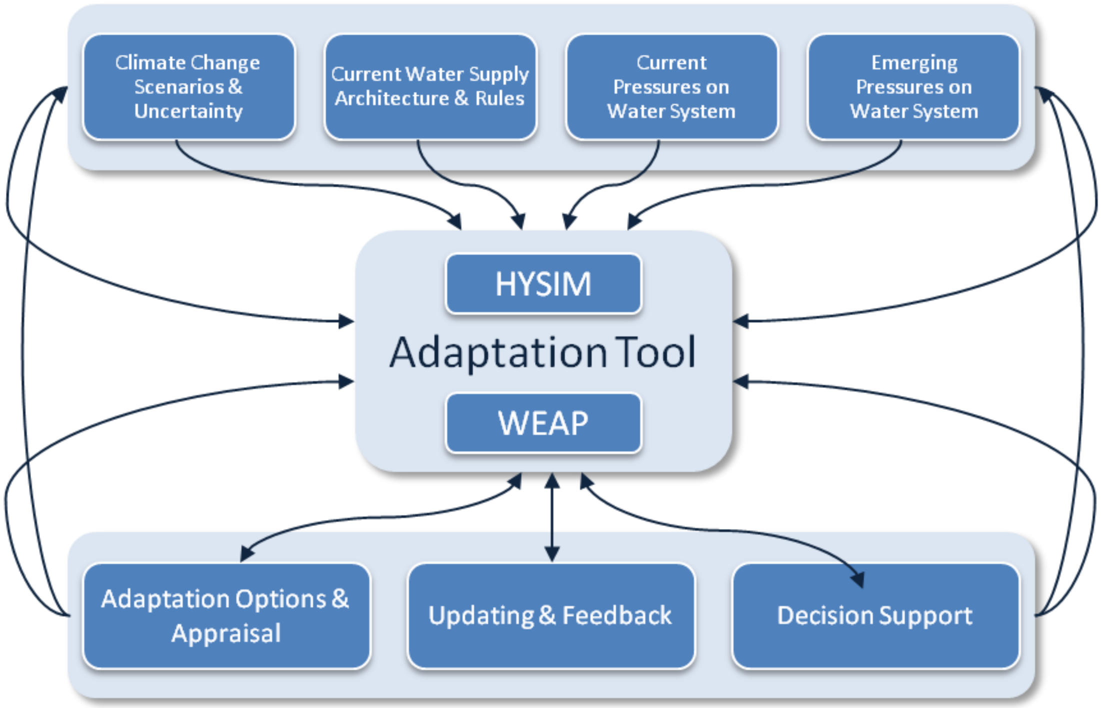


Figure 4.2 Schematic of inputs and possible feedback mechanisms of the adaptation decision-support tool.

Within WEAP, the current water supply infrastructure with its surface water abstraction points is simulated. The tool allows flexible input of data, i.e. future climate scenarios and emerging pressures and the uncertainties attached to them can be incorporated into the modelling framework. Additionally, the framework also allows adaptability of the modelling to new and updated input data information. The output of the modelling tool can be used to identify areas that might be vulnerable to future changes in climate and also allows the assessment of potential adaptation options.

4.2.3 Vulnerability Assessment

Before making any assessment of the state of future water resources, it is important to establish a good knowledge of the current water supply system, the operation rules and current pressures. This can give a first indication of where more information about the future system might be needed. This also allows the identification of possible sensitivities and vulnerabilities within the system, where a detailed modelling study will have priority; for example, water supply systems which are currently close to or approaching maximum capacity.

The second step of the vulnerability assessment involves the classification of possible future non-climatic pressures on the water resource system, such as population growth, changes in the water demand, change in the water infrastructure characteristics, or no change in the system with current trends being extrapolated into the future. This step still comprises the initial step of vulnerability assessment, where the aim is also to identify when and where possible vulnerabilities might emerge. Based on the knowledge of the system, critical thresholds and criteria of adaptation success are identified.

Once the future problems and aims are defined, an inventory of possible adaptation options can be compiled. This catalogue of different management possibilities can then be evaluated in the framework for robust adaptation assessment (light green loop in Figure 4.1). In this work the focus is on the assessment of what can be defined as robust adaptation options, as outlined in the next section.

4.2.4 Robust Adaptation Option Assessment

The uncertainties involved in modelling future climate and climate impacts pose questions on to the utility of a top–down 'predict-then-act' approach for policy analysis to adapt to climate change where predictions are used to derive a few optimum solutions. Hallegatte (2009) even states that uncertainties in future climate change are so large that it makes many traditional approaches to designing infrastructure and other long-lived investments inadequate. Therefore, new approaches to anticipatory adaptation are being sought aiming for successful adaptation to climate change. In responding to the challenges described above, a number of authors have highlighted the potential for strategies that are robust to uncertainty (Lempert & Schlesinger, 2000; Hallegatte, 2009; Wilby & Dessai, 2010).

Robust strategies have been described by Hallegatte (2009) and Wilby & Dessai (2010) as those that:

- Are low-regret, in that they are functional and provide societal benefit under a wide range of climate futures;
- Are reversible, by keeping at a minimum the cost of being wrong;
- Provide safety margins that allow for climate change in the design of current infrastructure or are easy to retrofit;
- Use soft strategies that avoid the need for expensive engineering and institutionalise a long-term perspective in planning;
- Reduce the decision time horizons of investments; and
- Are flexible and mindful of actions being taken by others to either mitigate or adapt to climate change.

Such robust approaches to anticipatory adaptation require a paradigm shift in how climate change data is used. It becomes necessary to move away from a 'predict-then-act' *top–down* approach towards a *bottom–up* approach that allows climate scenarios to be used in exploratory modelling exercises to test the performance of adaptation options to the uncertainties involved in such a modelling approach. Work in this respect is progressing and frameworks for robust adaptation and example applications in the water sector are beginning to emerge in the international literature (for example in the UK: Dessai & Hulme (2007) and Lopez *et al.* (2009) or in Ireland: Hall & Murphy (2011)). Key to these examples is the utility of moving away from considering climate change impacts explicitly, but rather identifying where and when vulnerability to climate change may emerge together with the application of such frameworks and tools for the identification and selection of robust adaptation options.

The schematic of the modelling framework of the decision support process (green loop in Figure 4.1) employed here is shown in Figure 4.3. The schematic combines the steps of vulnerability assessment and robust adaptation assessment into a single looping sequence consisting of several individual steps. In applying this modelling framework it might be necessary to revert back to any of the previous steps if information is updated or newly available (indicated by light green arrows), or if additional strategies need to be assessed for their robustness, resulting in a quasi-circular assessment of the water supply system and different adaptation options.

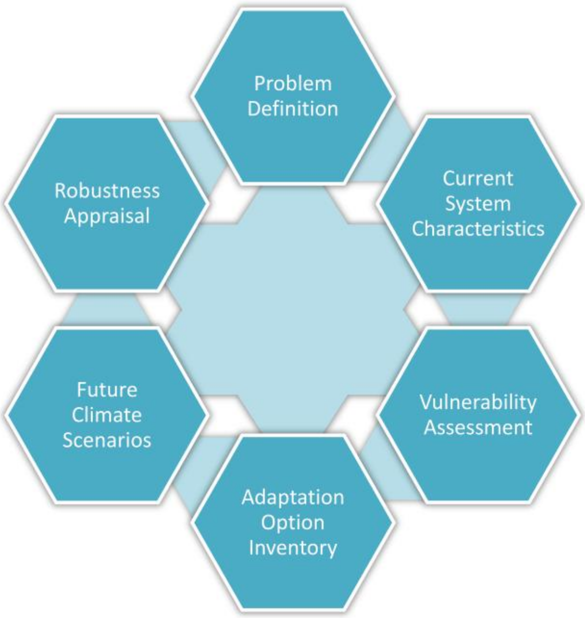


Figure 4.3 Modelling approach used in the tool with possibilities for feedbacks and information update.

The modelling approach starts with specifying the current water resource system characteristics and an analysis of the system vulnerability as an initial step before the robustness of adaptation option assessment under future climate scenarios is appraised. This is different from the traditional 'top-down-approach' where climate scenarios are used as the initial step of an assessment to drive impact models, and then identify adaptation options. Therefore, following the recognition of vulnerability and the identification of an inventory of adaptation options, climate change scenarios and time series of future hydrological conditions are used to 'stress test' the effectiveness of adaptation options to explore their robustness and functionality under assumed future conditions (i.e. scenarios). However, what strategies are considered to be appropriate and robust across a wide range of uncertainties primarily depends on the criteria used to define success of an adaptation measure, which is always context specific and final decisions can always be argued (Dessai & Hulme, 2007). The application of the modelling tool is fundamental to this modelling process and therefore the following sections outline in more detail the formulation and structure of the tool for Irish water resources systems.

4.3 Hydrological Modelling

Hydrological models are used for a variety of purposes in water management, such as hydrological research and flow estimation in un-gauged catchments to generate stream flow time series. Generally, hydrological models simplify the rainfall runoff processes that are occurring in a catchment with the help of mathematical equations. Properties and physical characteristics of catchments are represented by model parameters. Various types of hydrological models have been developed; commonly these models are classified as *lumped* and *distributed* models and *deterministic* and *stochastic* models (Beven, 2001). Within a lumped hydrological model, the processes occurring within a single catchment are simplified to represent average conditions, whereas within a distributed model, hydrological processes within a catchment are represented as local average conditions of multiple sub-catchments. The in a lumped model, catchment is treated as a single uniform entity, where parameters present average conditions, whereas distributed models divide the catchment into smaller elements, and local averages are used to represent the characteristics for each element (Beven, 2001).The difference between deterministic and stochastic models is that the former result in a single possible outcome under fixed conditions, whereas the latter introduce some random effects.

The majority of hydrological models are *conceptual*, where the processes are aggregated in time and space by the modeller to form the model structure and parameters (Wheater *et al.*, 2002). Generally, conceptual models take climatic data as input and produce stream flow as a model output. In conceptual models, parameters represent the hydrological properties of the catchments often do not have direct physical meaning or cannot be measured directly from the field and have to be estimated through a calibration process (Wagener *et al.*, 2004). The 'goodness-of-fit' between observed and simulated output values (stream flow) within a catchment is evaluated using one or more objective functions (Madsen, 2000). Traditionally, the aim of a calibration procedure is to identify a single optimum set of parameters. However, by relying on a single optimum parameter set uncertainty increases as the parameter set as a whole rather than individual parameter values result in a good simulation. The specific conditions under which the parameter set performs well compared to the observed data may change. Additionally, different combinations of different parameter values (parameter sets) within a hydrological model can simulate the observed flow equally well and therefore no single optimum parameter set exists (Beven & Freer, 2001). This is highlighted by the concept of equifinality, where the concept of an optimum parameter set is rejected, and where it is accepted that there are many parameter sets and models that can reproduce observed flow equally well (Beven & Binley, 1992; Beven & Freer, 2001; Beven, 2006). In hydrological models, the number of model parameters depends on the selected modelling approach and the spatial detail (lumped or distributed) used for describing the catchment's characteristics.

Calibration of model parameters can either be manual by the modeller, automatic or a combination of both. Generally, manual calibration is a time consuming procedure and can be considered of being subjective. Different modellers will obtain different optimum parameter sets, when calibrating the same model under the same conditions. To evaluate the 'success' of the model calibration different objective functions are used (Madsen, 2000). To get a complete assessment of the performance of the parameter sets, a suite of different model performance criteria including absolute and relative error measures should be used (Legates & McCabe, 1999), but until recently very often only a single objective function is used to evaluate model performance. Common agreement on whether a parameter set is fit for purpose is lacking, lack of agreement also relates to the selection of assessment criteria (Krause *et al.*, 2005). Moriasi *et al.* (2007) reviewed previously published ranges for the most commonly used objective functions, and recommends the use of the Nash Sutcliffe Efficiency (NS), the percent bias (PBIAS) and the Observations Standard Deviation Ratio (RSR), together with additional graphical techniques for model evaluation, and suggests guidelines as to whether stream flow simulations can be deemed acceptable. However, until now there is no common standard used within the hydrological modelling community.

4.3.1 Hydrological Simulation Model - HYSIM

The hydrological model used in this study is the *HYdrological SImulation Model* (HYSIM), which is characterised as a physically based lumped conceptual rainfall runoff model (Manley, 1975). HYSIM is selected in this study as the majority of the model parameters are based on measurable basin characteristics. This physical realism in model input parameters is of advantage as it makes it particularly applicable to simulating stream flow for un-gauged catchments, as this allows for transferring parameter values from similar gauged stations or from field measurements to the un-gauged site (Manley, 1975). In addition, HYSIM is a hydrological model that is being operationally used in water resources assessment and management, such as the Scottish Water supplies (Rodgers *et al.*, 2012).

The flow processes in a lumped conceptual model, like HYSIM, are mathematically described and the catchment is regarded as a single spatial unit. The catchment and its associated parameters are not spatially discrete but rather represent averages over the entire catchment area without considering topographical heterogeneity and the occurrence of different soils and land cover.

The input data requirements of HYSIM are the parameter values, daily precipitation and daily evapotranspiration time series to drive the model. The hydrological calculations and the hydraulic routing within HYSIM consist of seven internal stores (Figure 4.4). The 36 parameter values, which control the storages and the transfer processes within the lumped model, are classified as physically based and process based parameters (Table 4.1 and Table 4.2). The majority of parameters within HYSIM are physically based values and can be measured from field observations or extracted from spatial datasets. The minority of parameter values belong to the group of process parameters, which are not directly measurable and can rather be identified as ranges of parameters. These process parameters require additional handling during model conditioning (model calibration and model evaluation) as described further down, to reduce uncertainties associated with the estimation process (Sorooshian & Gupta, 1995).

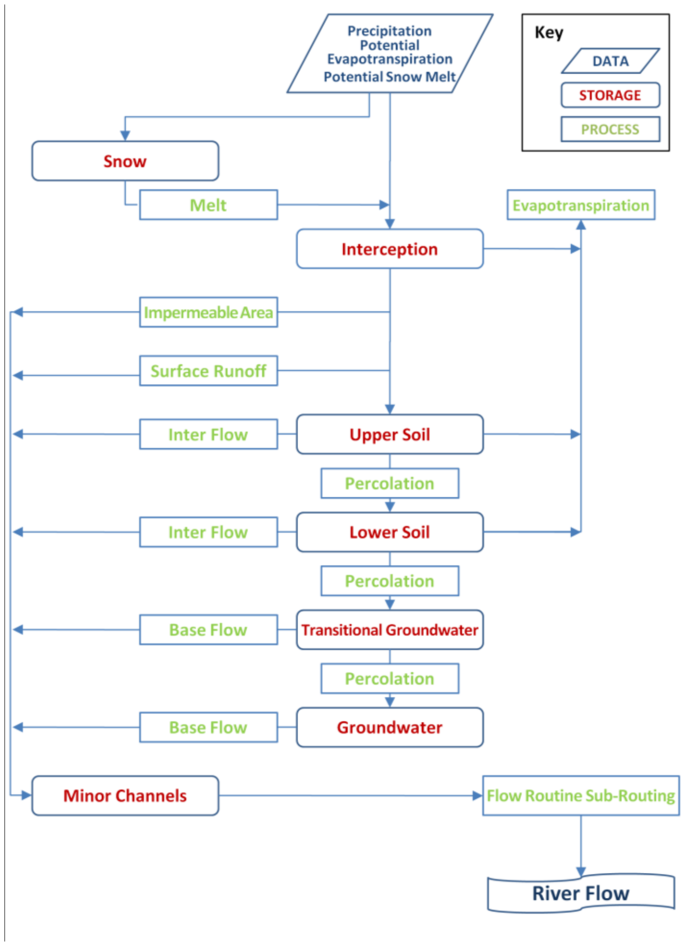


Figure 4.4 Conceptual model structure of HYSIM (adapted from (Manley, 2006)).

Table 4.1 HYISM; Hydraulic Parameters, Units, Data Sources and Default Values

Hydraulics Parameters	Unit	Source	Default
Channel Top Width	m	Manual	10
Channel Base Width	m	Manual	6
Channel Depth	m	Manual	1
Channel Roughness	--	Manual	0.3
Flood Plain Width	m	Manual	100
Flood Plain Roughness	--	Manual	0.05
Reach Gradient	--	GIS	0.001
Reach Length	m	GIS	1000

Table 4.2 HYISM; Hydrological Parameters, Units, Data Sources and Default Values

Hydrological Parameters	**Unit**	**Source**	**Default**
Basic			
Interception Storage	mm	Default	2
Impermeable Proportion	--	GIS	0.02
Time-to peak	hours	calc	2
Rooting Depth	mm	(*)	1000
Pore Size Distribution Index	--	Manual	0.15
Permeability – Horizon Boundary	mm/h	(*)	10
Permeability – Base Lower Horizon	mm/h	(*)	10
Interflow – Upper	mm/h	(*)	10
Interflow – Lower	mm/h	(*)	10
Groundwater Recession	1/month	calc	0.6
Precipitation Factor	--	Manual	1.04
PET Factor	--	Manual	1
Catchment Area	km^2	GIS	1
Advanced			
Permeability – Top Upper Horizon	mm/h	Default	1000
Proportion Upper Horizon	--	Default	0.3
Ratio Groundwater to Surface Catchment	--	GIS	1
Proportion of Catchment with No Groundwater	--	GIS	0
Riparian Proportion	--	Default	0
Porosity	--	Manual	0.48
Bubbling Pressure	--	Manual	100
Transitional Recession	1/month	calc	0.5
Proportion Transitional	--	calc	0
Interception Factor	--	Default	1
Snow Factor	--	Default	1.5
Groundwater Pumping Coefficient A	--	Default	0
Groundwater Pumping Constant B	--	Default	0
Snow Threshold	--	Default	0
Melt Rate	--	Default	0

(∗) ‘Process Parameters’

4.3.2 Physical Catchment Descriptors

Given the physically based nature of many of the HYSIM parameters, data from several sources need to be incorporated to determine the catchment descriptors which are used to obtain the physically based parameters in HYSIM. The data that needs to be processed to acquire values for the physically based parameter include spatial datasets, analysed using Geographical Information Software (GIS), measured hydrological data and climate data and can be classified as topographical, hydrometric and meteorological data. The following sections provide a summary of data assembly, data manipulation and catchment characteristics extraction. The schematic of the steps undertaken is shown in Figure 4.5

The Geographical Information Software (GIS) ArcGIS was the main tool used to obtain the hydraulics and hydrology parameters for the HYSIM parameter file. The basis for the determination of the physical catchment characteristics is a hydrologically corrected ('filled') Digital Terrain Model (DTM) obtained from the Irish Environmental Protection Agency (EPA) (Preston &Mills, 2002). The DTM is a bare earth surface model, with buildings and vegetation removed, at a 20-metre grid cell resolution. The hydrologically corrected DTM and its derivatives (flow direction and flow accumulation grids) were primarily used for stream line generation, and sub-catchment delineation to the flow measurement gauge or the water abstraction sites to generate the parameter input for the hydrological models (Figure 4.5).

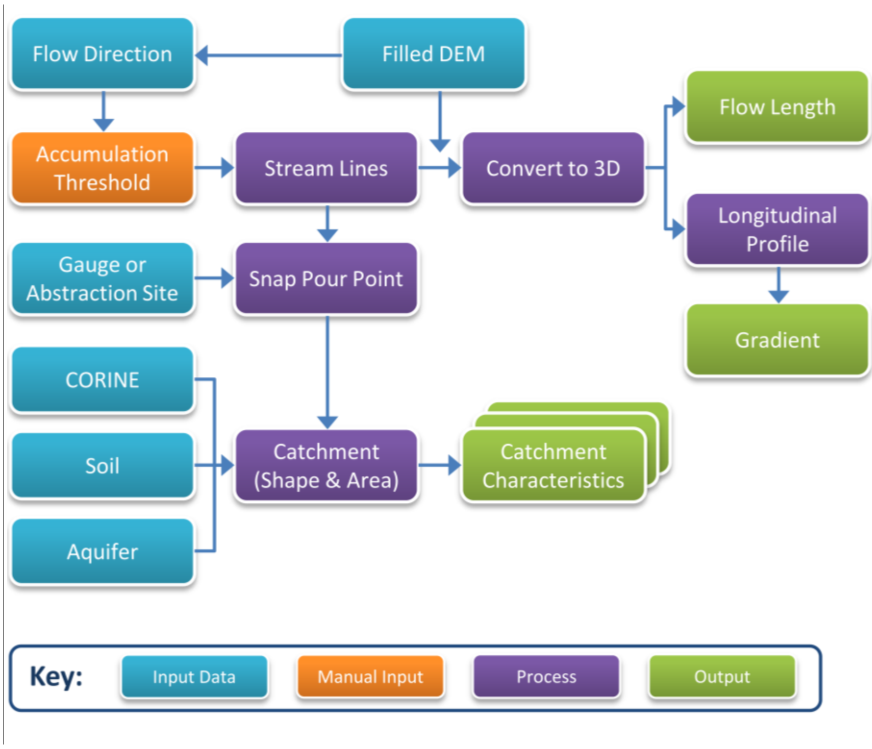


Figure 4.5 Schematic of derivation of catchment descriptors using ArcGIS, showing inputs, processing in ArcGIS and outputs.

The catchment characteristics that are relevant in determining hydrological properties, were derived from the CORINE (Co-ORdination of INformation on the Environment) land cover dataset GIS layer, issued by the Irish Environmental Protection Agency (EPA, 2006) and the digital version of the General Soil Map of Ireland (Gardiner & Radford, 1980). The Irish CORINE data is mapped at a 1:1,000,000 scale and provide 33 land-cover classes interpreted from satellite images recorded in 2006. The sub-catchments are delineated to the gauge or water abstraction site and the resulting catchment shape is used to determine the main soil texture and the dominant land cover type defined by the vegetation characteristics and land use parameters for each sub-catchment individually. The same applies to the aquifer characteristics, which are derived from the Geological Survey of Ireland's (GSI) *National Bedrock Aquifer Map* (1:100,000) (GSI, 2007) (Figure 4.6 D).

Most of the physically based parameters could be obtained through the use of a GIS, as the source columns in Table 4.1 and Table 4.2 indicate. For the remaining less sensitive parameters, the default HYSIM parameter values were used.

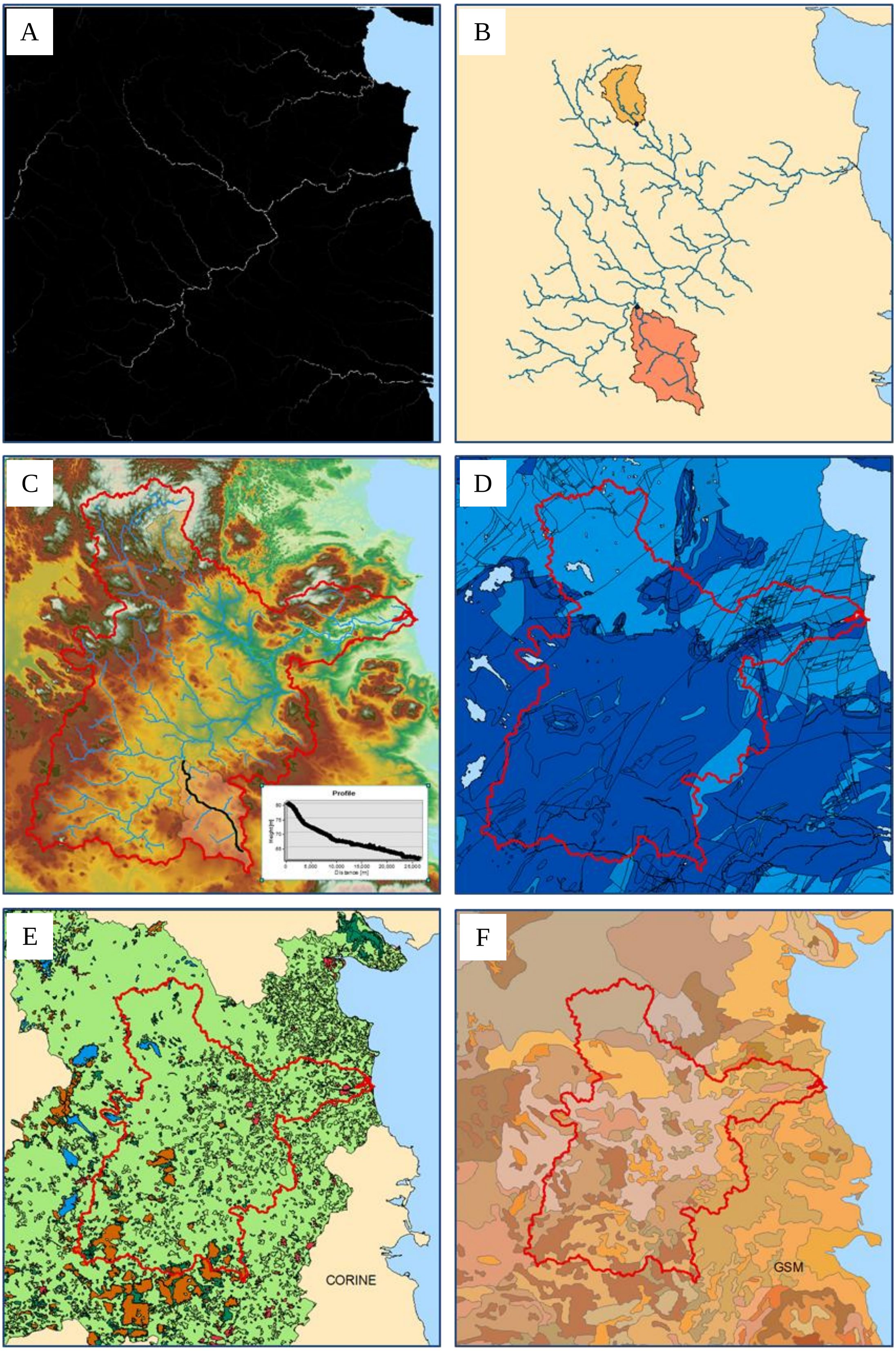


Figure 4.6 Example of the use of GIS to derive the following catchment characteristics. A) Flow accumulation grids; B) Streamlines and delineated sub-catchments; C) DTM and longitudinal stream profile; D) Aquifer characteristics; E) Land cover characteristics; F) Soil cover characteristics.

4.3.3 Hydrological and Climatic Time Series Input

The hydrometric data used for the hydrological model calibration and evaluation were obtained from the Environmental Protection Agency (EPA, 2010) and the Office of Public Works (OPW, 2010). The gauges are selected according to their upstream location of major settlements and surface water abstractions, their length of record and the representativeness of their catchment characteristics. Additional selection criteria are length of record, missing values and data quality.

The observed meteorological records at the synoptic stations located across the country (Figure 4.7), for daily precipitation and potential evapotranspiration used to force the hydrological models and were provided by MetÉireann (2010).

Figure 4.7 Location of synoptic weather stations in Ireland.

4.4 Hydrological Model Conditioning in Un-Gauged Catchments

After the determination of the physically based parameters in HSYIM, the process parameter values need to be obtained through a model conditioning procedure. Before comparing modelled and observed data an initial model 'warm-up' period is accounted for to equilibrate the internal stores of the hydrological model. In gauged catchments, the process model conditioning normally comprises of model calibration (fitting of the parameter values and therefore the model output to a historical stream flow series) and the model evaluation (also called validation, verification or confirmation) to an independent stream flow time series at the same location (Refsgaard, 1997). In this research, however the stream flow at un-gauged locations (surface water abstraction points) needs to be modelled, so that direct model calibration and evaluation with recorded stream flow is not possible.

Flows in un-gauged catchments are generally estimated based on the concept of hydrological similarity (Blöschl, 2005). The similarity of hydrological responses to precipitation input in terms of flow generation is thought to originate from an evolution under comparable geological, climatic and anthropogenic influences in spatial proximity (Wagener *et al.*, 2007). These influences determine the geomorphology, soils aquifer characteristics and land cover, which in turn influence the key hydrological processes and runoff generation in catchments. Although catchments in close spatial proximity with the same climatic regime might share the same co-evolution of catchment features, they will not exactly resemble each other. Due to slightly different catchment characteristics, the interaction between climate and key catchment processes results in modified stream flow generation processes and results in non-identical runoff. Therefore, the need to model runoff in un-gauged catchments introduces an additional source of uncertainty to the hydrological modelling approach.

In hydrology, modelling flows in un-gauged catchments is an area of on-going research and no international standard protocol of methods exists. The general approach to obtaining runoff in an un-gauged catchment is to transfer hydrologically relevant information from gauged to un-gauged catchments that are located in close proximity (Bárdossy, 2007). In doing this, it is important that these catchments are similar in terms of the climate and key catchment characteristics to ensure similarity in the hydrological catchment responses. In hydrological modelling, such key catchment characteristics determine for example, runoff and infiltration processes and soil and groundwater storages.

As described in the previous sections, the majority of parameters for physically based models can be obtained from measurable data without the need for calibrating to observed flows. However, some of the model parameters need to be obtained through a model calibration process. In un-gauged catchments, these model parameters also need to be estimated. The parameters can either be determined based on expert knowledge or calibrated model parameters from gauged catchments can be transferred to the un-gauged site which share similar catchment characteristics (Blöschl, 2005). This process of transferring hydrological information (e.g. model parameters) from one catchment to a neighbouring site is called regionalisation (Blöschl & Sivapalan, 1995).

Here the specific regionalisation process used to transpose calibrated parameters from gauged catchments, also referred to as donor or proxy-basins, to hydrologically similar un-gauged sites is used. The method employed takes the following steps; first, suitable gauged catchments are identified; second, the parameters for a hydrological model at the gauged site are calibrated; third, the non-measurable parameters are transferred to a hydrological model of the un-gauged catchment and fourth, another model of a gauged site is used for cross-evaluation of the modelled flow with the observed flow.

Such transfer methods can for example be based on regression between calibrated model parameters and catchment characteristics to establish an empirical relationship in gauged catchments. The model parameters at the un-gauged site are then estimated based on the relationship determined for the gauged catchments (Blöschl, 2005). However, to obtain a significant relationship between calibrated model parameters and catchment characteristics multiple calibrated hydrological models of gauging sites with homogenous catchment characteristics and natural flow regimes covering common periods are required.

While there is a dense network of river flow gauges in Ireland, it is difficult to find sites with a good quality natural flow regime in close proximity, that are not affected by human influence. Therefore to use the regression method to transfer model parameters from one site to another is complicated. This is particularly true for continuous discharge measurements at or close to un-gauged surface water abstraction points, which is the focus of this study. Therefore, a different approach is developed in the Irish context in which the process parameters for the water-abstraction sub-catchments in HYSIM are determined using a proxy-basin approach based on two proxy-basins (sub-catchments) and in which parameter set equifinality is also accounted for. The proxy-basin approach used is described in detail in the following section.

4.4.1 Proxy-Basin Split-Sample Method

To ensure transferability of the HSYIM model's process parameters between gauged and un-gauged catchments of the same geographical region, a combination of two testing methods: the split-sample test and a proxy-basin test is deployed.

In a split-sample test, the measured stream flow record is split into two segments of either 50/50 for long flow records, or 70/30, to obtain a longer record segment for calibration and the shorter one for model evaluation. If uneven splitting is applied two tests are required; one with the first 70% of the record used for calibration of the gauged catchment and the remainder for model evaluation and the last 70% for calibration and the first 30% for evaluation (Klemeš, 1986). The model is only acceptable when both evaluation results are acceptable.

When testing the geographical transferability of the model parameters within catchments, a proxy-basin test is applied. Two representative gauged sub-catchments with similar catchment characteristics are cross-checked during calibration and evaluation. The model is calibrated for one sub-catchment and the derived parameter values are then confirmed in the other sub-catchment and vice versa (Klemeš, 1986).

In this research, both tests are combined in the proxy-basin split-sample method, where the hydrological model process parameters are calibrated against observed historical stream flow in two sub-catchments close by the un-gauged sub-catchments (Figure 4.8 for model calibration and evaluation). The two sub-catchments have to be comparable in their characteristics to the un-gauged abstraction catchments and have to be located upstream to ensure low influence of major settlements and their water abstractions (Hall & Murphy, 2011).

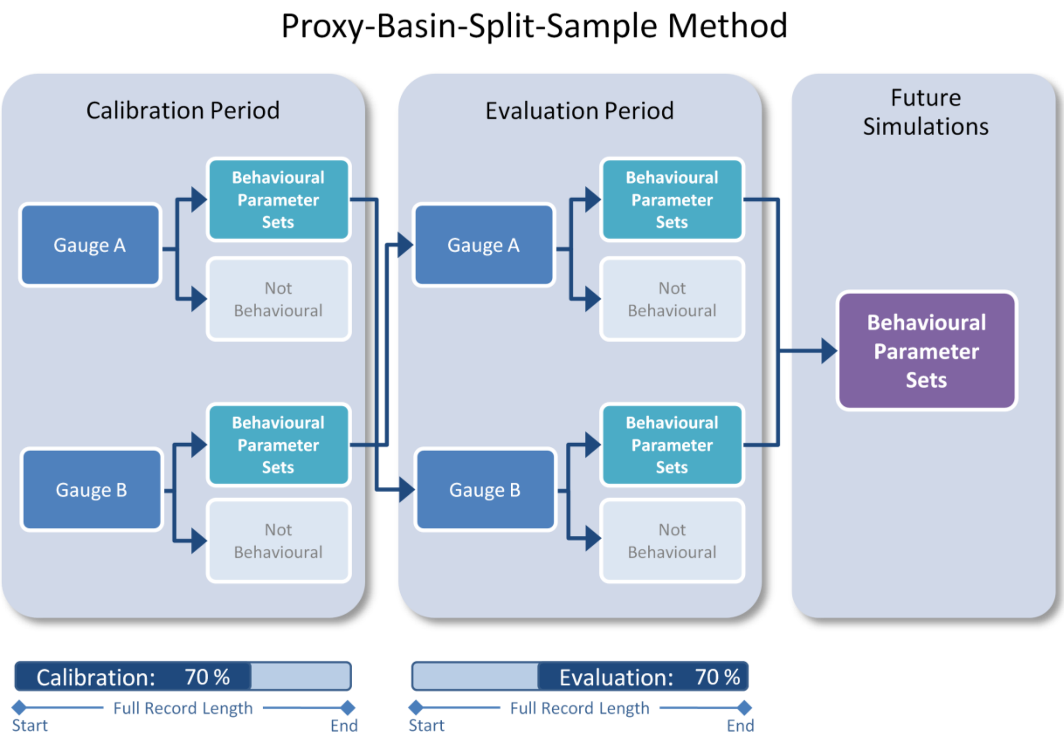


Figure 4.8 Schematic of the combination of a split-sample test (calibration and evaluation) with the proxy-basin test, expanded by an equifinality approach to parameter uncertainty.

4.4.2 Parameter Uncertainly and Equifinality

The proxy-basin split-sample approach is based on the assumption of the existence of a single model (Beven, 2000) and a single optimum parameter set. However, by relying on a single optimum parameter set uncertainty increases as the parameter set as a whole rather than individual parameter values result in a good simulation. The specific conditions under which the parameter set performs well compared to the observed data may change. Under the concept of equifinality different combinations of parameter values (parameter sets) within a hydrological model can simulate the observed flow equally well and therefore the existence of a single optimal parameter set is questionable (Beven & Freer, 2001). In this study, special attention is given to hydrological model equifinality, as the effect of parameter uncertainty is highest during low flow periods (summer and early autumn) (Arnell, 2011). For Ireland, this increase in the spread of flow produced by equifinal parameters can also be observed in an assessment of climate change impacts of hydrology (Figure 11 in Steele-Dunne *et al.* (2008)). This finding is of particular importance when assessing the performance of adaptation options as such a wide spread has a high influence on water availability for water supply purposes, during the low flow periods.

4.4.3 Process Parameters Values and Model Performance Measures

The concept of equifinality of parameter sets was incorporated into the model conditioning procedure and therefore present an extension of the traditional proxy-basin split-sample approach. During the model conditioning of the two proxy-basins, the parameter values for the precipitation factor and/or the potential evapotranspiration factor are adjusted to obtain an initial fit. The remaining five process parameters are first manually calibrated to obtain a good agreement between modelled and observed stream flow for each proxy-catchment individually, as a starting point of the model conditioning process. Then, the combined feasible parameter ranges for the process parameters are defined by the lowest possible parameter value and twice the maximum value of both catchments of the manually calibrated optimum parameter following Wilby (2005).

The parameter space of each parameter is individually approximated a-priori by assuming a continuous uniform distribution for each parameter, where all parameter values are equally probable. Monte Carlo random sampling from a prior probability distribution of parameter values is used to produce random parameter values. From each of the five process parameters and their individual uniform distribution 20,000 random parameters were sampled and randomly combined into 20,000 parameter sets. This Monte Carlo approach to calibration allows accounting for the interaction between parameters and evaluating them as a parameter set as a whole, compared to varying a single individual parameter and keeping the other parameters constant.

For the two proxy-basins, the sample ranges of the process parameters are the same, based on plausible ranges derived from catchment characteristics. To obtain the parameter sets that are geographically transferable out of the 20,000 parameter sets, the sets are run for the calibration period in each proxy-basin (70% of stream flow record) and the behavioural parameter sets are then used in the other catchment for evaluation (30% of record) and vice versa (Figure 4.8). The behavioural parameter sets obtained in both catchments for the evaluation period are combined and then used to simulate the future catchment hydrology at the un-gauged abstraction points (with have similar catchment characteristics).

To get an complete assessment of the performance of the parameter sets, a suite of absolute and relative error measures are used, as recommended by Legates & McCabe, (1999). Additionally, the criterion of water balance is introduced to account for the changes in water balance with changing process parameter sets.

The following selection criteria (underlined in the text below) are used to determine the behavioural parameter sets, where: *O* is the observed flow, *P* is the predicted flow, and *Ô* is the average of all observed flows.

Water balance equals zero within the HYSIM model.

Absolute error measure:

Mean absolute error (MAE) (Equation 4.1,) is the difference between the observed and predicted flow. MAE is mean of the absolute value of the residuals and has a low sensitivity to outliers. The criteria for classification as a behavioural simulation is a difference of *less than half the standard deviation* of the observed flow ($STDEV_{obs}$) (Singh *et al.*, 2004; Moriasi *et al.*, 2007).

$$MAE = 1 - \frac{\sum_{i=1}^{n} |O_i - P_i|}{n}$$ **Equation 4.1**

Relative error measures (Goodness of Fit):

Nash-Sutcliffe Efficiency Coefficient (EC) (Nash & Sutcliffe, 1970) (Equation 4.2), is a commonly used measure to describe the predictive accuracy of hydrological models based on error variance and is a good indicator for the overall fit of the hydrograph (Moriasi *et al.*, 2007). Generally, EC is a measure of the goodness of fit to the 1:1 line when the observed flow is plotted against predicted flow (Moriasi *et al.*, 2007). EC shows sensitivity to differences in observed and predicted means and variances but is also biased towards higher flows due to the use of the sum of squared errors. *EC* can range from $-\infty$ to +1. A coefficient of $EC = +1$ corresponds to a perfect fit of modelled to observed flow. Generally, the closer the Efficiency Coefficient is to 1, the more accurate is the hydrological model. A coefficient ≤ 0 indicates that the average of observed flows predicts the flow better than the modelled flow. Throughout hydrological studies, various acceptable levels of model performance are used as found by an extensive literature review by Moriasi *et al.*, (2007).

$$EC = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \hat{O})^2}$$ **Equation 4.2**

Percent Bias (PBIAS) (Yapo *et al.*, 1996) is used to express the hydrological model bias. PBIAS measures the average tendency of the simulated flows to be larger or smaller than the observed flows (expressed as a percentage). An optimum model with no bias has a PBIAS value of 0, increasing values indicate less accurate model simulations. However, a zero PBIAS value can conceal large absolute differences between observed and modelled flows, in cases where the model is equally over- and underestimating. An overestimation of the simulated flow is expressed with a negative sign and a systematic underestimation of the observed flow is indicated by positive PBIAS values (Equation 4.3).

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(O_i - P_i) * 100}{\sum_{i=1}^{n} O_i}\right]$$ **Equation 4.3**

Root Mean Square Error-Observations Standard Deviation Ratio (RSR),

RSR is the error measure Root Mean Square Error (RMSE) standardised by the observed flows standard deviation (Equation 4.4) (Singh *et al.*, 2005; Moriasi *et al.*, 2007). The optimal RSR value is 0, which indicates zero RMSE (average error between observed and modelled). Generally the lower RSR, the lower the RMSE, and the better the model simulation performance.

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}(O_i - \hat{O})^2}\right]} \qquad \textbf{Equation 4.4}$$

For the proxy-basins parameter sets were considered as behavioural, when they at least fulfilled criterion (i) (zero water balance) and criterion (ii) (MAE less than half the observed standard deviation), and (iii) had a ‘Very Good’ performance rating in criteria for EC, PBIAS and RSR (Table 4.3). In the case where no ‘Very Good’ performance rating had been achieved, the selection criterion had to be relaxed to ‘Good’ performing parameter sets. Parameter sets obtaining an ‘Unsatisfactory’ rating were excluded from further modelling. The behavioural sets where then used as parameter sets for the model evaluation (30% of available time series) in the proxy-catchments. Again, the same criteria were employed to obtain the combined parameter sets, which can be used in future models. If after model evaluation, more than 500 behavioural parameters were obtained for future simulations, random sampling of 500 sets from a uniform distribution of these parameter sets, assuming equally good performance, was applied to limit the computational time required to produce future simulations.

Table 4.3 Performance ratings for the relative error measures as suggested by Moriasi *et al.* (2007) based on monthly time steps as recommend. Nash-Sutcliffe Efficiency Coefficient (EC), Percent Bias (PBIAS), Root Mean Square Error-Observations Standard Deviation Ratio (RSR).

Performance Rating	EC	PBIAS	RSR
Very Good	0.75 < EC ≤ 1.00	PBIAS < ±10	0.00 ≤ RSR ≤ 0.50
Good	0.65 < EC ≤ 0.75	±10 ≤ PBIAS < ±15	0.50 < RSR ≤ 0.60
Satisfactory	0.50 < EC ≤ 0.65	±15 ≤ PBIAS < ±25	0.60 < RSR ≤ 0.70
Unsatisfactory	EC ≤ 0.50	PBIAS ≥ ±25	RSR > 0.70

The aim of this Monte Carlo approach to model calibration and evaluation is to incorporate parameter uncertainty into the hydrological modelling approach in addition to future climate uncertainty. The stream flows simulated in the proxy-basin catchments, i.e. their hydrological response to the climate input is not represented a single optimum flow according to a selected objective function but rather as a stream flow range under all the behavioural parameter sets (see Figure 5.6 in Chapter 5).

As mentioned above, for most of the water abstraction points in Ireland no observed stream flow time series exist. Therefore, the water abstraction sites analysed in this study are treated as un-gauged catchments and the regional behavioural parameter sets derived through the proxy-basin approach are used to simulate future ranges of stream flow at these sites. Following the same approach described in section 4.3.2, the sub-catchments were delineated up to the surface water abstraction site to obtain the catchment characteristics from which the physically based model parameters are derived. Time invariant physical and process based parameters for future stream flow simulations are used, assuming no changes in these parameters in future. These future stream flow simulations are then coupled with the water resources system model (described below), with a user interface written in Visual Basic code to access the application programming interface (API) of the water resources tool.

4.5 Water Evaluation and Planning System - WEAP

The Water Evaluation and Planning (WEAP) system is a tool used to model and analyse water resource systems. It can be used for the assessment of the current water resource system as well as modelling tool for integrated assessment of hydrological and water supply modelling and assessment based on the water accounting principle (Yates, Purkey, *et al.*, 2005; Yates, Sieber, *et al.*, 2005). Within WEAP, the water mass balances are calculated on node structures, which are linked to water supply and water demand sites. In this setting, different sets of management strategies for the water resource system can be modelled and analysed. The WEAP system has been applied in many international settings with regard to water resources and climate change (Loucks, 2006; Götzinger, 2007; Purkey *et al.*, 2007, 2008; Groves *et al.*, 2008; Yates *et al.*, 2009; Barthel *et al.*, 2010; Höllermann *et al.*, 2010; Hall &

Murphy, 2011). Here the difference too many of these studies is that WEAP is not used as an optimisation tool to identify the best possible adaptation option under given climate scenarios. The novelty is that WEAP is used to explore different future states of the system by incorporating uncertainties associated to climate and hydrological modelling, to test the robustness of adaptation options.

The main criteria for selecting WEAP to model the Irish water resource systems is that it allows the use of an application programming interface (API), which permits the use of self-written programming scripts written in visual basic to automate modelling and analysis procedures. Consequently, this allows handling a high number of possible future states of the system brought about by the wide range of future uncertainties.

4.5.1 Water Resources System Components within WEAP

To be able to use the API, the water resources system components need to be established manually within WEAP using the graphical user interface. In the modelling approach employed here, the key components of each investigated water resources system are the water abstraction points connected to and linked by the river network. For each abstraction point information such as population, per capita water consumption and leakage levels needs to be supplied to the model for the start year of simulation. Then different growth or reduction rates can be provided to the WEAP and used to simulate various scenarios of population growth rates or water usage reduction scenarios based on the original values provided.

To be able to use the streamflow derived from a physically based hydrological model, which is important for ungauged water abstraction points, the hydrological component was generated outside WEAP using HYSIM (see Section 4.3 and Section 4.4). For each water abstraction point the streamflow is generated using HYSIM based on the characteristics of sub-catchments draining to that site. Within WEAP, abstraction point A (shown in the schematic in Figure 4.9) does only receive the discharge simulated for sub-catchment A. Based on the water accounting principle; water abstractions at point B have the total discharge simulated for sub-catchment A and sub-catchment B available for potential abstraction.

After establishing the water resources system components within WEAP and having derived the streamflow in HYSIM, the API is used to automate the input of multiple future streamflow scenarios in combination with the different water resources system scenarios defined within WEAP. Due to the assumption of water conservation in the system and the analytical, algebraic use of WEAP to account for the water balance, no additional sources of uncertainty are introduced by the use of the API and WEAP. Under these conditions, the uncertainties associated to the WEAP model output will only stem from the input data (hydrological time series) and the water resources system scenarios considered.

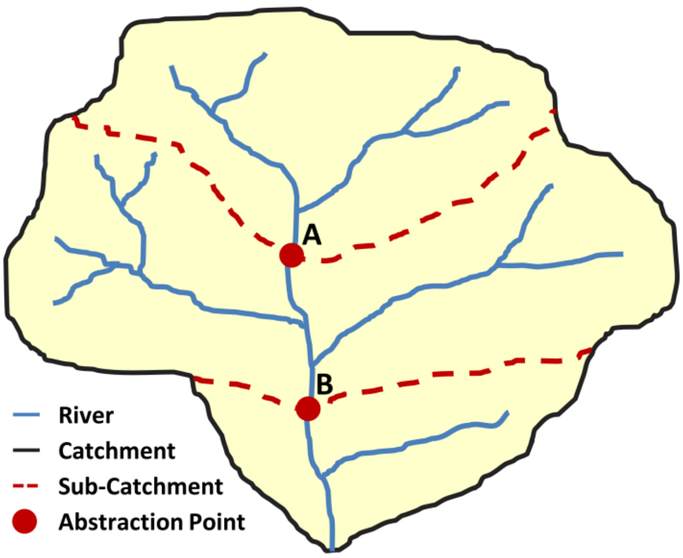


Figure 4.9 Schematic of water resources system components within WEAP. Showing river network and surface water abstraction points with associated sub-catchment boundaries.

4.6 Regional Climate Projections for Ireland

To derive future stream flow projections, which can be evaluated in WEAP, future climate projections are needed as input to the hydrological model. The aim of the second part of the thesis is to develop and apply a tool to inform decision appraisal in the Irish water resources sector. Therefore, existing national climate scenarios are used, as decision makers are already accustomed to these scenarios and have an understanding of the limitations associated with the use of these. It is beyond the scope of this thesis to develop future climate scenarios to be specifically employed in this first-pass modelling framework. However, it is recognised that future application of the tool, to assess the robustness of adaptation options, should include a wider range of possible future climate realisations, than those currently available in the national scenario database.

Currently, there are two main sets of future climate scenarios available in Ireland, statistically downscaled and probabilistic scenarios. In the following sections, an overview of the different scenarios is given together with the reasoning regarding the selection of the climate scenarios used in the modelling approach.

4.6.1 Statistically Downscaled Scenarios

Statistically downscaled climate scenarios are derived from Global Climate Models (GCMs) by establishing relationships through mathematical transfer functions. Though regression, surface environmental variables such as temperature and precipitation are derived from large-scale atmospheric variables.

In Ireland the statistically downscaled climate scenarios were derived from three different GCMs (the Hadley Centre (HadCM3), the Canadian Centre for Climate Modelling and Analysis (CCCma) (CGCM2) and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) (Mark 2)) forced with two emissions scenarios (Fealy & Sweeney, 2007, 2008; Sweeney *et al.*, 2008). The future greenhouse gas emissions used by Fealy and Sweeney were taken from the IPCC Special Report on Emission Scenarios (SRES). The emission scenarios predict a more regionally imbalanced future development trajectory with either a more market economic (A2, medium-high) or environmental focus (B2, medium-low) (IPCC, 2000). The coarse grid resolution data from the six GCMs projections was empirically statistically downscaled to 14 synoptic weather stations located across Ireland (for the station location see Figure 4.7) (Fealy & Sweeney, 2007, 2008). To improve the correspondence between the statistically downscaled temperature and precipitation data bias correction was applied to both the baseline period (1961-1990) and future time periods, thereby removing a systematic bias (Fealy, 2010).

In this work, the six individual GCMs scenarios for Ireland are considered as being equally likely and employed with equal weights, without a subjective attribution of likelihood. The six scenarios provide daily series of precipitation and temperature from 1961 to 2099. Across Ireland the ranges of projected changes vary for both temperature and precipitation across the three GCMs with the spread increasing when comparing the 2020s (2010-2039) with the 2050s (2040-2069) and the 2080s (2070-2099) (see Figure 4.10 as an example).

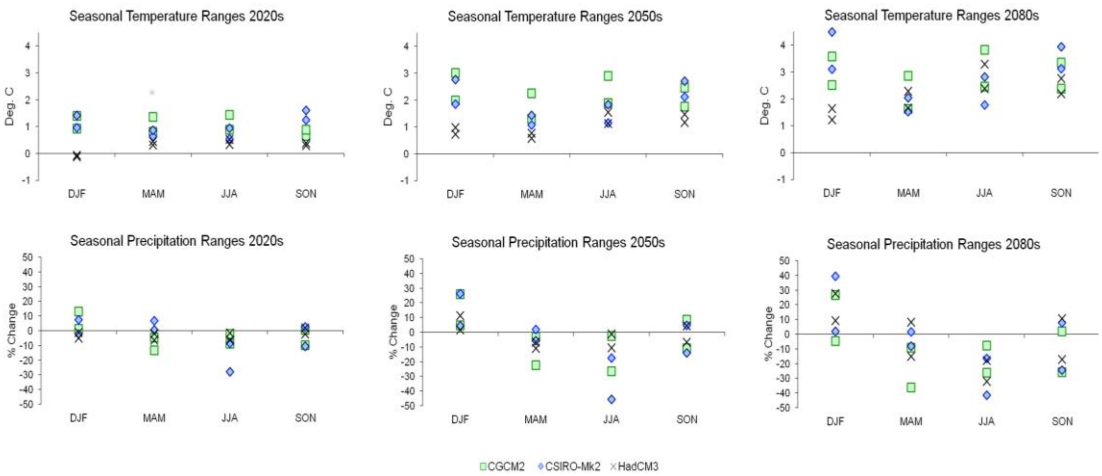


Figure 4.10 Seasonal temperature and precipitation ranges for all stations analysed, showing the smallest and largest changes for the A2 emissions scenario. (Data taken from Sweeney *et al.* (2008).)

Future time series of potential evapotranspiration (PE) were obtained using a different technique that temperature and precipitation, due to a less dense observational network of synoptic stations for which PE is calculated based on the Penman–Monteith equation. Instead of using the large-scale forcing provided from the reanalysis data (as in the case of temperature and precipitation), Fealy & Sweeney (2008) adapted a technique that is employed in conventional weather generators to derive PE. The modified technique involves the calibration of a multiple regression model using local climate variable from the relevant synoptic station as predictors in conjunction with the large-scale predictors. For the baseline climatology (1971-1990), the local-scale predictors radiation, precipitation occurrence and precipitation amounts were used as input into the regression model to predict PE for each of the synoptic stations (Fealy & Sweeney, 2008; Sweeney *et al.*, 2008).

Although the authors of that study acknowledge the omission of the important variable wind in calculating potential evapotranspiration, they justify their approach with regard to the Irish climatology in which the influence of wind on seasonal PE is variable. The influence of wind during the winter months is high and diminishing during the spring, summer and autumn months. However, the calculated potential evapotranspiration values at the synoptic stations are at a minimum during the winter months. Due to this reasoning and based on previous research undertaken by the authors (Sweeney *et al.*, 2003), they concluded that the exclusion of the wind variable is unlikely to significantly impacted the predicted values of potential evapotranspiration (Fealy & Sweeney, 2008; Sweeney *et al.*, 2008).

The ranges and ensemble means of projected future potential evapotranspiration obtained across Ireland, from the six individual GCMs scenarios, are shown in Figure 4.11.

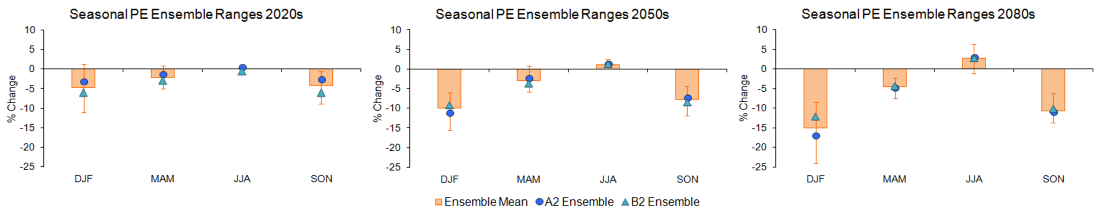


Figure 4.11 Potential evaporation ranges for all stations analysed, showing the ensemble of all GCMs and emission scenarios as bars. The error bars show the smallest and largest changes for all emission emissions scenario. The circles and triangles show the A2 and B2 ensemble mean respectively (Data taken from Fealy & Sweeney (2008).)

4.6.2 Probabilistic Scenarios

The second set of future climate scenarios available are probabilistic based regional climate scenarios for Ireland for the period 2070-2099, which are based on the statistically downscaled scenarios described above. Fealy (2010) used seasonal mean changes for both the A2 and B2 scenarios for the 2080s for each of the 14 synoptic weather stations modelled by Fealy & Sweeney (2007, 2008) to derive estimates of the range of seasonal future mean climate change in percent. By employing a pattern scaling approach, the seasonal changes for the A1F1 (rapid growth & fossil fuel intensive) and the B1 (rapid growth, peaking in mid-century) emission scenario for each of the three GCMs were derived.

For each station, response rates of temperature and precipitation per °C of global warming were calculated for each GCM and emission scenario. The uncertainty ranges of climate model output at a station level were assumed to be bounded by the maximum and minimum response rates to create a uniform distribution of local change. Then for each synoptic station, a Monte Carlo random sampling was used to generate probability distributions for changes in temperature and precipitation for four emission scenarios (A1FI, A2, B1 and B2). For a detailed description of the methods employed, see Fealy (2010).

Due to the inclusion of the A1F1 and B1 emission scenarios, the projected changes in temperature based on the probabilistic approach, indicate a greater warming range for the 2080s compared to the statistically downscaled ensemble. The projected changes in precipitation show lower projected decreases compared to the statistically downscaled data. While the probabilistic-based mean seasonal projected changes in precipitation was found to be more conservative than that of the statistically downscaled ensemble mean, the range in projected changes was found to vary. Particular seasons exhibited an equal likelihood of both positive and negative changes associated with precipitation. Overall, the projected mean changes in temperature and precipitation using the probabilistic approach, were found to be comparable to the statistically downscaled ensemble.

4.6.3 Hydrological Comparison of Climate Scenarios

Bastola *et al.* (2012) generated estimates of hydrological responses to both sets of future climate scenarios for selected catchments in Ireland. To generate time series from the probabilistic scenarios derived by Fealy (2010), Bastola *et al.* (2012) employed a weather generator (WGEN) to derive daily time series of precipitation as input to a suite of conceptual rainfall runoff models. In applying WGEN, samples of changes in precipitation were randomly drawn from its probability distribution for each season to generate 100 future climate time series for the period 2070-2099 (2080s) for each of the catchments analysed in their study.

Both the WGEN simulated probabilistic scenarios and the statistically downscaled scenarios were used to drive hydrological models. For the control period used in that study (1971-1990), the prediction uncertainty quantified with WGEN was found to be high in comparison to that from the statistically downscaled scenarios due to the climate variability incorporated in the WGEN scenarios. For the future period (2080s) however, the differences in prediction intervals of stream flow were found to be of a similar order of magnitude.

Figure 4.12 shows the probability density functions for the seasonal mean stream flow estimated from both statistically downscaled and WGEN generated (probabilistic) scenarios for control period (1971-1990) and the future (2070-2099), for the two catchments of interest in this thesis. The density is calculated based on the proportion of future daily mean flow lying within the specified interval. Generally, the distribution derived from statistical downscaling is flatter compared to the probabilistic one. The sharp distribution of seasonal stream flow for WGEN scenarios is likely to be attributed to a larger number of scenarios, which results in an improved sampling procedure. In this particular application, the uncertainty ranges associated with the statistical downscaled scenarios were considered to be comparable to the ones derived from the probabilistic scenarios using WGEN, particularly with regard to low flows, which are of particular interest to this study.

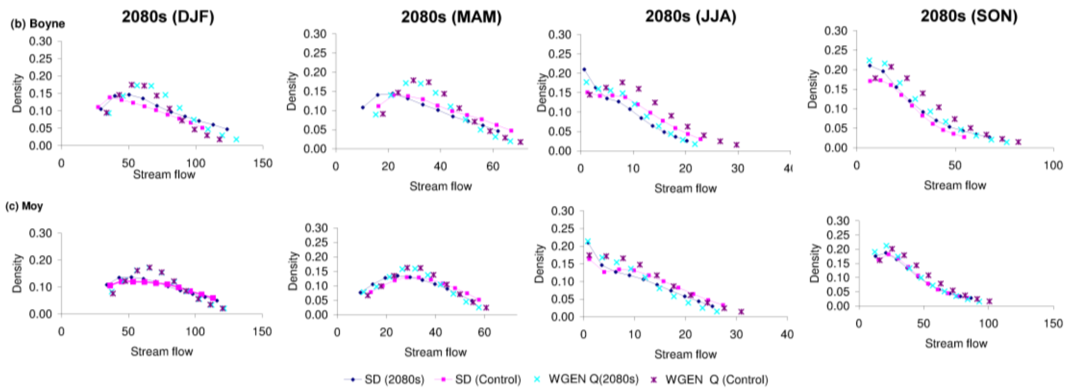


Figure 4.12 Probability distribution of estimated seasonal mean flows derived from conceptual hydrological models using statistically (SD) and probabilistically downscaled scenarios (WGEN) in catchments analysed by Bastola *et al.* (2012). Here only the Boyne (b) and Moy Catchment (c) are shown.

For the illustrative studies presented in this thesis, future climate time series for two synoptic weather stations are used. Station 1034 (Belmullet) in the West and Station 2922 (Mullingar) in the East of Ireland. As the water resource model uses monthly time steps, the analysis of the characteristics of future climate data, is also based on monthly data. With precipitation being the key driver of hydrological models an analysis of precipitation only is performed. Figure 4.13 shows the monthly total precipitation cumulative distribution (CDF) of the observed control period (1971-1999) against the two suites of GCM series (transient statistically downscaled and probabilistic scenarios (WGEN)). Higher monthly precipitation is underestimated particularly for the statistically downscaled climate scenarios, whereas for Mullingar (St 2922) the probabilistic climate scenarios bound the higher precipitation totals for the control period. For drier months, which are of most interest here, both sets of scenarios capture the observed data well. The ranges from the probabilistic scenarios tend to be wider for Mullingar, representing the climate variability incorporated in the application of weather generator. However, the additional ranges derived tend to be towards higher rainfall amounts. The statistically downscaled scenarios tend towards the lower ranges in Mullingar or are within the bound of the WGEN scenarios. There is evidence of systematic underestimation for wetter months for both stations, particularly for the wetter West (St 1034-Belmullet).

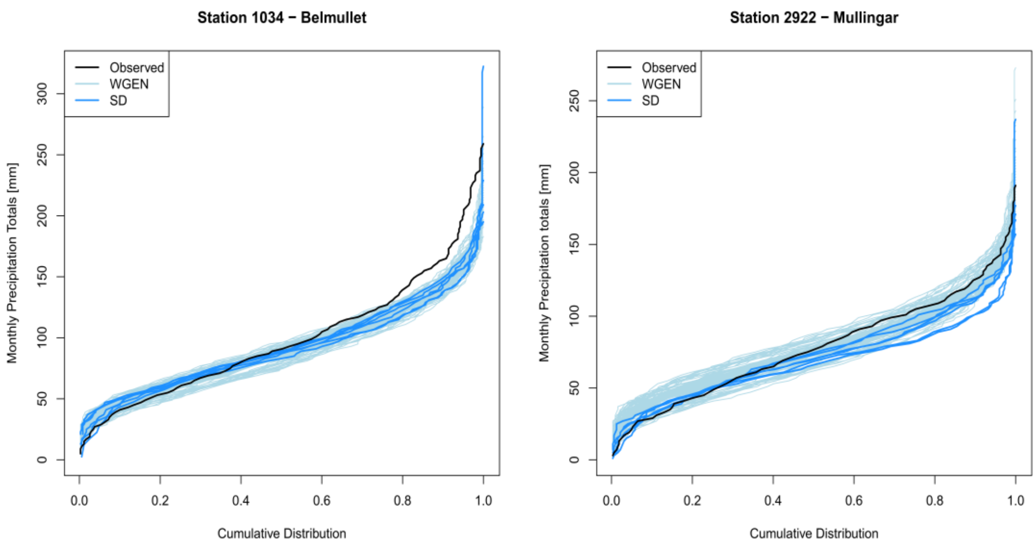


Figure 4.13 Monthly precipitation totals cumulative distribution for observed (black line), statistically downscaled (SD, blue) and probabilistic scenarios generated with WGEN (light blue) over the control period (1971-1999).

In addition to comparing the seasonal mean flow derived from hydrological models driven by statistically downscaled and probabilistic scenarios, Bastola *et al.* (2012) also compared the probability distribution of seasonal mean flows generated with the probabilistic scenarios with those derived from a sample of 17 GCMs that were part of the Coupled Model Intercomparison Project Phase 3 (CMIP3). Regional climate scenarios from the CMIP3 models were derived using a simple change factor approach for monthly precipitation estimates. The difference to the approach above is that the change factor method was only calculated for a single grid box representing Ireland, and not specific to a synoptic station. WGEN was used to derive regional time series for the change factor approach by adjusting the parameters of the model proportional to the precipitation change using a relationship derived between the parameters of the weather generator and the mean precipitation.

Figure 4.14 compares the probability distribution for percent change in seasonal mean flows for both the CMIP3 samples (CF) and the probabilistic scenarios described above (SDprob), which represent the four SRES scenarios. In general, the shapes of the probability distributions of the seasonal mean flows are quite similar for both sets of scenarios, with the SDprob scenarios being slightly shifted to lower percent changes for spring and summer.

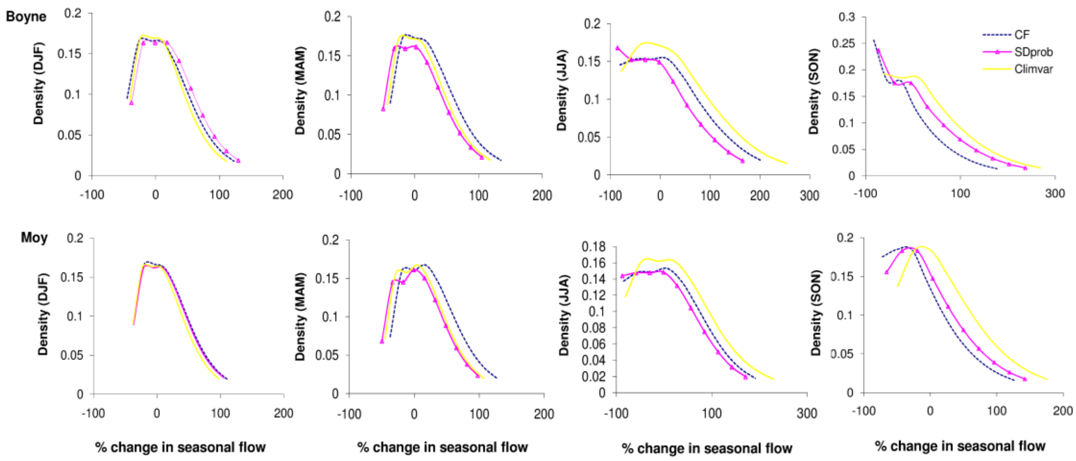


Figure 4.14 Probability distribution of mean seasonal stream flow for catchments analysed by Bastola *et al.* (2012). From left to right: winter, spring, summer and autumn for the Boyne (upper) and Moy catchment (lower). Showing flows modelled with probabilistic scenarios derived using 17 GCMs with the change factor method (CF), the probabilistic scenarios (SDprob) and the multiple realisation of climate scenarios over the control period (Climvar).

4.6.4 Selection of Future Climate Scenarios

The choice of scenarios to be used in the decision information tool is important, as any of the results derived are dependent on the scenarios selected. There is no optimum solution as each of the scenario sets contains both positives and negatives. For example, while the statistically downscaled scenarios provide a transient representation of climate for the period 1961-2099 they do represent a relatively small sample of the uncertainties associated with GCMs, which are known to be a major contributor to possible future uncertainty ranges. At the same time however, the comparison above suggests that the statistically downscaled scenarios do represent a sample from the more extreme, dry end of the uncertainty range as evidenced from the probabilistic and CMIP3 scenarios considered by Bastola *et al.* (2012).

On the other hand, the probabilistic scenarios are derived using a weather generator which is trained to represent historical records and it cannot be assumed that the future weather will directly correspond to the regimes found in the historical records. Additionally, the construction of probabilistic scenarios is very much dependent on the methods and assumptions used during their construction. Furthermore, the WGEN employed in the production of probabilistic scenarios for Ireland cannot represent accurately longer duration dry spells due to the Markov chain model used (Bastola *et al.*, 2012), which can be a disadvantage for future water resources analysis. As shown above, the ranges of the GCM space from the probabilistic scenarios is not much greater than the sampling ranges obtained from the statistically downscaled scenarios. Under drier conditions and for drier months, even lower extremes can be found in the statistically downscaled scenarios. Moreover, the probabilistic scenarios are pattern scaled and do not represent a transient time series with no information available for the early part of the century which would be needed in the application of the tool here.

Therefore, there is a trade-off to be made in selecting and incorporating the future scenarios currently used in Ireland. The main aim of this work is to develop a tool for informing decision-making on adaptation options and applying the tool to Irish hydrological conditions, incorporating hydrological modelling uncertainties. For the reasons discussed above it is decided to use the statistically downscaled scenarios in this setting, as the transient scenarios also allow evaluating system changes over time. However, future use of the tool should as a matter of priority explore a much greater selection of climate scenarios. The selection of the statistically downscaled scenarios is done with caution due to the following limitations:

1. While the scenarios selected are found to fall within the lower end of the ranges of changes explored, they do represent only a partial sample of the uncertainty space associated with GCMs. As with all such work, the results that are derived should be seen as highly dependent on the scenarios used.

2. While the scenarios selected are transient and provide information for analysing future impacts and adaptation scenarios in short- and longer-term there is no guarantee that they do capture future extremes and variability. There is a widespread discussion as to whether GCMs and climate scenarios are capable of capturing extremes and whether they contain the detail of information required for water resources planning and management.

3. While the scenarios selected are bias corrected to observational records, there is no guarantee that this correction holds true for future conditions.

4.7 Future Water Resource System and Adaptation Scenarios

The WEAP model is coupled with HYSIM and used to identify abstraction points that might be vulnerable under ‘Business as Usual’ conditions and to assess sample scenarios of what are deemed robust water adaptation options against the full range of uncertainties obtained from the modelling approach presented in the previous paragraphs. It needs to be noted that the uncertainty ranges obtained are highly conditional on all the assumptions made and decisions taken throughout modelling approach. However, in an Irish context the ranges obtained are the currently best available uncertainty ranges against which to evaluate future water management plans. The future water resource management scenarios are examples of possible strategies that could be conducted. However, these example scenarios are based on actual plans stated by Irish planning authorities.

The water demands for each investigated scenario are based on the population number obtaining their water from each individual water abstraction point and the corresponding per capita water abstractions based on ‘The Provision and Quality of Drinking Water in Ireland, A Report for the Years 2007 – 2008’ (EPA, 2009). The populations growth scenario, used to project the increases in water demand into the future, was derived from the report ‘Population and Labour Force Projections: 2011-2041’ (CSO, 2008) using the most likely scenario M1F2 (moderating migration levels and total fertility rate of 1.9) as shown in Figure 4.15. Beyond 2041 there are no official population growth rate projections available, therefore the rate is kept constant on the level of the last estimate from 2041 onwards.

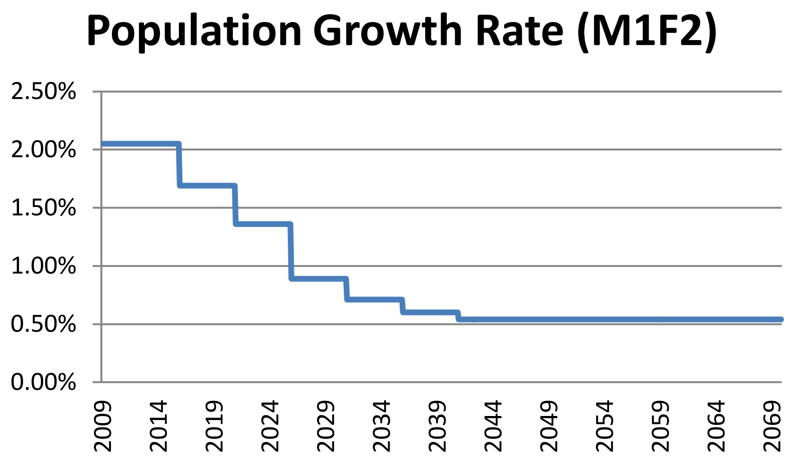


Figure 4.15 Population growth rate projections based on CSO (2008).

National average estimates of leakage levels (unaccounted for water) of 43% are based on a report compiled by Forfás (2008). The leakage is accounted for in the WEAP modelling approach by increasing the water abstraction requirements according to the leakage level. The future percentage decline of unaccounted for water is based on the report projections by CMD (2004).

In this work, four adaptation options are analysed as shown in the scenario matrix in Figure 4.16. These four options are assessed in terms of their performance against the future uncertainty ranges derived. The options include no-measures or business as usual (Scenario A), demand side measures (Scenario B), supply side measures (Scenario C) and an integration of supply and demand side measures (Scenario D).

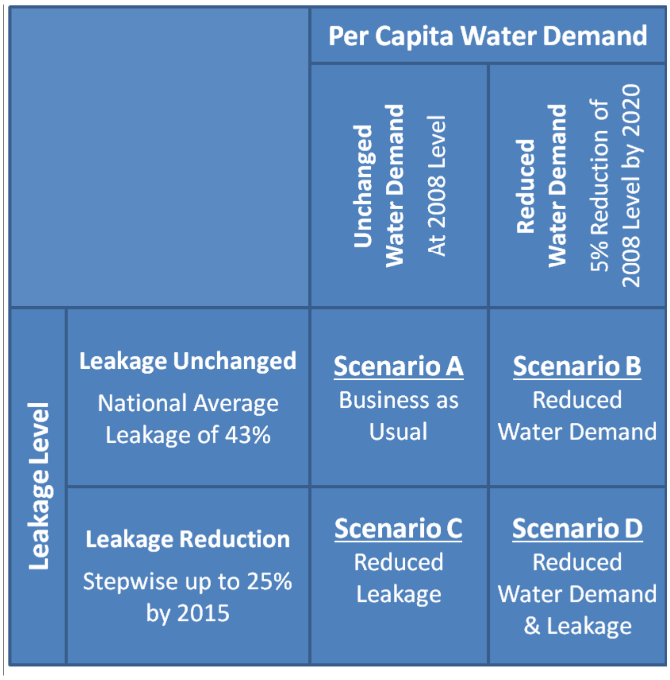


Figure 4.16 Scenario matrix showing the four investigated scenarios (A-D).

The four investigated scenarios can be summarised as follows:

For all scenarios the population of 2008 is extrapolated into the future using the annual average change rate of the CSO projections (as shown in Figure 4.15).

<u>Scenario A – 'Business as Usual':</u>

Per capita water abstractions and supply infrastructure remain constant on the 2008 values. The level of unaccounted for water is the national average of 43%.

<u>Scenario B – 'Reduced Water Demand':</u>

Increasing awareness in water conservation results in a stepwise annual per capita water demand reduction of up to 5% by 2020. The level of unaccounted for water remains unchanged at 43%.

<u>Scenario C – 'Reduced Leakages':</u>

Improved water supply infrastructure results in an annual stepwise-reduced leakage level from 43% to 25% by 2015. Daily per capita water demand remains unchanged at its 2008 level.

<u>Scenario D – 'Reduced Demand and Reduced Leakages':</u>

Integration of Scenario B and Scenario C. Rates of reduction of the per capita water demand and leakage reduction, as described above.

Scenarios B, C and D presented can be characterised as “low- or no-regrets” and “win-win-strategies”, which can potentially cope with climate uncertainty and provide benefits, even in absence of climate change (Hallegatte, 2009). Therefore, in uncertain conditions their application is to be favoured over high cost, potentially high regret strategies, which are not included in the examples given here. Consequently, no attempt is made to assess trade-offs or perform a monetary evaluation of these future strategies

Each of these four scenarios is modelled for each individual investigated surface water abstraction point and assessed against the ensemble of possible future stream flow ranges incorporating the range of uncertainties associated with the assumptions and decisions resulting from the previous modelling steps.

4.8 Threshold-Based Scenario Analysis

To assess the performance of the different adaptation scenarios for each individual water abstraction point, a threshold-based approach is employed. Management thresholds are commonly based on either expert judgement on important variables of the water resource system or according to a predefined performance matrix, which makes results more comparable across different systems. Threshold-based analysis can also been seen as a first pass assessment of the system, to indicate emerging issues in the system or responses of the system to climate change, which can then be followed by a more in depth analysis. To be able to compare the results of the individual water abstraction points, the modelling outcomes are analysed using predefined system independent performance measures.

There are several methodologies and water scarcity indexes or water stress indices used to evaluate water resources vulnerability in terms of water scarcity or water stress (Brown & Matlock, 2011). Depending on the aim of the study and data availability, the criterion on which to base the water resource assessment has to be selected. Such indicators are based on human water requirements, water resources or a combination of both. The aim of the use of indicators is to obtain a quantification of the pressure put onto the water system by external factors (for example volume of water withdrawal or amount of water consumed). Commonly used indicators are for instance, the water 'use-to-resource ratio', the 'consumption-to-Q90 ratio', per capita water availability (Falkenman indicator) or the 'Water Stress Indicator' (Smakhtin *et al.*, 2004; Alcamo *et al.*, 2007; Brown & Matlock, 2011). Generally, thresholds applied to water management systems are not considered to be permanent, but rather flexible (Arnell, 2000), depending on water management and planning priorities. Predefined threshold-based indicators should only be used as guides to highlight certain system characteristics that require a more in depth analysis.

In this study a widely used threshold-based indicator is employed that reflects the physical pressure on the water resource system, the water 'Use-to-Resource Ratio' (URR) (Raskin *et al.*, 1997), also referred to as 'water resource vulnerability index' (Brown & Matlock, 2011), 'withdrawals-to-availability ratio' (Alcamo *et al.*, 2007), or 'relative water demand' (Vörösmarty *et al.*, 2000). Here the original name 'Use-to-Resource Ratio' (URR) is used as introduced by Raskin *et al.* (1997), where the term 'Use' includes all water abstractions not only the amount of water that is finally used. The URR indicator has been selected, as this indicator has low data requirements and the relative simplicity of the indicator is also beneficial in assessing the water resource systems in future simulations. Here the URR index relates (divides) the water demand (withdrawals) to renewable water supply (runoff), which provides a representation of the state of the water resource. By splitting the index into four categories (Table 4.4), an indication of local water stress can be obtained (Vörösmarty *et al.*, 2000), which allows the identification of water abstractions that put the water resource system under water pressure.

Table 4.4: Water Use-to-Resource Ratio (URR) (Raskin *et al.*, 1997).

Withdrawal / Runoff	<10%	10%–20%	20%–40%	>40%
Classification	No Stress	Low Stress	Stress	High Stress

A Use-to-Resource-Ratio higher than 20% 'can begin to be a limiting factor on economic development' (Raskin *et al.*, 1997) and a ratio lager than 40% is termed the *critical* ratio (Alcamo *et al.*, 2000), commonly used in studies analysing water resources (Alcamo *et al.*, 2007; Brown & Matlock, 2011). As with other threshold-based indicators, the physical processes are simplified and sometimes the interpretation of such classifications schemes can be difficult. However, such indicators allow an assessment of water resources with low computational demand and also allow identification the current/future state of water resources systems and their comparison.

The original URR index developed by Raskin (1997) is based on values derived from annual calculations. However, in regions with pronounced seasonality of surface water availability (here; high winter and lower summer flows) and no/little water storage facilities, like Ireland, an assessment of the water resources can result in underestimation and misleading outcomes if computed on an annual level. In Ireland, the seasonal variation in water availability results in large seasonal differences in the URR (particularly for summer months). To be able to represent temporal variability of water stress, a refined URR index is employed, which takes seasonality and/or lack of storage into account by employing monthly calculations (Hall & Murphy, 2010, 2011; Wada *et al.*, 2011).

4.9 Water Resource System Performance Metrics

To assess and quantify the water resource system performance under the investigated water resource scenario, ‘stress tests’ should be employed (Stakhiv, 2011). Again, to facilitate comparison of results across the investigated water abstraction points, common performance metrics are used. Ideally, these metrics include qualitative measures of reliability, resilience and vulnerability and brittleness (Stakhiv, 2011).

In this study, the Reliability, Resilience, and Vulnerability (RRV) metrics first introduced by Hashimoto *et al.* (1982) are used to evaluate the performance of the water abstraction points in relation to the URR threshold. These statistical RRV measures have been used in various studies on water resources, also in relation to climate change. For example, Lettenmaier *et al.* (1999) for a US regional assessment, Fowler *et al.* (2003) for a water resource system in the UK or Kim & Kaluarachchi (2009) for the Blue Nile in Ethiopia. All of these studies using the RRV metrics have used different threshold criteria to evaluate the performance of different characteristics of the water resources system. The flexibility of the RRV framework with different threshold criteria to define satisfactory and unsatisfactory system performance is important when performing assessments within a decision-support framework as described above.

The RRV metrics allows summarising the system performance over time according to a pre-defined threshold value or the so-called criterion C. With the help of the threshold criterion, the time series of interest is divided into *satisfactory* (S) and *unsatisfactory* (U) system performance values (Hashimoto *et al.*, 1982). Depending on the threshold analysed, the threshold criterion can be an upper limit (UC) or a lower limit (LC) (Figure 4.17).

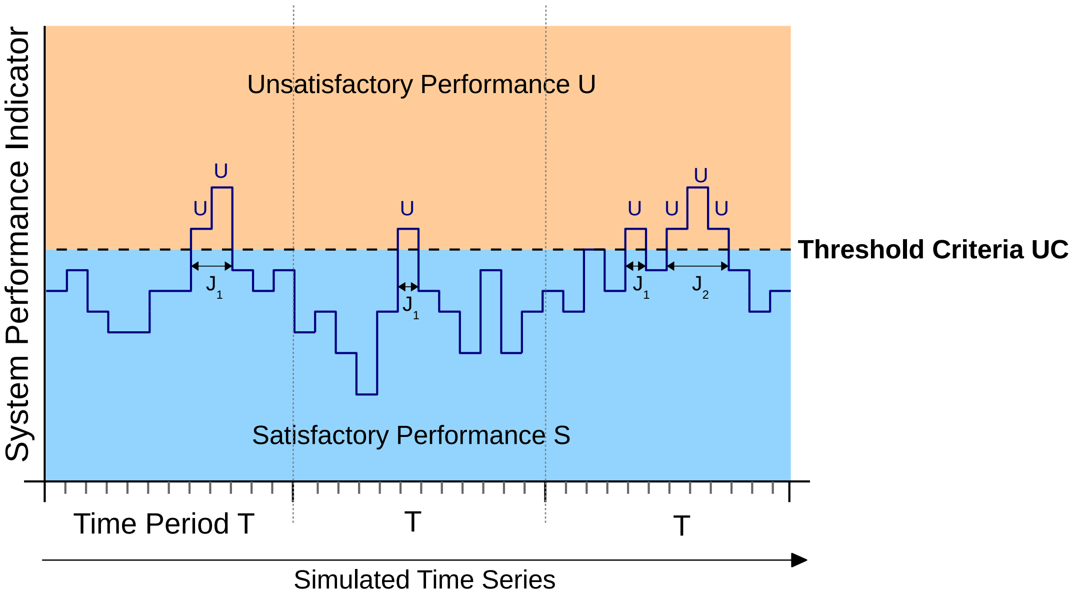


Figure 4.17 Derivation of system performance indicators from a time series, using a threshold criterion.

To use the RRV metrics to analyse and compare simulated time series, static conditions over the evaluation periods are required (Kjeldsen & Rosbjerg, 2001). Therefore, a stepwise dynamic change (increase or decrease) of the modelled variables (e.g. population growth or leakage level) used in the water resource scenarios is employed, instead of linear changes. For example in Figure 4.18 the blue time series represents the stepwise dynamic modelling of leakage reduction compared to a linear approach (black line), where the leakage levels are calculated as annual averages and modelled over a year, with the change applied at the end of each step (year).

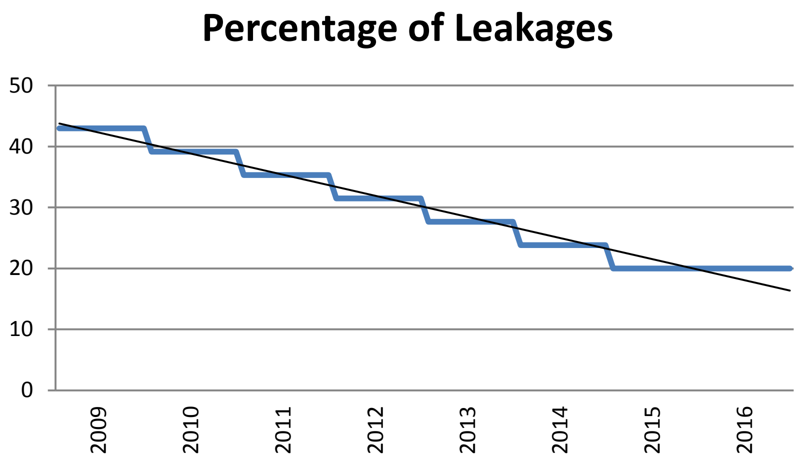


Figure 4.18 Example of stepwise dynamic modelling approach employed within WEAP.

To be able to evaluate RRV mathematically, several annotations need to be established, for example, the time series value is denoted X_t and the future evaluation time period is *T* (Hashimoto *et al.*, 1982; Fowler *et al.*, 2003). In this work, the system performance indicator used is the Water Use-to-Resource Ratio (URR) which requires an upper limit threshold criterion (UC) to be analysed. The individual time steps in the time period *T* are evaluated as follows:

If $X_t \leq UC$ then $X_t \in S$ and $Z_t = 1$

else $X_t \in U$ and $Z_t = 0$

Additionally, W_t indicates the transition from an unsatisfactory to a satisfactory event (Hashimoto *et al.*, 1982; Fowler *et al.*, 2003)

$$W_t = \begin{cases} 1, & \text{if} \quad X_t \in U \quad \text{and} \quad X_{t+1} \in S \\ 0, & \text{otherwise} \end{cases}$$

The continuous periods of unsatisfactory events are defined as $J_1, J_2, ..., J_N$ (including single unsatisfactory time steps (Hashimoto *et al.*, 1982; Loucks, 1997) with each $J_1, ..., N = 1$ within each time period *T*.

The *Reliability*, *Resilience*, and *Vulnerability* (RRV)-indices are defined as follows:

Reliability measures the probability of a system being in a satisfactory state. *Temporal Reliability* is the ratio of the number of satisfactory time steps divided by the total number of values per time period considered (Hashimoto *et al.*, 1982; Kjeldsen & Rosbjerg, 2004).

$$\mathrm{Rel} = \frac{\sum_{t=1}^{T} Z_t}{T} = \frac{\text{number of satisfactory timesteps}}{\text{total number of time steps}} \qquad \textbf{Equation 4.5}$$

Resilience is a measure of the ability of the system to recover after being in an unsatisfactory state, which gives an indication of the speed of system recovery. Resilience is computed as the number of times an unsatisfactory outcome (U) is followed by a satisfactory outcome (S), divided by the number of unsatisfactory values within a specified time interval. Resilience measures the ability of a system to recover from an unsatisfactory event (Hashimoto *et al.*, 1982).

$$\mathrm{Res} = \frac{\sum_{t=1}^{T} W_t}{T - \sum_{t=1}^{T} Z_t} = \frac{\text{number of times an U timesstep is followed by a S timestep}}{\text{total number of U timesteps}} \qquad \textbf{Equation 4.6}$$

Vulnerability can be calculated either by the extent or by the duration of unsatisfactory conditions. In this study, the *Expected Duration-Vulnerability* is used, which is a measure of the average duration of the water resource system being in an unsatisfactory state. It is calculated by the total number of unsatisfactory time steps divided by the number of occurrences of continuous unsatisfactory events (including single unsatisfactory time steps) (Loucks, 1997).

$$\mathrm{Vul_D} = \frac{T - \sum_{t=1}^{T} Z_t}{\sum_{i=1}^{N} J_i} = \frac{\text{total number of unsatisfactory timesteps}}{\text{number of continuous unsatisfactory timesteps}} \qquad \textbf{Equation 4.7}$$

The RRV metrics are a means of combing the output of the multiple future simulations and can allow for a cross-comparison of different water abstraction points and scenarios modelled. The system performs best with high *Reliability* and high *Resilience* values (near the maximum value of 1) and low *Duration Vulnerability* values. As the RRV indices primarily depend on the criterion used to define satisfactory or unsatisfactory performance, this approach is highly flexible and can be used to evaluate different performance criteria for each water scheme. However, the outcomes of an analysis will always be dependent on the criterion used to evaluate the water scheme. Therefore, to be able to compare the performance of several water resources systems, the threshold criteria used should be the same. This might involve a compromise between the comparability and the selection of the most appropriate performance measure. Here, the 'Use-to-Resource Ratio' (URR) metrics is applied to individual surface water abstraction points.

4.10 Discussion and Conclusion

The iterative framework proposed here is based on the main features of a decision-making framework proposed by Willows & Connell (2003). Connell *et al.* (2005) highlight the importance of viewing adaptation as iterative tiered processes, which are reviewed over time within a decision-support framework. The framework presented here has all these elements; however, the tools and methods presented in the decision-support loop are specific to the context of Irish surface water resources.

The tool presented aims to incorporate a wide range of uncertainties. However, it needs to be noted that the uncertainty ranges obtained are highly conditional on all the assumptions made and decisions taken throughout modelling approach.

Additionally, the climate scenarios employed and the uncertainty ranges associated with them are specific to an Irish context. Although the number of future projected climate scenarios is small compared to other studies, for example Lopez *et al.* (2009) used an ensemble of 246 perturbed physics climate model members to investigate changes in water availability in southwest England. The main aim of this work is to provide a tool that can be used for adaptation option assessment. It was considered important that such a tool should function with the information currently available to water managers and decision makers in Ireland, but also be flexible enough to incorporate new or additional climate information. Due to the flexible setup of the tool in terms of coupling the hydrological model with a water resource model the tool allows future work to include a state of the art analysis of a fuller sample of the uncertainty space associated with Global Climate Models in terms of model structure and also parameterisation uncertainties from experiments such as *climateprediction.net*. This point is returned to in the final chapter on Discussion and Conclusions.

A detailed reasoning and notes of caution for choosing the statistically downscaled climate scenarios produced by Fealy & Sweeney (2007, 2008) are provided above. To summarise, for a first-pass development and application of the tool presented here, the scenarios are fit for purpose, as they fall within the lower end of the ranges of changes explored, and provide a transient time series that can be used to evaluate the water resource system performance over time. However, the scenarios represent a relatively small sample of the climate model uncertainties. As with all such work, the results that are derived within such a modelling tool should be seen as highly dependent on the scenarios used. Future work will need to include a larger sample of uncertainty stemming from climate scenarios to ensure robustness of such assessments.

The proposed framework uses a single conceptual rainfall runoff model. Possible wider ranges of hydrological simulations could have been obtained by using more than one hydrological model to account for model structure uncertainty (Bastola *et al.*, 2011b). However, within this framework, the priority has been placed on accounting for hydrological parameter uncertainties in an un-gauged setting.

The “low- or no-regrets” and “win-win” adaptation strategies assessed in this framework are based on real plans for the Irish water resources sector. These scenarios are applied to all water abstraction points to examine the effect of such strategies that are favourable compared to large and long-term infrastructural investments investigated. However, adaptation strategies need to be context specific, therefore a detailed assessment of adaptation options, which are specific to each water abstraction point, are recommended before implementing such measures.

The Water Use-to-Resource Ratio (URR) employed in this decision-support tool within the adaptation framework is an example of the threshold-based approaches that allow the evaluation of future water resource system performances or adaptation measure. However, depending on the threshold indices selected, the performance results will be different. Such threshold indicators can provide information in an iterative framework, and depending on the water managers' needs, the indices employed can be analysed and evaluated accordingly. In a further application of the too, such thresholds should be determined though stakeholder engagement. Additionally the thresholds employed do not have to be static, but can rather change over time in their magnitude and importance for the water resource system.

4.11 Chapter Summary

In this chapter, a framework and methods are presented which will be used in the following two chapters to assess the vulnerability of future Irish water abstractions to changes and to support decision-making when faced with ranges of future climate uncertainties through adaptation option appraisal.

- The modelling and analysis methodology described in this chapter allows the incorporation of ranges of change as derived from Irish climate scenarios and hydrological models into the decision-making framework. The tool developed is also flexible in that given computation time and resources the next generation of scenarios or results from international experiments can be incorporated.
- Non-climatic pressure in the form of population changes are added into to the water resources analysis to allow an understanding of the potential success of adaptation options combined with non-climatic pressures.
- The threshold-based framework allows the evaluation and comparison of multiple future outcomes in a water resource model across different water supply systems.
- The individual components of the decision-support tools (i.e. climate scenarios, hydrological models, adaptation measures, threshold indices) are context specific.

- The framework and the decision-support tool allow for update, amendment and incorporation of information over time, as adaptation is an iterative process and not a once off assessment.
- The selected climate scenarios are fit for a first pass assessment. However, future work will need to include a larger sample of scenarios to increase the uncertainty ranges.
- The modelling tool is flexible in that it can be applied to existing or new gauged or un-gauged water abstraction points, can be readily updated when revised climate change information become available and allows the integration of different pressures.
- The hydrological modelling approach presented extends the application of the proxy-basin approach by incorporating parameter uncertainty. Additionally, the WEAP model is coupled for the first time with a catchment based hydrological model that has been used extensively for simulating water resources in Ireland.
- Here; WEAP is applied for the first time in an uncertainty framework to explore the robustness of anticipatory adaptation options.
- The water resource system performance metrics allow assessing the reliability, resilience and vulnerability of the water abstraction points and are a means of summarising the change in system characteristics over time with regard to multiple uncertain futures.

5 Tool Application: Future Water Resources Availability

5.1 Introduction

In this and the following chapter, the tool described in the previous chapter is applied to twelve Irish illustrative case study water abstraction points. Within this chapter, the ranges in future stream flows and future water resource availability is derived and analysed. Chapter 6 uses the results from this chapter to appraise the performance of adaptation options for each of the twelve water abstraction points.

The chapter is structured as follows; Section 5.2 explains the reasoning for selecting the study catchments. In Section 5.3, presents the selected case studies together with the results of model calibration and evaluation. Section 5.4 illustrates the hydrological modelling process and derived stream flow series (Section 5.4.1), together with projected changes in future water resources for each of the abstraction points analysed (Section 5.4.2). Results are discussed and conclusions are drawn (Section 5.5) and finally the chapter is summarised in Section 5.6.

5.2 Case Study Catchment Selection

In hydrometrical terms, Ireland is divided into eight River Basin Districts (RBDs) as shown in Figure 5.1. These basins provide the basis for planning and implementation of measures in water resources management, particularly with regard to the implementation of the European Water Framework Directive (WFD). Of the eight RBDs, four are entirely within the Republic of Ireland: the Eastern, South Eastern, South Western and the Western RBDs. Additionally, there are three International RBDs (IRBDs) shared between the Republic of Ireland and Northern Ireland, namely the Shannon, South Western, Neagh-Bann and the North Western RBDs. The North Eastern RBD is entirely situated in Northern Ireland.

Each River Basin District is made up of a minimum of two and up to eight Hydrometric Areas (HAs), which amount to a total of 40 HAs (Figure 5.1), which in turn consist of several catchments. The numbering system for the hydrological gauging stations in Ireland are also related to the HAs, with the first two digits indicating the HA within which the station is located and the last three digits are used to identify a unique station.

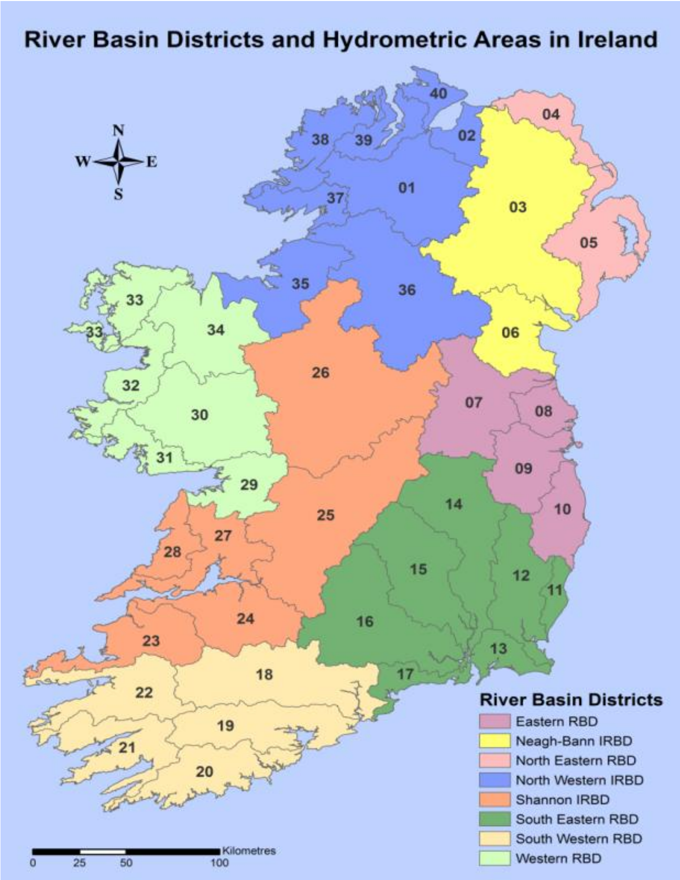


Figure 5.1 River Basin Districts (RBD) and hydrometric areas (HAs) in Ireland.

The modelling framework developed in the previous chapter is applied to two Irish case study areas to provide an illustrative application of the framework. The HAs lying in these areas were chosen to be representative of different hydrological and water infrastructural characteristics and climatological regimes representative for Ireland. Figure 5.2 shows the selected case study areas of the Boyne River catchment (HA 07) in the East of Ireland and the Moy River catchment (HA 34) and the Erriff-Clew Bay (HA 32) in the West of the country. Within the selected HAs, the public water systems for the surface water abstractions, which supply water to a population, greater than 100 are investigated. This amounts to six in the West and six in the East, or 12 abstraction points in total. The following paragraphs will describe the characteristics of these illustrative case study areas and water abstraction points.

Figure 5.2 Case study areas, streams and synoptic stations used.

5.3 Characteristics of Case Study Areas

For the case study areas employed, a detailed investigation of the hydrological, infrastructural and climatological characteristics is necessary. These characteristics become important for the hydrological simulations outlined later, particularly for calibrating and evaluating the hydrological model using the proxy-basin split-sample approach. The following paragraphs describe the characteristics of the illustrative sample catchments and water resource systems in detail.

5.3.1 HA 07 – The Boyne Catchment

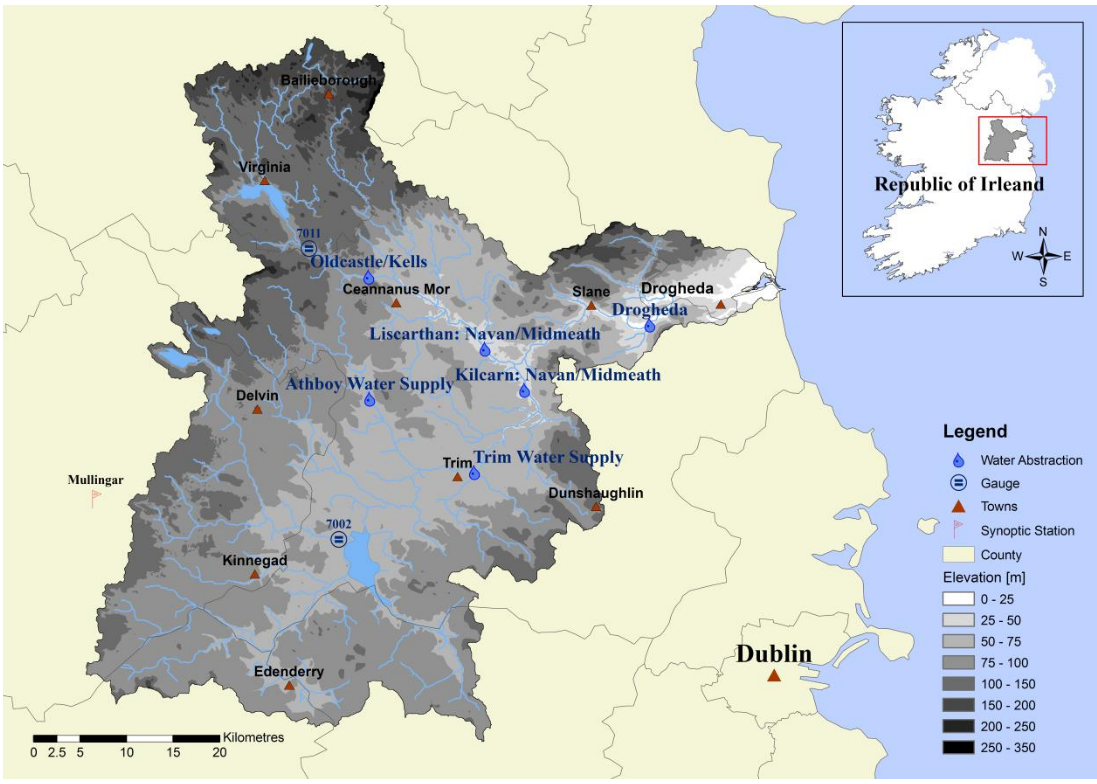


Figure 5.3 The Boyne catchment. Including catchment elevation, water abstraction points, hydrometric gauges, synoptic weather stations and towns.

The Boyne River catchment is located in the Eastern RBD (Figure 5.3) and extends over an area of ~2692 km^2. The catchment has an average elevation of 89 meters and ranges from zero to about 338 meters in the northern part of the catchment. The slopes in the catchment range from 0% to 38%, on average the slopes are gentle with a mean slope of 1.6%. Flat and undulating lowlands are the prevailing physiographic feature with Grey Brown Podzolics being the principal soil class (30.6%), followed by Gleys (24.5%.) and Minimal Grey Brown Podzolics (20.5%). The parent material of the dominating soils is Limestone Glacial Till (24%), Limestone Shale Glacial Till (21.6%) and Alluvium (12%) resulting in low productive aquifers underling about 68.6% of the catchment. The main land use types within the catchment are pasture (79.4%) and arable land (8%), as well as peat bogs (4.2%) mainly located in the southern parts of the catchment.

The climate data of the catchment is best described by the synoptic station at Mullingar (Station No. 2922), located just outside the catchments western border (see

Figure 5.3). The mean annual temperature at Mullingar (thirty-year average (1961-1990)) is 8.8°C and a thirty year mean-annual precipitation of 931.6 mm. Daily precipitation and evapotranspiration time series from Mullingar are used to drive the hydrological model.

While there is a dense network of river flow gauges in Ireland, it is very rare to find continuous discharge measurements at or close to surface water abstraction points. This provides challenges for hydrological modelling; where in the case of the Boyne catchment all of the six investigated water abstraction points have no stream flow gauging station close by. This characteristic also applies to the water abstraction points in other catchments; for example, five out of the six analysed water abstraction points in the West are not in the vicinity of a hydrometric station. As a result, abstraction points are treated as un-gauged catchments in the modelling process using the commonly applied proxy-basin-split-sample approach to derive a quantification of stream flow for the water abstraction points. Given the widespread nature of this problem, which is likely to exist outside of Ireland also, additional uncertainties are added to the cascade of uncertainty in assessing the range of future impacts in a practical setting

For model calibration and evaluation, stations in upstream sub-catchments were selected due to their low human disturbances. Additional criteria for selection were a common time period of flow measurements with good data quality and little missing flow values. Within the Hydrometric Area 07 two stations (07002 - Killyon at the River Deel and 07011 - O'Daly's Bridge at the River Blackwater) were identified due to their upstream location, data quality and representativeness of catchment characteristic (Table 5.1). Although both stations have longer flow records available, they are both affected by drainage during which no flow measurements were recorded resulting in missing data, therefore only a short overlapping period for model calibration and evaluation period is available. For the proxy-basin-split-sample approach, a period of 15 years (1984-1999) with nearly complete overlapping flow records is identified. The flow regime and the corresponding quality rating for the overlapping record of both stations are shown in Figure 5.4 (a detailed description of quality codes is given in Chapter 3). The percentage of missing data points per month over the overlapping period is shown Figure 5.5.

Table 5.1 Selected Hydrometric Stations from the HA 07 – Boyne River Catchment

Station	Available Record	Arterial Drainage	Full Missing Years	Overlapping Period
07002	1970-2004	1974-1979	1974-1980	1984-1999
07011	1957-1999	1980-1983	1980-1984	

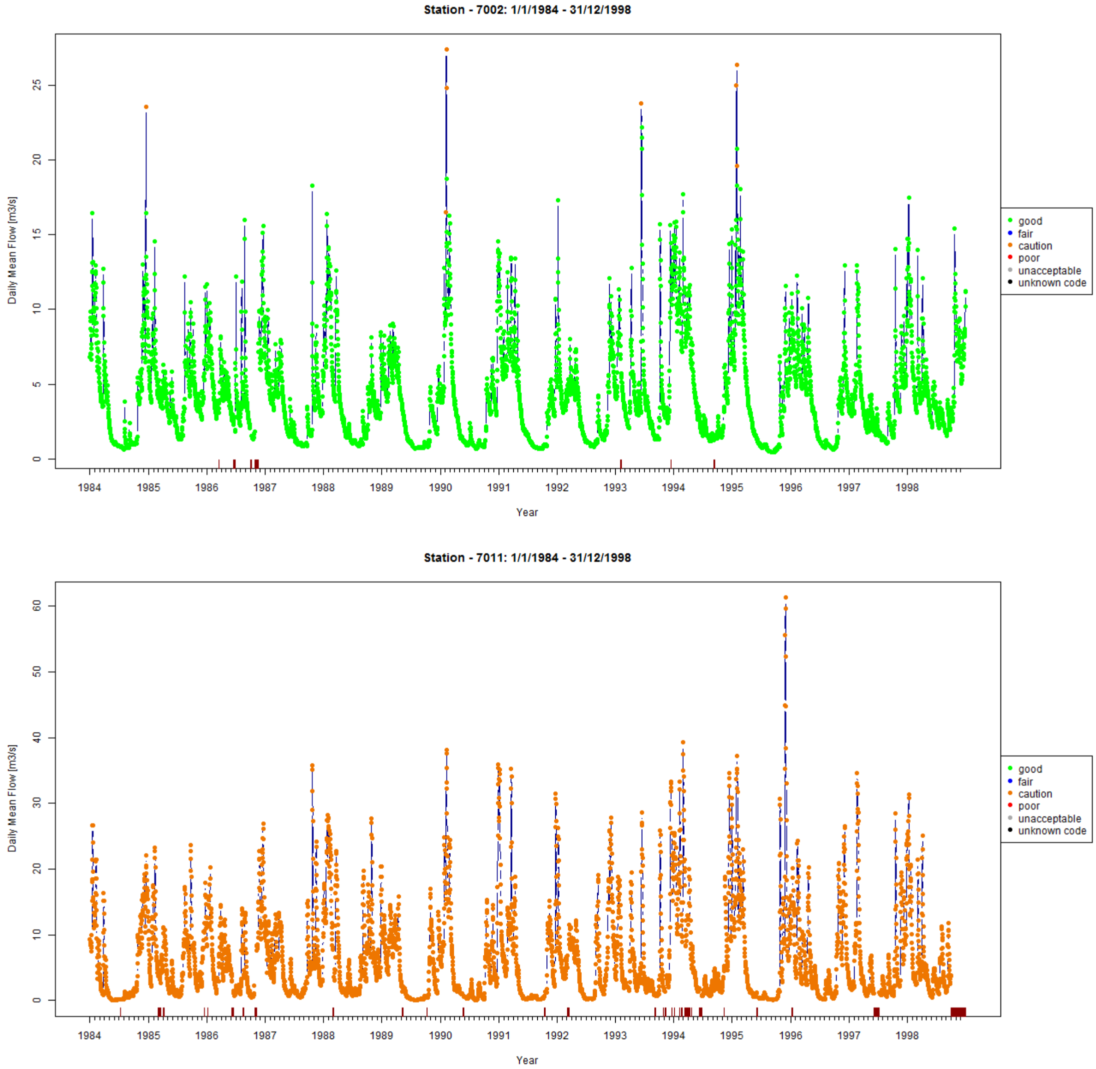


Figure 5.4 Flow regimes and data quality rating for Station 07002 and 07011.

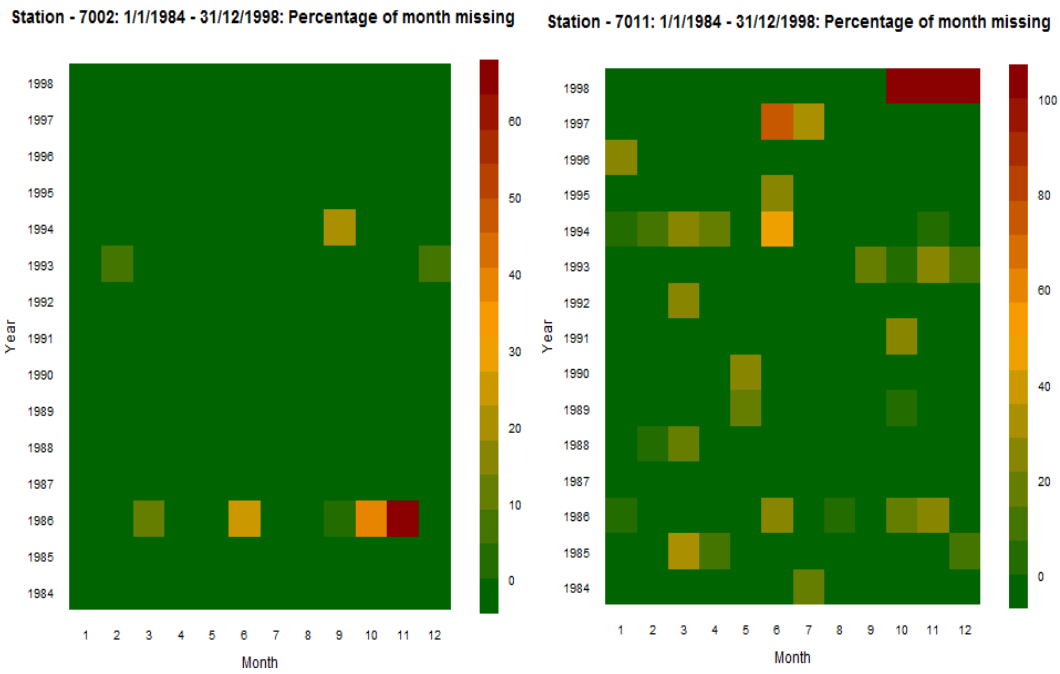


Figure 5.5 Percentage of missing days per month for station 07002 (left) and 07001 (right).

In the proxy-basin-split-sample procedure used for model training and evaluation, 15 years of overlapping flow record (1984-1999) are split into 10 years of data used for model calibration and the remaining period (5 years) for parameter evaluation in the proxy-basin. The threshold criteria used to determine behavioural parameter sets out of the 20,000 randomly sampled parameter sets are shown in Table 5.2. For details on the performance ratings and colour coding, see Table 4.3. (For ease of interpretation the table is shown again and the following paragraph summarises the criteria discussed.) The following rules were employed in identifying acceptable/behavioural parameter sets for use in model simulations. Only the parameter sets that satisfied the continuity equation by achieving a catchment water balance of zero were further evaluated with regard to the other objective functions used. The MAE value given in Table 5.2 is half of the standard deviation of the observed flow; all parameter sets above this absolute error threshold were also excluded from the assessment of model performance. In Figure 5.6 an example of the parameter values, the parameter space and model performance is given.

Table 4.3 Performance ratings for the relative error measures as suggested by Moriasi *et al.* (2007) based on monthly time steps Nash-Sutcliffe Efficiency Coefficient (EC), Percent Bias (PBIAS), Root Mean Square Error-Observations Standard Deviation Ratio (RSR).

Performance Rating	EC	PBIAS	RSR
Very Good	0.75 < EC ≤ 1.00	PBIAS < ±10	0.00 ≤ RSR ≤ 0.50
Good	0.65 < EC ≤ 0.75	±10 ≤ PBIAS < ±15	0.50 < RSR ≤ 0.60
Satisfactory	0.50 < EC ≤ 0.65	±15 ≤ PBIAS < ±25	0.60 < RSR ≤ 0.70
Unsatisfactory	EC ≤ 0.50	PBIAS ≥ ±25	RSR > 0.70

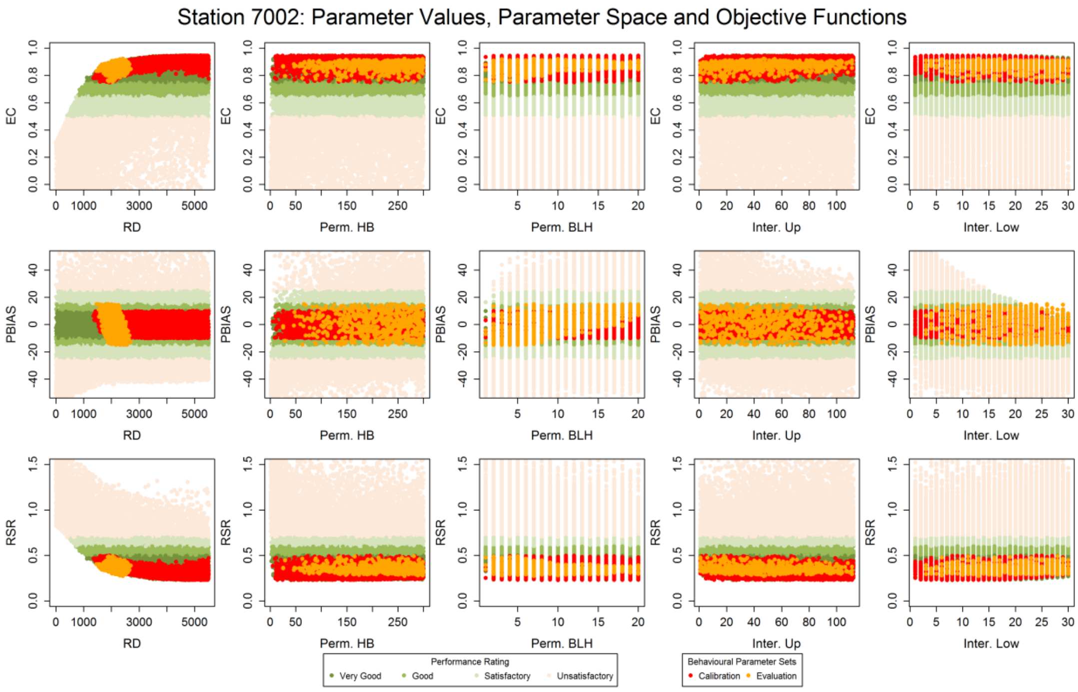


Figure 5.6 Station 7002; Parameter values and objective functions obtained from 20,000 random samples from five process parameters (RD (Rooting Depth), Perm HB (Permeability Horizon Boundary), Perm BLH (Permeability Lower Horizon), Inter Up (Interflow Upper) and Inter Low (Interflow Lower)).

Figure 5.6 shows three of the objective functions employed (Nash-Sutcliffe Efficiency Coefficient (EC), Percent Bias (PBIAS) and Root Mean Square Error-Observations Standard Deviation Ratio (RSR)). Areas with low point density (EC<0, -45<PBIASE>45, and RSR>1.5) are not plotted. The behavioural parameter sets (red points for calibration and orange points for the evaluation period) were selected based on the criteria described in Section 4.4.3 (Water balance = 0, Mean Absolute Error (MAE) less than half the standard deviation of observed flow) and all three objective functions.

For example for station 7002 (Figure 5.6), it can be seen that for both calibration and evaluation periods at least ‘good’ model performance is obtained, with most of the performance criteria obtaining ‘very good’. For PBIAS a slightly higher model performance criteria is used to determine behavioural parameter sets for calibration (red points), compared to the model evaluation period (orange points) as shown in Table 5.2 for the respective period. This adjustment during the evaluation period became necessary due to more variable river flow, which is also indicated by a higher standard deviation and therefore a higher threshold for MAE. Only the parameter sets that were behavioural in both catchments during the evaluation period were retained.

Table 5.2 HA07 Boyne River catchment: Station and performance criteria used in model calibration and evaluation

Station	Calibration (1984-1993)				No. Behav. Sets	Evaluation (1994-1999)				No. Behav. Sets
	MAE	EC	PBIAS	RSR		MAE	EC	PBIAS	RSR	
07002	< 1.360	> 0.75	< ±10	≤ 0.50	3,418	<1.654	> 0.75	< ±15	≤ 0.50	637
07011	< 2.578	> 0.75	< ±10	≤ 0.50	4,314	<3.196	> 0.75	< ±15	≤ 0.50	981

MAE, mean absolute error; EC, Efficiency Coefficient; PBIAS, Percent Bias; RSR, Root Mean Square Error-Observations Standard Deviation Ratio.

To determine the final number of behavioural parameter sets to use in future simulations, the effect of the number of sets on simulated river flows is assessed. Figure 5.7 compares the spread of summer mean monthly modelled stream flow (June, July and August) depending on the number of behavioural parameter sets selected, for the two flow stations over the period 1984-1999. In Figure 5.7 each point (blue box) represents an equally likely monthly stream flow value derived when the model is run with a parameter set. With an increasing number of parameter sets (from 100 to 700 behavioural parameter sets for each month), the envelope of modelled stream flow increases. For station 07002, the inclusion of 500 parameter sets upwards results in a good spread of stream flow values. Increasing the number to 600 or 700 parameter sets does not yield an increasing envelope of possible stream flow values. For Station 07011, a similar pattern emerges; however, for this station 400 behavioural parameter sets are sufficient to obtain the possible spread of flows. To ensure a best possible representation of the potential spread of simulations, 500 parameter sets are selected in this study, due to their good presentation of streamflow spread also in the other catchments (not shown). Therefore, from the total number of behavioural parameter sets obtained in the proxy-basin-split-sample approach, 500 parameter sets were randomly sampled for use in future hydrological simulations to derive the stream flow at the individual water abstraction points.

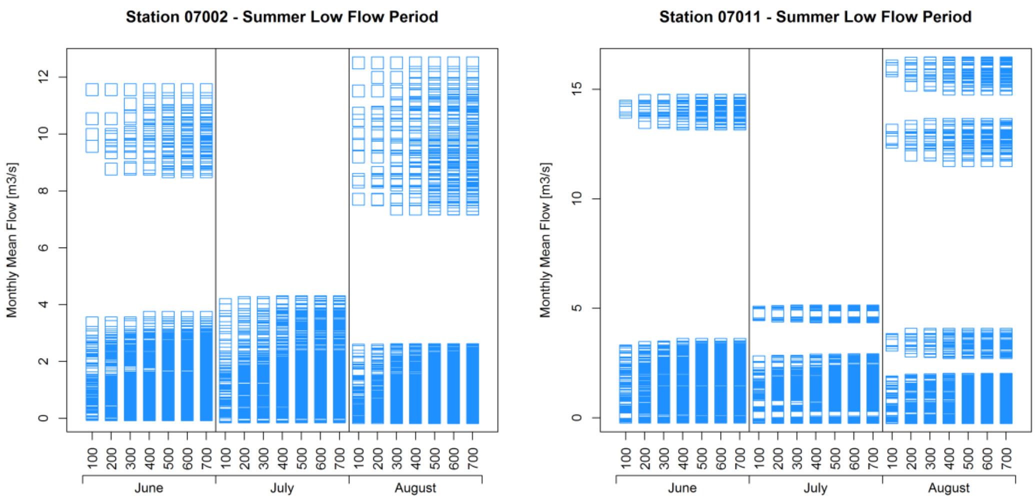


Figure 5.7 Mean monthly stream flow for three summer months depending on number of behavioural parameter sets, for station 7002 and 7011.

To assess the outcome of the proxy-basin-split-sample method used with 500 behavioural parameter sets, the simulated stream flows are shown in Figure 5.8 for the entire time period (calibration and evaluation). Generally, the months with lower stream flow are captured well in both catchments, which are of particular importance when water is abstracted directly from surface water.

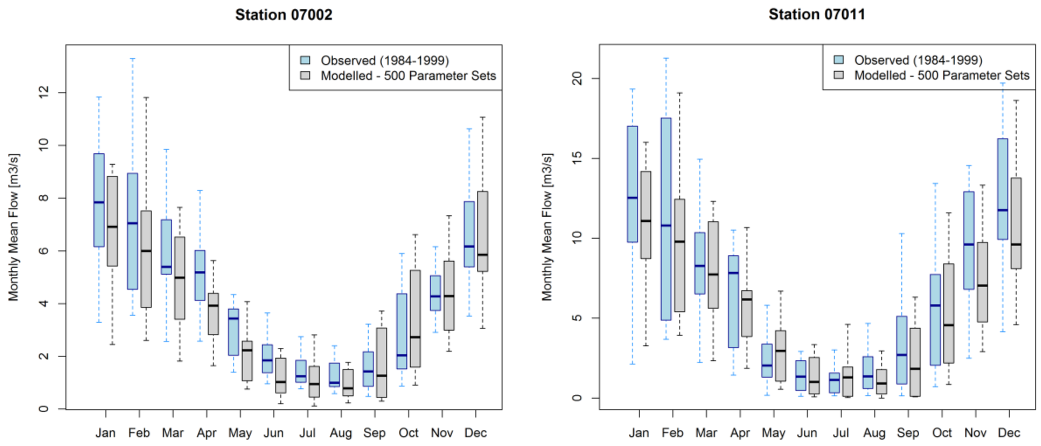


Figure 5.8. Comparison of monthly mean flow; observed (light blue) and ensemble of 500 model parameter set (light grey) over the period 1984-1999. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

The public water supply schemes analysed in this study are the schemes for which both population data and surface water abstraction volume data are available. This data was obtained from the database accumulated by the report 'The Provision and Quality of Drinking Water in Ireland, A Report for the Years 2007 – 2008' (EPA, 2009). For some water schemes, especially smaller ones, it was not possible to obtain information. The same applied to agricultural and industrial water abstractions. Therefore, analysis focuses solely on the surface water abstractions of public water supply schemes. Table 5.3 shows the investigated water abstraction points, the population served and the average daily water abstraction at the 2008 level.

Table 5.3 Boyne surface water abstractions studied, scheme code and water supply system information.

Scheme Name	Scheme Code	Population Served	Volume (m^3/day)
Athboy	2300PUB1001	3,000	2,200
Drogheda	2100PUB1019	23,077	27,692
Kilcarn: Navan/Midmeath	2300PUB1016	5,600	2,800
Liscarthan: Navan/Midmeath	2300PUB1016	22,400	11,200
Oldcastle / Kells	2300PUB1011	2,024	1,447
Trim	2300PUB1009	8,000	3,200

5.3.2 HA 34 – The Moy Catchment

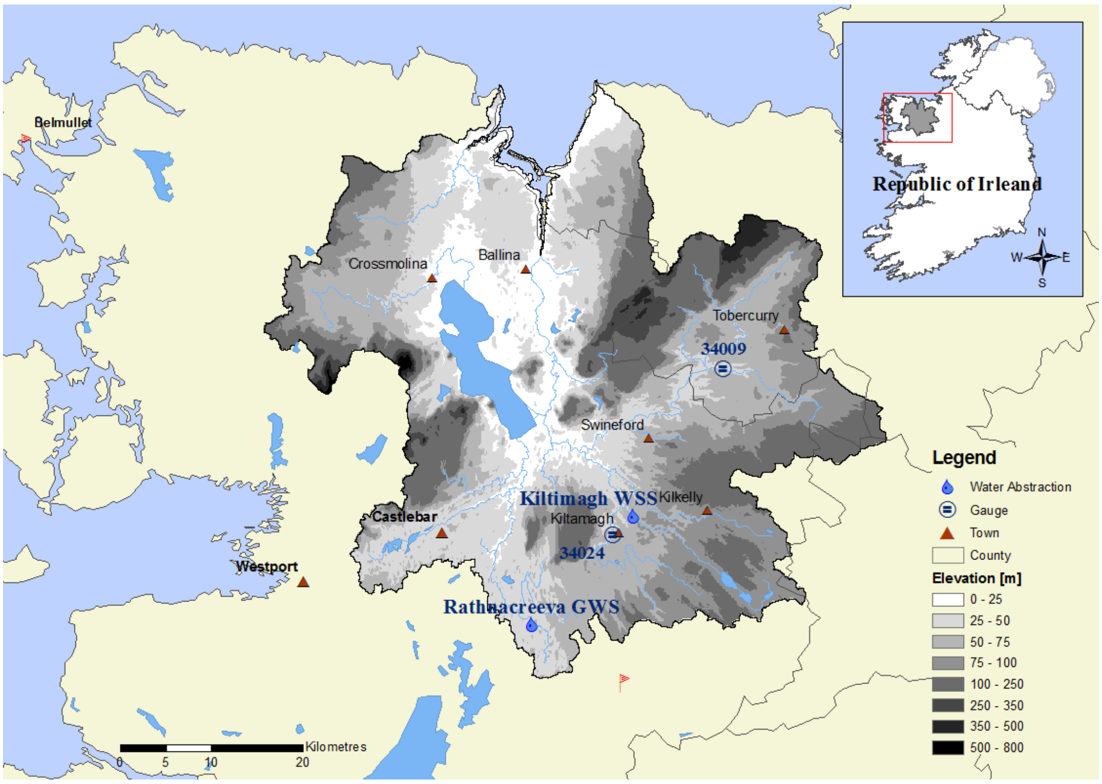


Figure 5.9 The Moy catchment. Including catchment elevation, water abstraction points, hydrometric gauges, synoptic weather stations and towns.

Hydrometric Area 34, located in Western RBD is made up by the Moy River catchment show in Figure 5.9 and encompasses an area of ~2381 km^2, with an average elevation of 77.8 meters ranging from zero to about 800 meters. The slopes in the catchment range from 0% to 40%, on average the slopes are gentle with a mean slope of 2.7% degree. Flat and undulating lowlands (41%) and rolling lowland (29%) are the prevailing physiographic features with Grey Brown Podzolics (16%), Rendzinas (14%) and Acid Brown Earth (12%) dominating the soil classes, followed by 3% of the catchment being covered by water. The Moy catchment is mainly underlain by 'Poor Aquifer - Bedrock which is Generally Unproductive except for Local Zones' and 'Regionally Important Aquifer - Karstified (conduit)' (both 27%) and 'Locally Important Aquifer – Karstified' aquifers (22%).

The climate data used to drive the hydrological simulations are taken from Bellmullet (Station No. 1034) located outside the HA at the Irish Western seaboard. At Belmullet the annual average 30-year annual temperature (1961-1990) is 9.6°C and the 30-year mean-annual precipitation is 1142.5 mm. Compared to the HA 07 located in the East of Ireland, this case study area is located in the wetter part of the country.

For HA 34, stations 34009 (Curraghbonaun at the River Owengarve) and 34024 (Kiltimagh at the River Pollagh) are selected to serve as proxy-basin catchments for model calibration due to their similar land cover, soil and groundwater characteristics to the water abstraction catchments modelled in the later part of the analysis (Table 5.4). For the proxy-basin-split-sample procedure the available overlapping time period of 23 years (1977-1999) between station 34009 and 34024 was split into two parts, with the first 16 years used for calibration and the remaining 7 years for hydrological model evaluation. The flow records used are of ‘good’ (34009) and ‘fair’ (34024) flow rating quality, with no complete year missing (Figure 5.10 and Figure 5.11)

Table 5.4 Selected hydrometric stations from HA 34 – Moy River Catchment.

Station	Available Record	Arterial Drainage	Full Missing Years	Overlapping Period
34009	1960-1999	1960-1971	Non	1977-1999
34024	1977-2007	Not available	Non	

The same proxy-basin-split-sample methodology as described for the Boyne is applied to both selected hydrometric stations. ‘Satisfactory’ model performance is achieved for the PBIAS performance measure over the calibration period, for all other performance measures ‘good’ and ‘very good’ ratings are obtained (Table 5.5). From the parameter sets identified as being behavioural for both calibration and evaluation 500 parameter sets were randomly sampled.

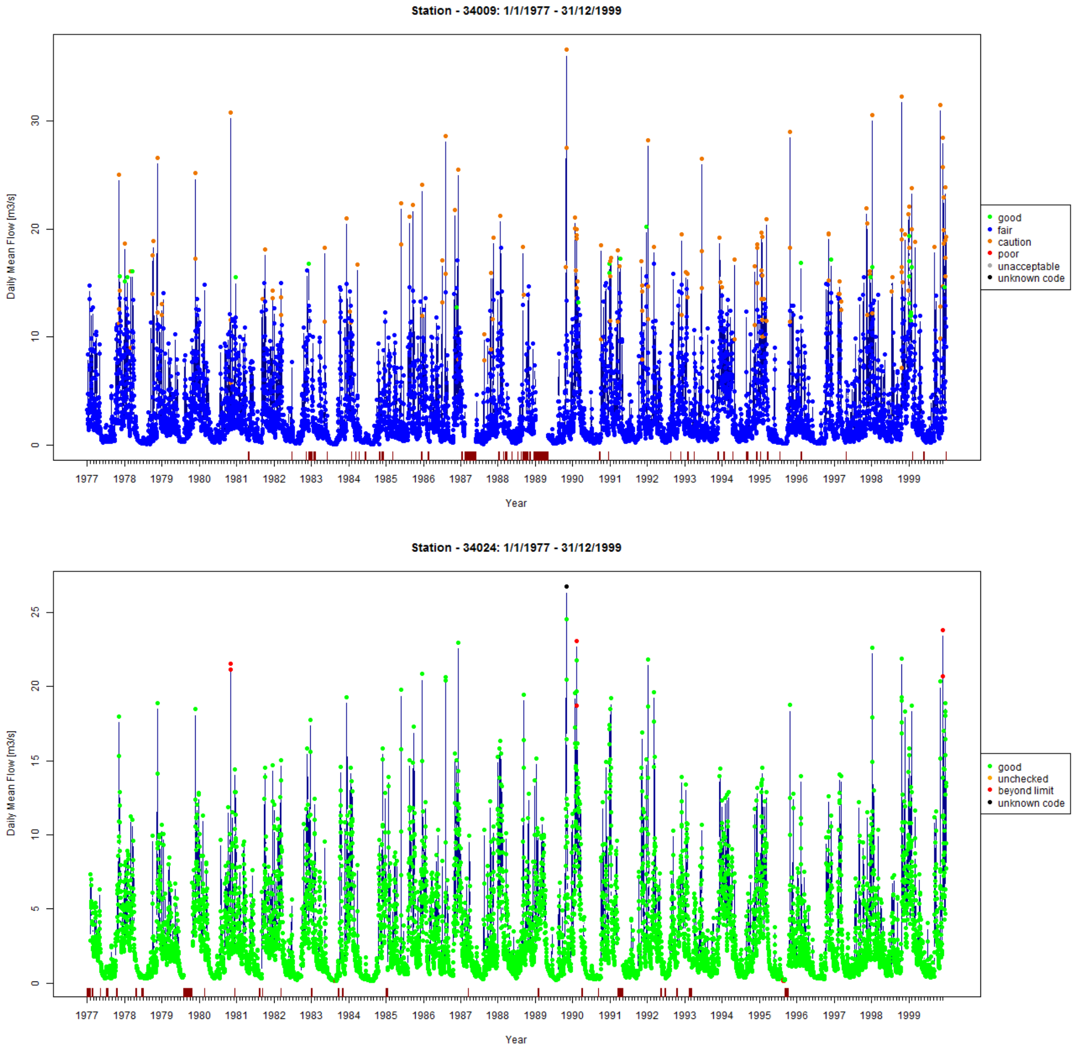


Figure 5.10 Flow regimes and quality rating for station 34009 (upper) and 34024 (lower).

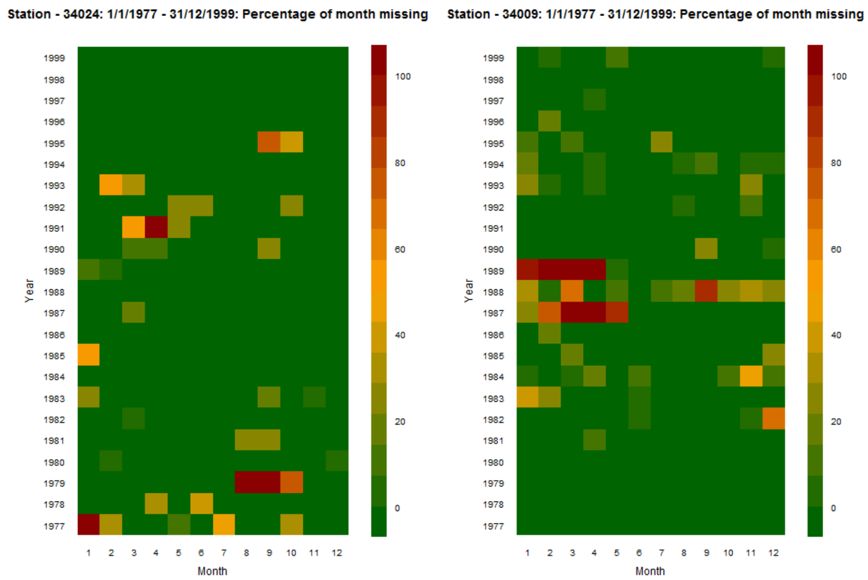


Figure 5.11 Percentage of missing days per month for station 34009 (left) and 34024 (right).

The simulated flows compared to the observed flows over the entire overlapping period are shown in Figure 5.12, there is generally a good agreement of the simulated and observed flows derived over the summer low flow periods.

Table 5.5 HA34 Moy River Catchment: Station and performance criteria used in model calibration and evaluation.

Station	Calibration (1977-1992)				No. Behav. Sets	Evaluation (1993-1999)				No. Behav. Sets
	MAE	EC	PBIAS	RSR		MAE	EC	PBIAS	RSR	
34009	< 1.041	> 0.75	< ±25	≤ 0.50	9,597	<1.219	> 0.75	< ±15	≤ 0.50	11,313
34024	< 1.110	> 0.75	< ±25	≤ 0.50	13,984	<1.312	> 0.75	< ±15	≤ 0.50	612

MAE, mean absolute error; EC, Efficiency Coefficient; PBIAS, Percent Bias; RSR, Root Mean Square Error-Observations Standard Deviation Ratio.

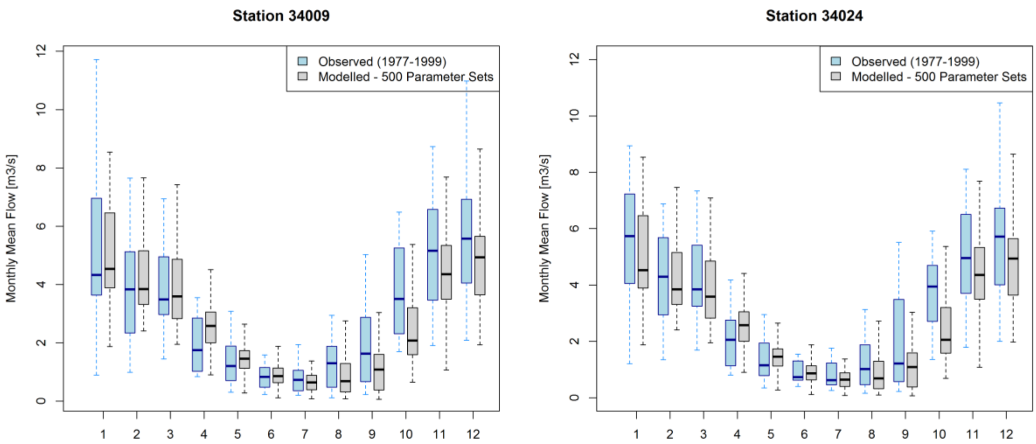


Figure 5.12 Comparison of monthly mean flow; observed (light blue) and ensemble of 500 model parameter set (light grey) over the period 1977-1999. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

Within HA 34 there are two surface water abstraction points abstracting water from the river where data on population and water abstractions is available for the year 2009, as shown in Table 5.6. These water abstraction points together with the surface water abstractions from Hydrometric Area 32 are used as case studies for the West of Ireland.

Table 5.6 Moy Surface Abstractions studied, Code and Water Supply Information

Scheme Name	Scheme Code	Population Served	Volume (m^3/day)
Kiltimagh WSS	2200PUB1017	1,555	616
Rathnacreeva GWS	2200PRI2099	164	128

5.3.3 HA 32 – The Erriff-Clew Bay Catchment

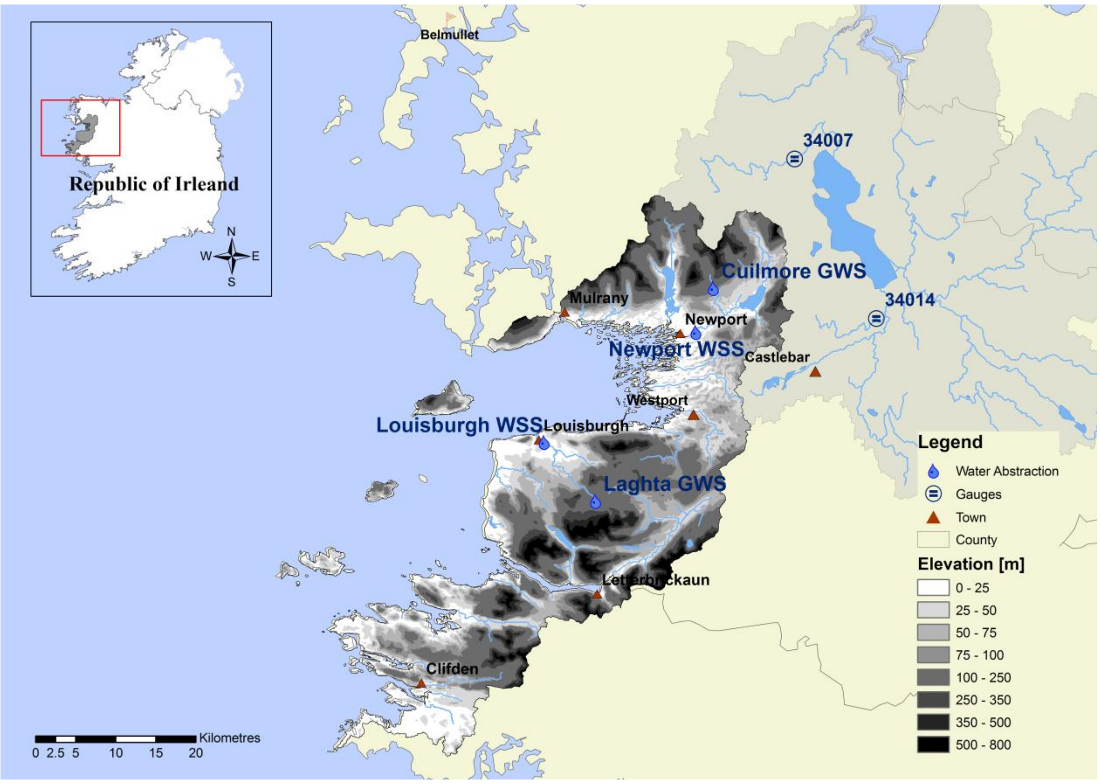


Figure 5.13 HA 32. Including catchment elevation, water abstraction points, hydrometric gauges, synoptic weather stations and towns.

The Erriff-Clew Bay Hydrometric Area is located in the Western RBD on the Irish Western Seaboard (Figure 5.13) and covers ~ 1410 km^2. The boundaries of HA 32 are made up of upland and mountainous areas with a maximum height of about 810m. The dominant land cover is peat bogs (59%), 24% of the catchment is covered by agricultural land, pastures and grassland, and about 13% with woodland and coniferous forests and 2% with water bodies (lakes). Blanket Peats and Peaty Podzols account for 77% of the soils in HA 32, with an additional 11% of Gleys and 9% of Lithosols. The HA has poor aquifer potential. Within the HA 32 no suitable proxy-basin catchments with low confounding factors and similar dominant land cover (peat) to the catchments used for water abstraction simulations is available. Therefore, two stations located within the HA 34 (Figure 5.13) are used as proxies in the calibration and evaluation procedure. The catchments draining to the hydrometric stations are both affected by arterial drainage. For station 34007 (Ballycarroon at the River Deel) only records after the drained period are available and the records for station 34014 (Mill Bridge at the River Clydagh) end in 2000. This results in an overlapping period of 28 years, of which the first 20 years (1973-1992) were used for calibration and the remaining 8 years (1993-2000) for model evaluation (Table 5.7). Almost one entire year of flow records is missing during the evaluation period for station 34007 (Figure 5.15).

Table 5.7 Selected hydrometric stations from the HA 34 to be used in HA32.

Station	Available Record	Arterial Drainage	Full Missing Years	Overlapping Period
34007	1973-2008	1960-1972	1994	1973-2000
34014	1960-2000	1960-1971	Non	

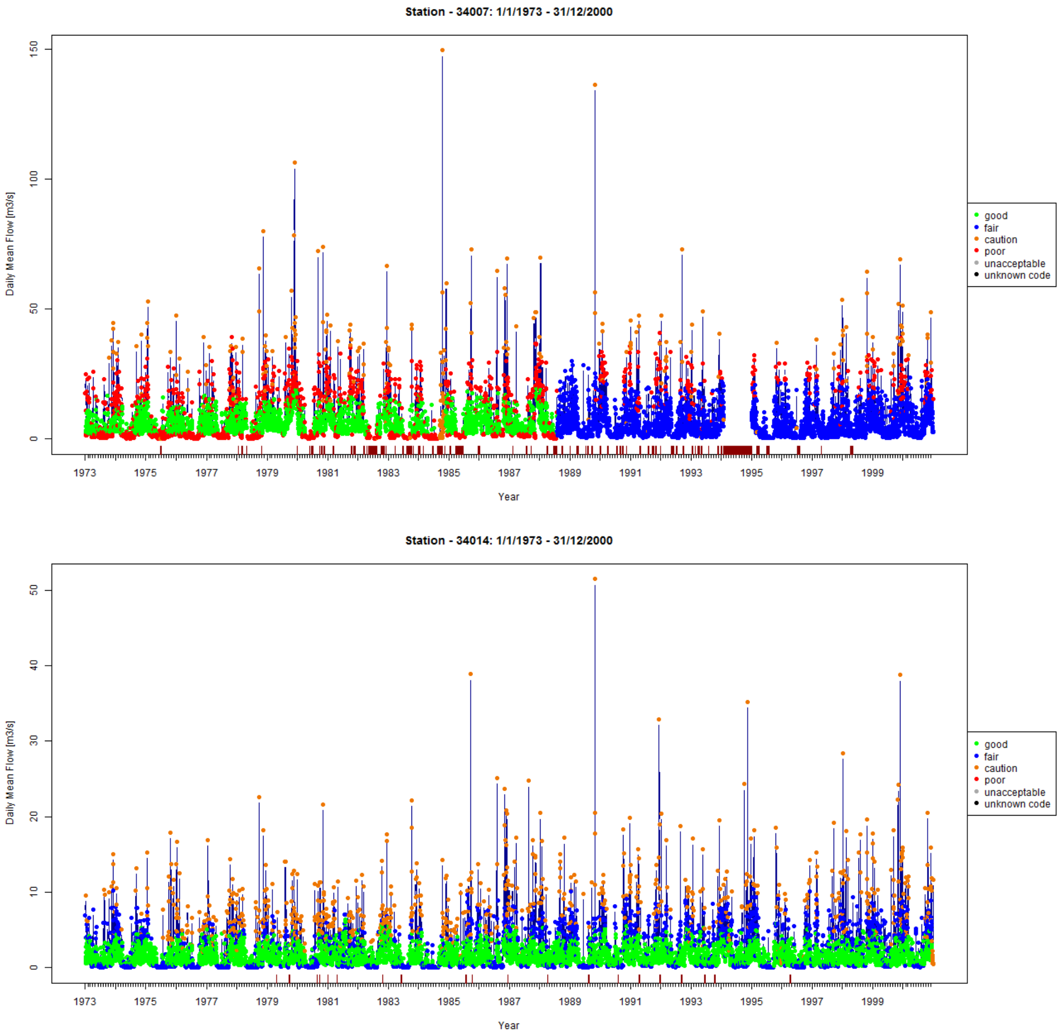


Figure 5.14 Flow regimes and data quality rating for station 34007 (upper) and 34014 (lower).

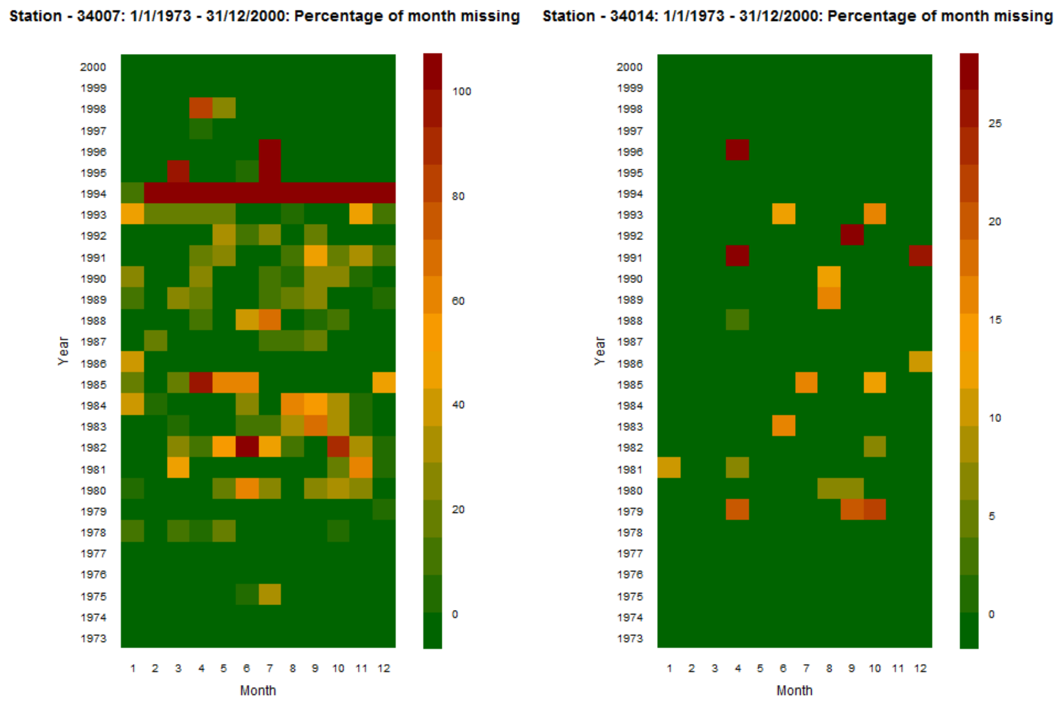


Figure 5.15 Percentage of missing days per month for station 34007 (left) and 34014 (right).

Table 5.8 shows the performance ratings obtained for both the hydrological model calibration and evaluation. ‘Satisfactory’ and ‘good’ performance ratings are obtained for the calibration period. These ratings increased by one class during the model evaluation period to ‘good’ and ‘very good’ respectively. This increase in performance during model evaluation might be caused by a change in the quality ratings, with more accurate flow measurements in the latter half of the flow record for 34007 Figure 5.14). Over the entire overlapping period, low flows are simulated well and span similar ranges for both stations, with a slight overestimation of the median flows for station 34014 (Figure 5.16).

Table 5.8 HA34 Moy River Catchment: Station and performance criteria used in model calibration and evaluation

Station	Calibration (1973-1992)				No. Behav. Sets	Evaluation (1993-2000)				No. Behav. Sets
	MAE	EC	PBIAS	RSR		MAE	EC	PBIAS	RSR	
34007	< 2.454	> 0.65	< ±25	≤ 0.60	7,762	<2.177	> 0.75	< ±15	≤ 0.50	11,070
34014	< 0.745	> 0.65	< ±25	≤ 0.60	11,196	<0.800	> 0.75	< ±15	≤ 0.50	7,078

MAE, mean absolute error; EC, Efficiency Coefficient; PBIAS, Percent Bias; RSR, Root Mean Square Error-Observations Standard Deviation Ratio.

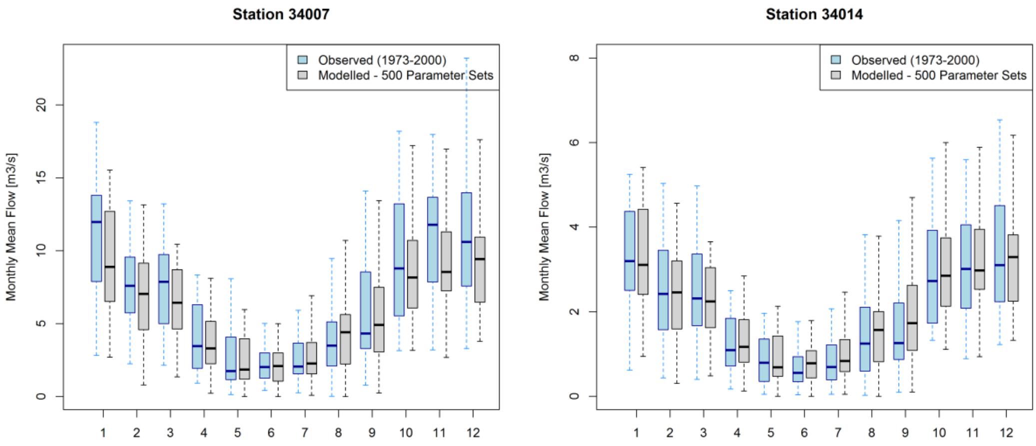


Figure 5.16 Comparison of monthly mean flow; observed (light blue) and ensemble of 500 model parameter set (light grey) over the period 1973-2000. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

Four surface water abstraction points are located within the Hydrometric Area 34 (Table 5.9). Together with the two water abstractions located in the HA 34, six illustrative sample case studies are located in the West of Ireland.

Table 5.9 HA 32; Surface abstractions studied, scheme code and water supply system information.

Scheme Name	Scheme Code	Population Served	Volume (m^3/day)
Culimore GWS	2200PRI2039	420	400
Laghta GWS	2200PRI2079	203	145
Louisburgh WSS	2200PUB1020	1480	400
Newport WSS	2200PUB1022	803	273

In the Erriff-Clew Bay HA the Louisburgh WSS is the only water abstraction point in this case study with a flow metering station (St 32011 at Louisburgh Weir) in proximity. This setting is used to investigate the functionality of the proxy-basin-split sample approach. The ability to compare the observed flow (1981-1996) at station 32011 with the modelled flow for Louisburgh WSS is of particular importance, as the behavioural parameters sets were derived in HA34 and then transferred to HA32. Figure 5.17 shows the comparison between the observed flow at station 32011 (light blue) and the modelled stream flow for the surface water abstraction point for the Louisburgh WSS (light grey) using the 500 behavioural parameter sets obtained in HA34. Summer low flows are generally captured well and therefore it can be assumed that the parameter sets obtained through the proxy-basin-split-sample approach in HA34 can be used to model stream flow for the water abstraction points in HA32.

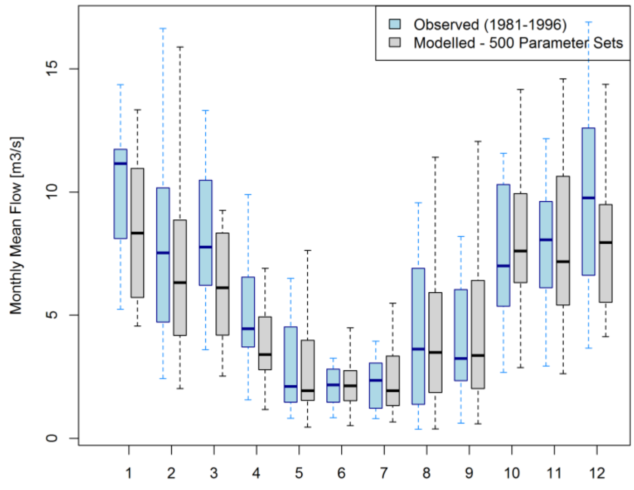


Figure 5.17 Comparison of monthly mean flow; observed at station 32011 (light blue) and ensemble of 500 model parameter set modelled for Louisburgh WSS (light grey) over the period 1981-1996. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

5.4 Future Stream Flow Modelling

Once the physical parameters for each catchment draining into a water abstraction point are determined using the GIS approach described in the previous chapter, they are used together with behavioural values for the process parameters. For each water abstraction point the flow is modelled individually using future climatological time series of precipitation and evapotranspiration to drive the hydrological model (HYSIM) to produce future daily stream flow series, which are then converted into monthly mean flows to be used as input into the water resource model - WEAP.

5.4.1 Comparison of Stream Flow Simulations under Climate Scenarios

In the previous chapter the available future climate scenarios for Ireland have been presented in detail. The influence of the choice of the future projections (i.e. transient statistically downscaled versus probabilistic scenarios) on stream flow is investigated more fully, as there is no linear response between changes in the climate variables and the catchment responses. First, the modelled stream flow is compared under historical conditions, then the different flows obtained for future flow simulations are analysed.

5.4.1.1 Stream Flow Simulations under Climate Scenarios - Control Period

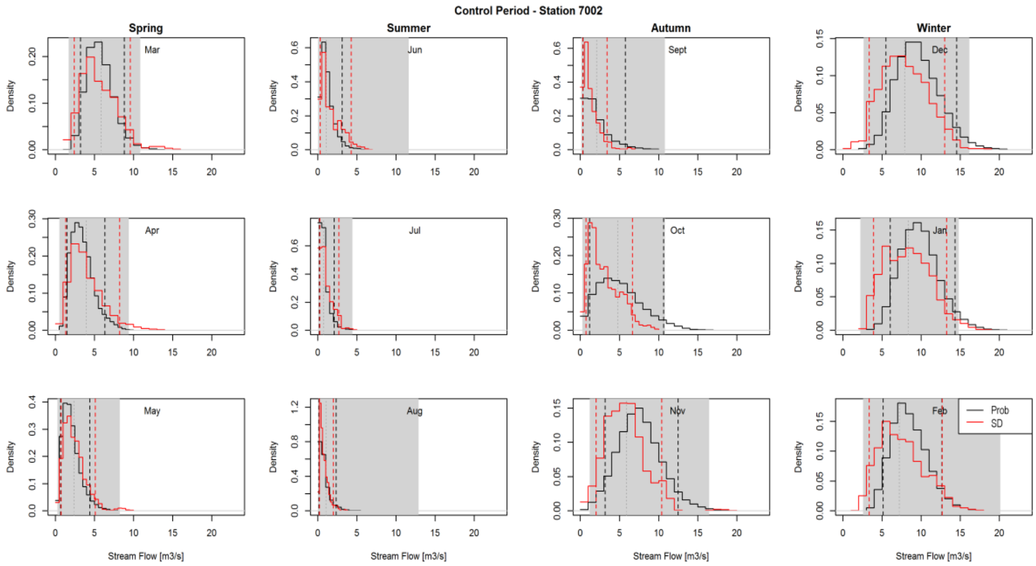
To allow comparison, stream flow time series for each of the proxy-basin-catchments described in the previous sections are generated using the 500 behaviour parameter sets. To evaluate the influences of the choice of the different types of ensembles on the monthly histograms of simulated stream flow the hydrological model is driven with the control time series (1971-1999) and compared to the spread of stream flow modelled with the 500 behavioural parameter sets and driven by observed precipitation and evaporation data.

Figure 5.18 to Figure 5.20 show the histograms of monthly mean flows obtained over the control period (1971-1999) over which all stations had observed data available. For proxy-basin stations, the modelled monthly mean flow (m^3/s) is shown for each month separately. The flows obtained when forcing the hydrological model with the climatological data from the transient statistically downscaled (SD) scenarios are shown in red, the flow series that are obtained from the probabilistic scenarios are shown in black. The grey shaded areas in the background show the maximum and minimum ranges of river flow obtained from the model when forced with the observed climate data for that period.

Over the control period, the ranges of stream flow between the two possible sets of ensembles are similar, especially during the times of lower flow (spring and summer months) when flows are of particular interest to water managers. During these months, the SD scenarios provide slightly larger flow ranges (particularly for the lower flow ranges) compared to flows obtained from the probabilistic scenarios. These larger ranges of possible flows are apparent in the extremes (minimum and maximum) and flows that represent 90% of modelled flow (indicated by the vertical dashed lines) during all spring and summer months for all investigated stations (with the exception of August for stations 7002, 7011, 34007 and 34014).

During the autumn and winter months, the stream flow derived from probabilistic scenarios shows higher maximum and minimum flows compared to the monthly flows obtained from the SD scenarios. One notable difference between the SD and probabilistic climate scenarios exists in October, particularly in Hydrometric Area 07, where the distribution of the two ensembles differs considerably in shape. The majority of flows derived from the SD scenarios are in the lower flow spectrum, whereas with the probabilistic scenarios the stream flow has a long tail towards the higher flows. The high flows derived from the probabilistic scenarios spread beyond the maximum flow range obtained from observed climate data.

Overall, the transient SD scenarios provide a good representation of the spread of possible stream flow when evaluating the control period. Of particular importance for water management is the wider ranges obtained for the lower component of all monthly flows ensuring that the lowest possible conditions are represented in the stream flow simulation.



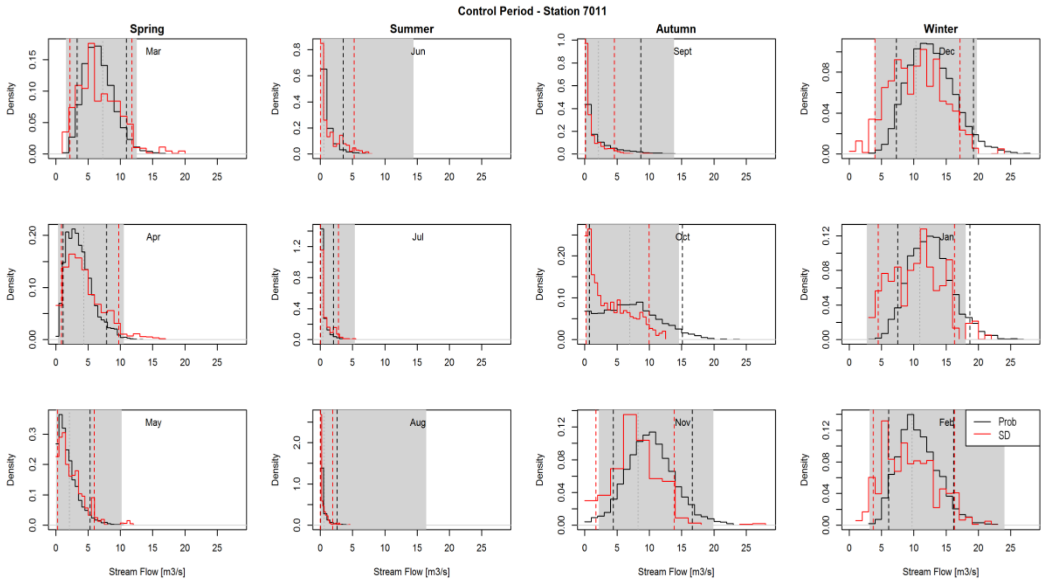


Figure 5.18 HA 07; Histogram of modelled monthly mean flow derived from the statistically downscaled (red) and the probabilistic (black) time series (Top: Station 7002; bottom: Station 7011). Grey area in the background indicates the range of modelled stream flow derived from observed climate (1971-1999). Dashed lines in red and black enclose 90% of the monthly simulations. Grey dotted line is the median of the observed.

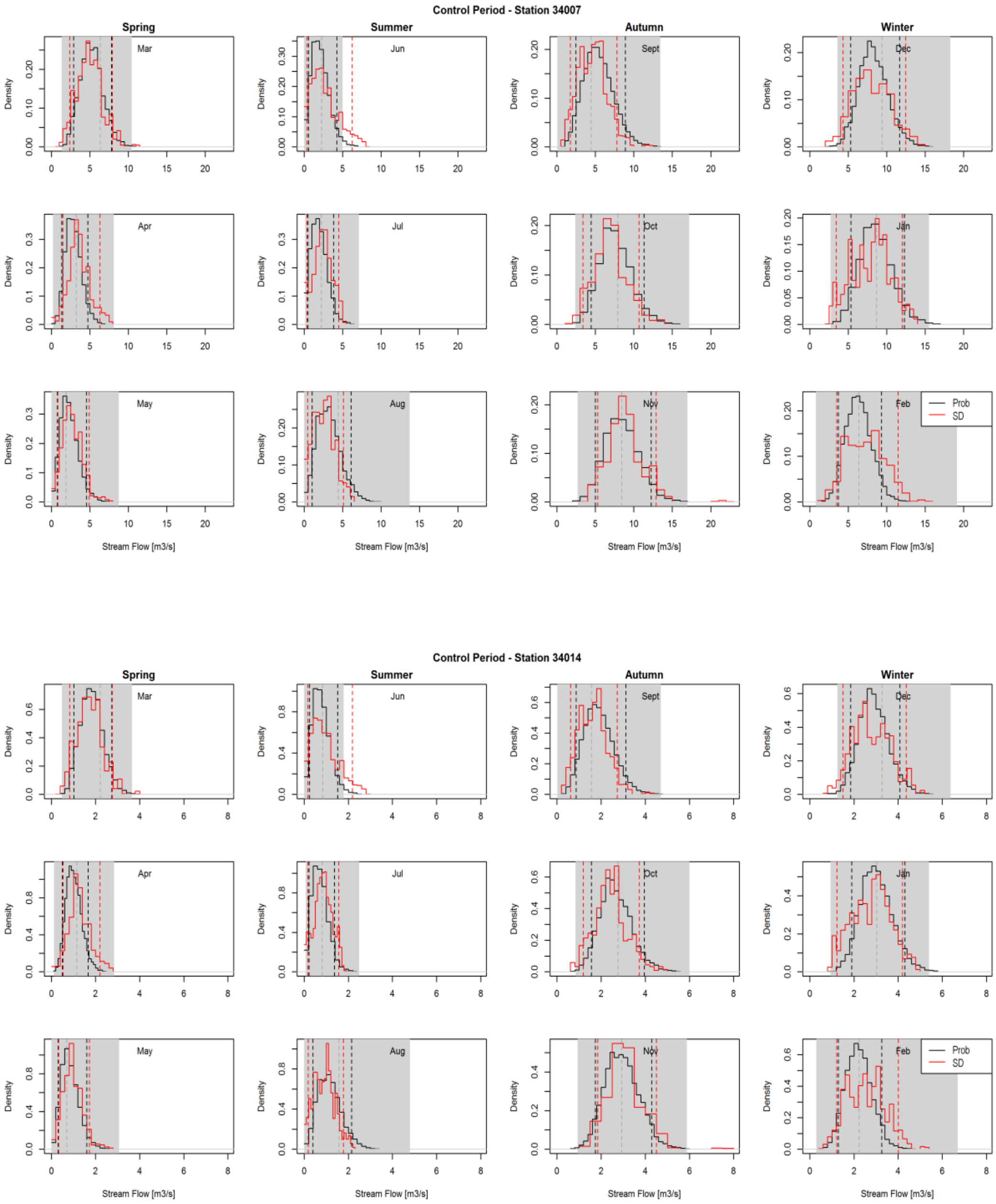


Figure 5.19 HA 32; Histogram of monthly mean flow derived from the statistically downscaled (red) and the probabilistic (black) time series (Top: Station 34007; bottom: Station 34014). Grey area in the background indicates the range of modelled stream flow derived from observed climate (1971-1999). Dashed lines in red and black enclose 90% of the monthly simulations. Grey dotted line is the median of the observed.

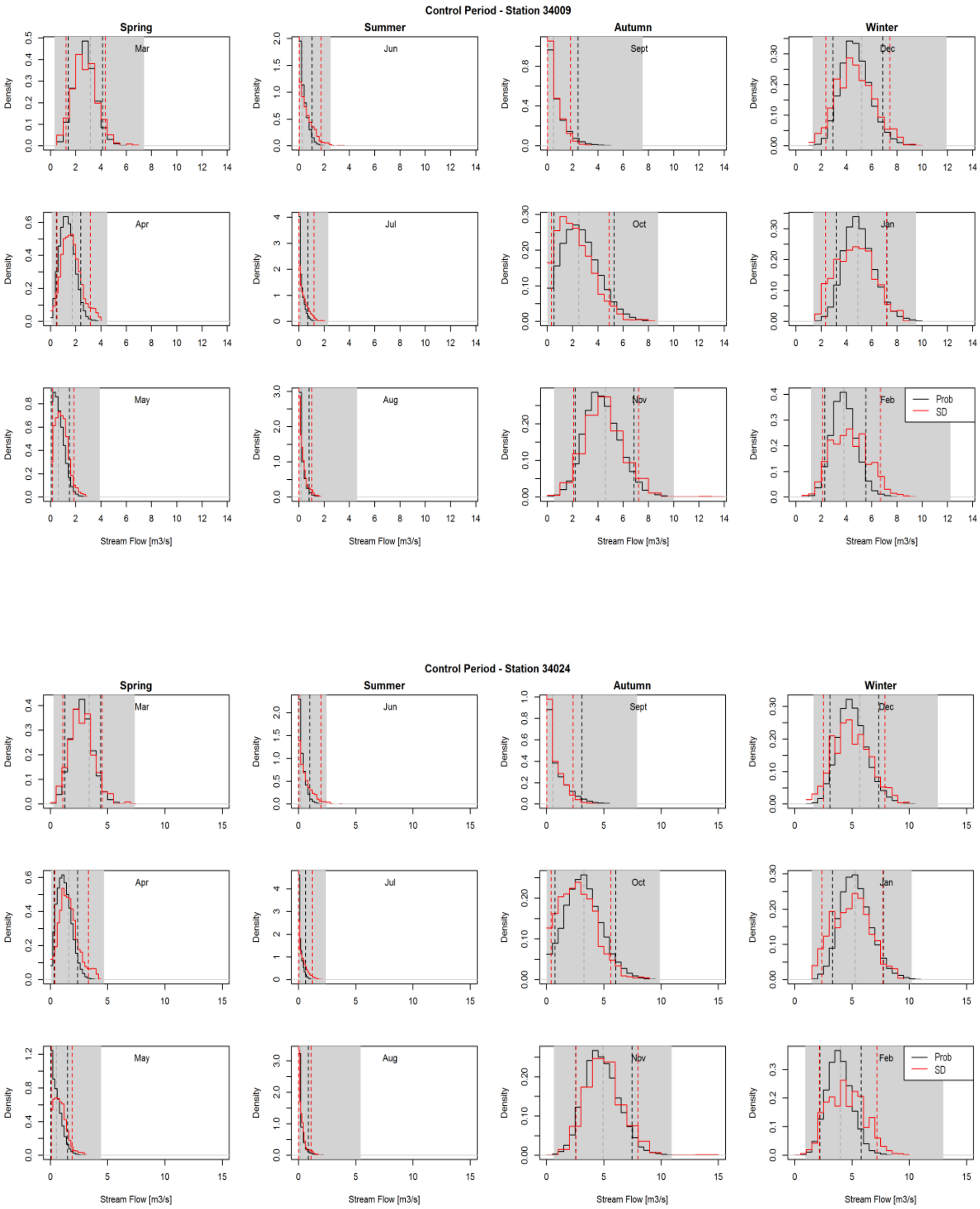


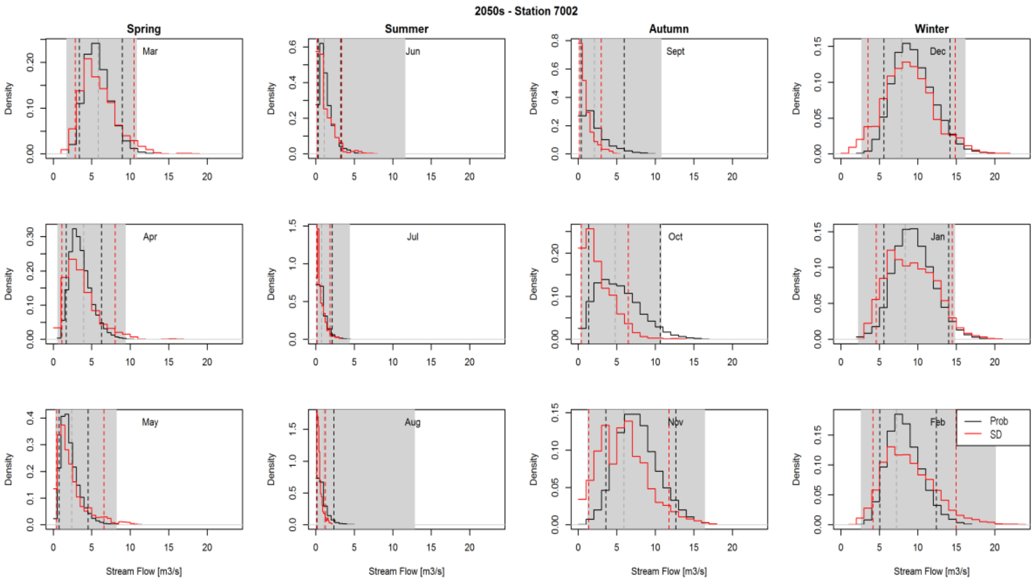
Figure 5.20 HA 34; Histogram of monthly mean flow derived from the statistically downscaled (red) and the probabilistic (black) time series (Top: Station 34009; bottom: Station 34024). Grey area in the background indicates the range of modelled stream flow derived from observed climate (1971-1999). Dashed lines in red and black enclose 90% of the monthly simulations. Grey dotted line is the median of the observed.

5.4.1.2 Future Stream Flow Simulations under Climate Scenarios – 2050s

To further investigate if the transient statistically downscaled (SD) scenarios also generate comparative future ranges of stream flow as the probabilistic scenarios the same procedure as in the previous section was used to produce future stream flow series for the 2050s (Figure 5.21 to Figure 5.23).

Again, the ranges obtained from the hydrological simulations obtained with 500 behavioural parameter sets forced with the SD and probabilistic scenarios are comparable for spring and summer. The high flow components in autumn are larger for the probabilistic scenarios, whereas in winter the SD scenarios produce larger ranges for all stations. Similar to the control period, the lower monthly ranges of flow are obtained for the SD scenarios, which is of importance for future stream flow modelling and the analysis of future water resources.

The transient SD scenarios for Ireland have been developed for impacts and adaptation assessments for various sectors in Ireland and they are widely available to and used by decision makers. Given that the key aim of these two chapters in this thesis is to produce a tool that can be used for adaptation appraisal in the Irish water resources sector the six SD scenarios will be used to appraise future adaptation options in the following modelling approach, as they have a comparable performance in producing stream flow ranges as the probabilistic scenarios particularly during spring and summer months which are important for water resources. Additionally, from a computational perspective the selection of the SD scenarios reduces the number of input time series for the water resources model to 3,000 hydrological time series (2 emission scenarios x 3 GCMs x 500 behavioural parameter sets) compared to 50,000 hydrological scenarios (100 probabilistic scenarios x 500 behavioural parameter sets). The SD scenarios are employed here with the recognition that future work on the tool should incorporate a wider range of the uncertainty space, by employing large multi-model ensembles.



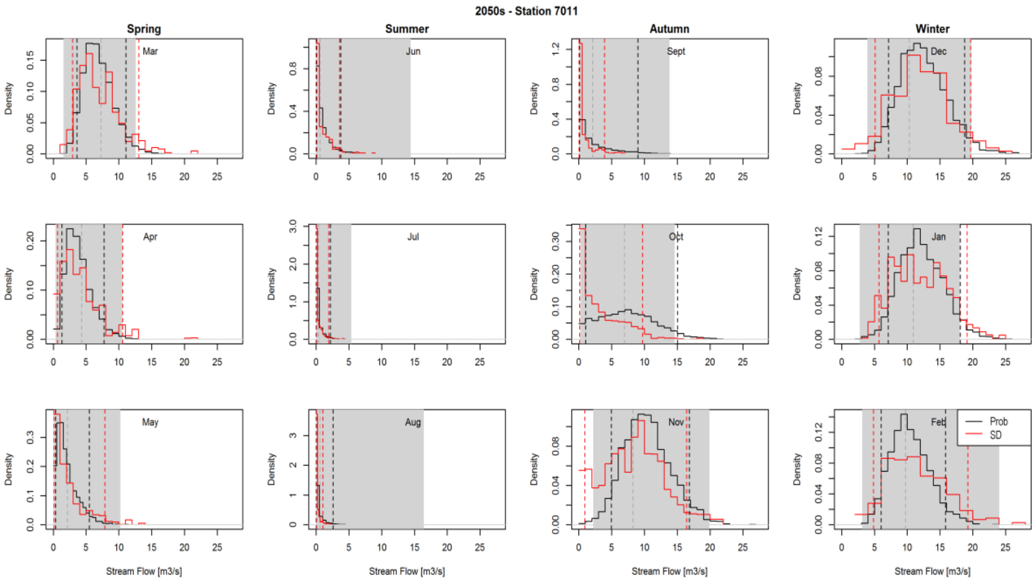


Figure 5.21 HA 07; Histogram of monthly mean flow derived from the statistically downscaled (red) and the probabilistic (black) time series (2040-2069). Top: Station 7002; bottom: Station 7011. Grey area in the background indicates the range of modelled stream flow derived from observed climate (1971-1999). Dashed lines in red and black enclose 90% of the monthly simulations. Grey dotted line is the median of the observed.

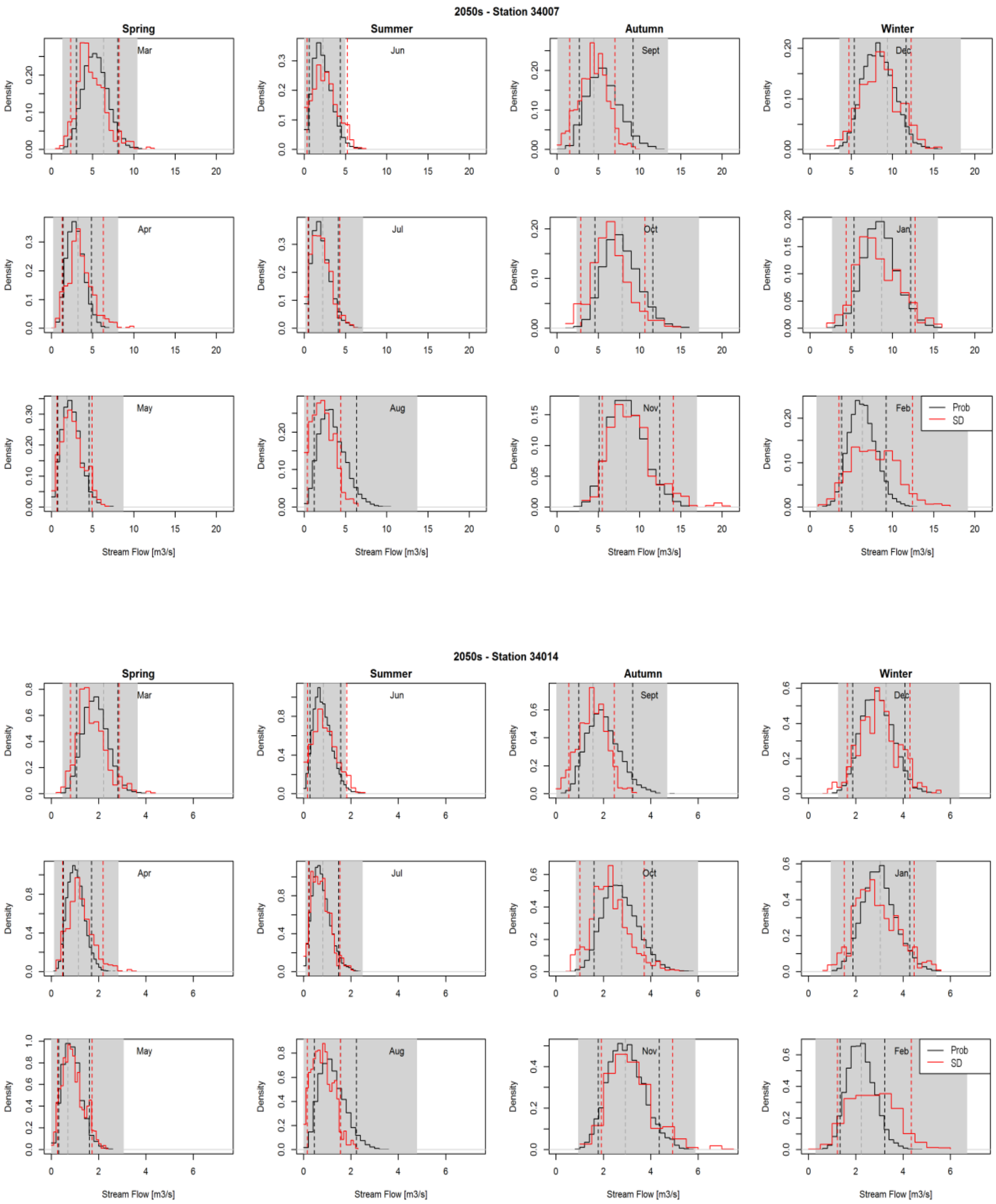
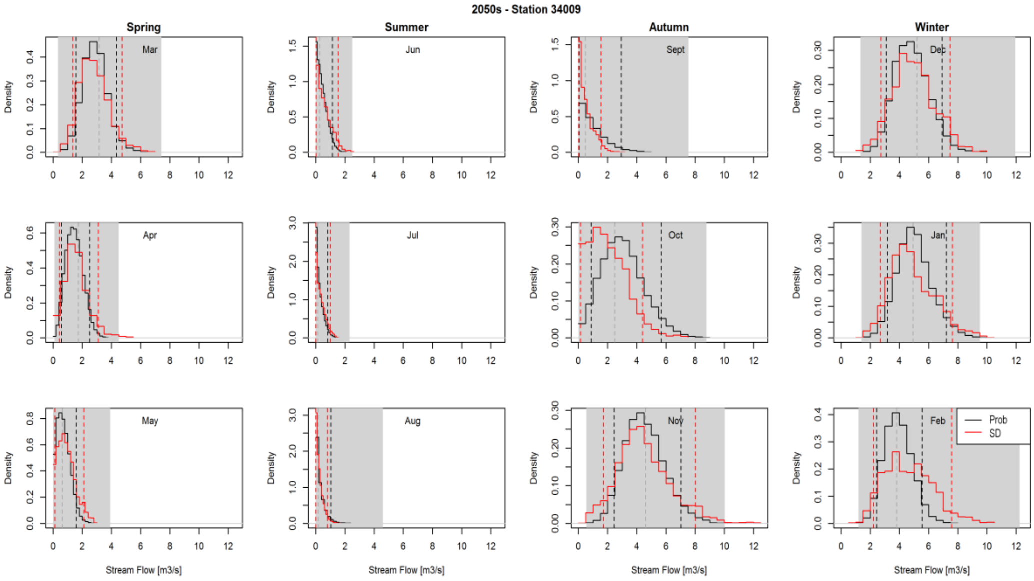


Figure 5.22 HA 32; Histogram of monthly mean flow derived from the statistically downscaled (red) and the probabilistic (black) time series (2040-2069). Top: Station 34007; bottom: Station 34014. Grey area in the background indicates the range of modelled stream flow derived from observed climate (1971-1999). Dashed lines in red and black enclose 90% of the monthly simulations. Grey dotted line is the median of the observed.



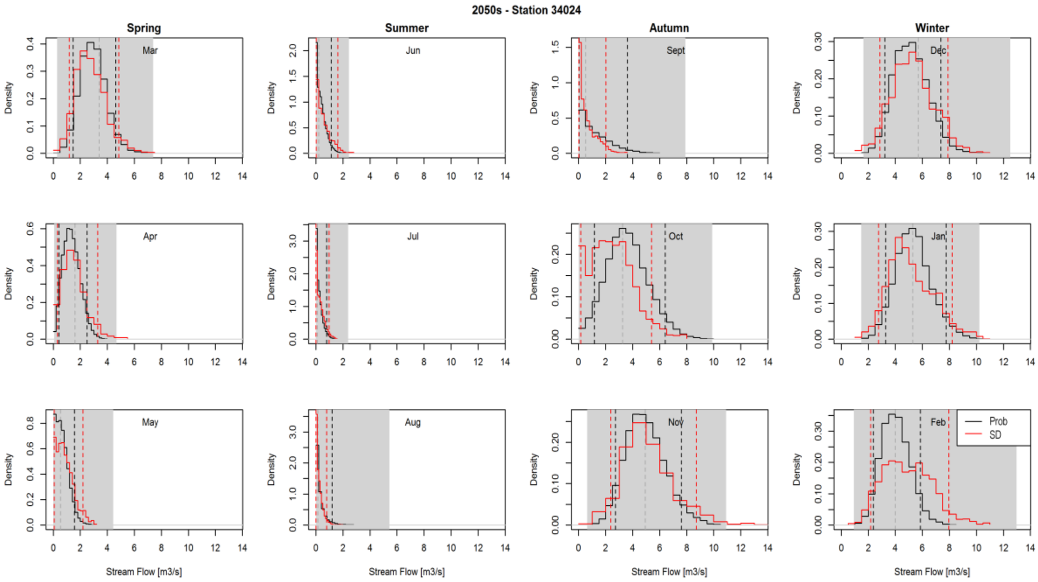


Figure 5.23 HA 34; Histogram of monthly mean flow derived from the statistically downscaled (red) and the probabilistic (black) time series (2040-2069). Top: Station 34009; bottom: Station 34024. Grey area in the background indicates the range of modelled stream flow derived from observed climate (1971-1999). Dashed lines in red and black enclose 90% of the monthly simulations. Grey dotted line is the median of the observed.

5.4.1.3 Stream flow Simulations over Control Period - Statistically Downscaled Scenarios

The six transient statistically downscaled climate scenarios have been selected in the previous section to be suitable to produce a wide range of flow conditions. In his section these scenarios are used to force the hydrological model for a final check on the ability of the hydrological model to produce stream flow in the historical hydrological records.

The monthly mean flow hydrographs for each of the proxy-basin catchments are analysed for a thirty-year control period. The control period 1971-1999 is defined by the available observed climatological record and different to the 'baseline' period (1961-1990) which is used later when only modelled climatological data is used. Figure 5.24 shows the comparison over all 500 behavioural parameter sets for the simulations driven by the observed climate data ('Control Observed') and the flow simulations derived with the input of the six future climate scenarios ('Control Modelled'). In Figure 5.24 the flow derived from modelled climate series generally falls within the limits of the flow derived from the observed climate series. For the catchments in the West the upper bound of simulations (Q5) in June is slightly higher within the modelled climate time series, whereas in the East it tends to be lower. Generally, mean and low flows are captured well, with exception of autumn flows where the mean is underestimated, particularly in the East. This underestimation could be due to difficulties of the model in reproducing the seasonal switch in the direction of soil water movement in humid catchments. Such seasonal changes between vertical water movement in summer and horizontal water movement in winter have been first reported by Grayson *et al.* (1997).

Overall, the representation of the hydrological conditions is acceptable; therefore, the selected modelled future climate projections were then used to drive a hydrological model for each sub-catchment feeding a water abstraction point. Apart from these characteristics the transient SD scenarios were also selected due to their characteristic of producing a continuous time series of change, which is important for evaluation the future performance of a water resource system, which is the ultimate goal of this modelling framework.

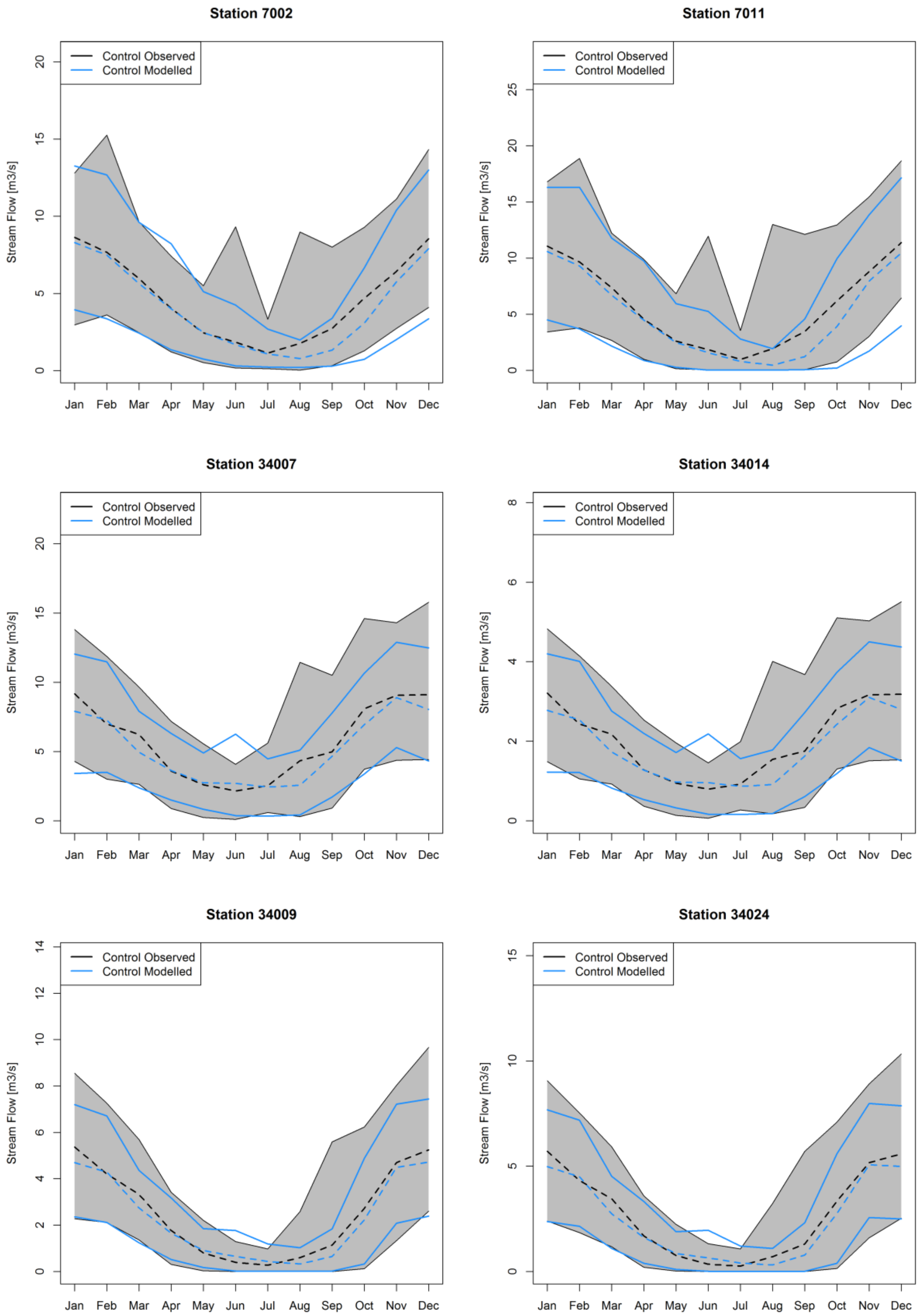


Figure 5.24 Modelled monthly mean flows between 1971-1999 (control period) for proxy-basin stations in HA 07, and HA34. Grey shaded areas show the 90 percent confidence interval. Solid lines Q5 and Q95 respectively. Dashed lines represent mean flow.

5.4.2 Future Stream Flow Simulations at Water Abstraction Points

The differences in overall changes in precipitation and stream flow between the simulated baseline period (1961-1990) and the two future simulated time periods, the 2020s (2010-2039) and the 2050s (2040-2069) is analysed to obtain an overall picture of the projected changes in the future water resources availability. Future stream flow series are derived by forcing the hydrological model with 500 behavioural parameter sets with the climate time series from the six different future climate projections resulting in 3000 hydrological time series for each of the twelve investigated stream flow water abstraction points.

5.4.2.1 Projected Changes in Future Precipitation

To be able to put the projected changes in stream flow into context, first an analysis of the monthly precipitation totals is performed. The percentage changes in average monthly precipitation totals between the baseline period 1961-1990 and the two future periods of interest the 2020s (2010-2039) and the 2050s (2040-2069) are shown in Figure 5.25. The relative percentage changes in monthly precipitation totals are calculated as follows:

Percent Change = 100 x (future precip– baseline precip)/baseline precip

In Figure 5.25 there is an overall tendency for uncertainty ranges to grow with time of simulation (relative to the baseline). In the east (St 2922) the positive and negative magnitudes of projected changes are larger compared to those in the west (St 1034), for both future periods. For station 1034 in the 2020s, there is no clear seasonal signal, although winter tends to be wetter relative to the baseline, whereas summer tends to be drier. The same tendency is apparent for station 2922, however with a higher magnitude, particularly for the reductions in summer precipitation totals. In the 2050s precipitation totals at station 1034 show strong decreases during spring and summer months (up to 35% relative to 1961-1990), with the exception of June where only minor decreases are projected. Summer precipitation totals at station 2922 are more pronounced and for July and August, projected relative changes of almost 40 percent are shown. Again as in all other projections June is at odds with the general seasonal pattern showing less relative changes.

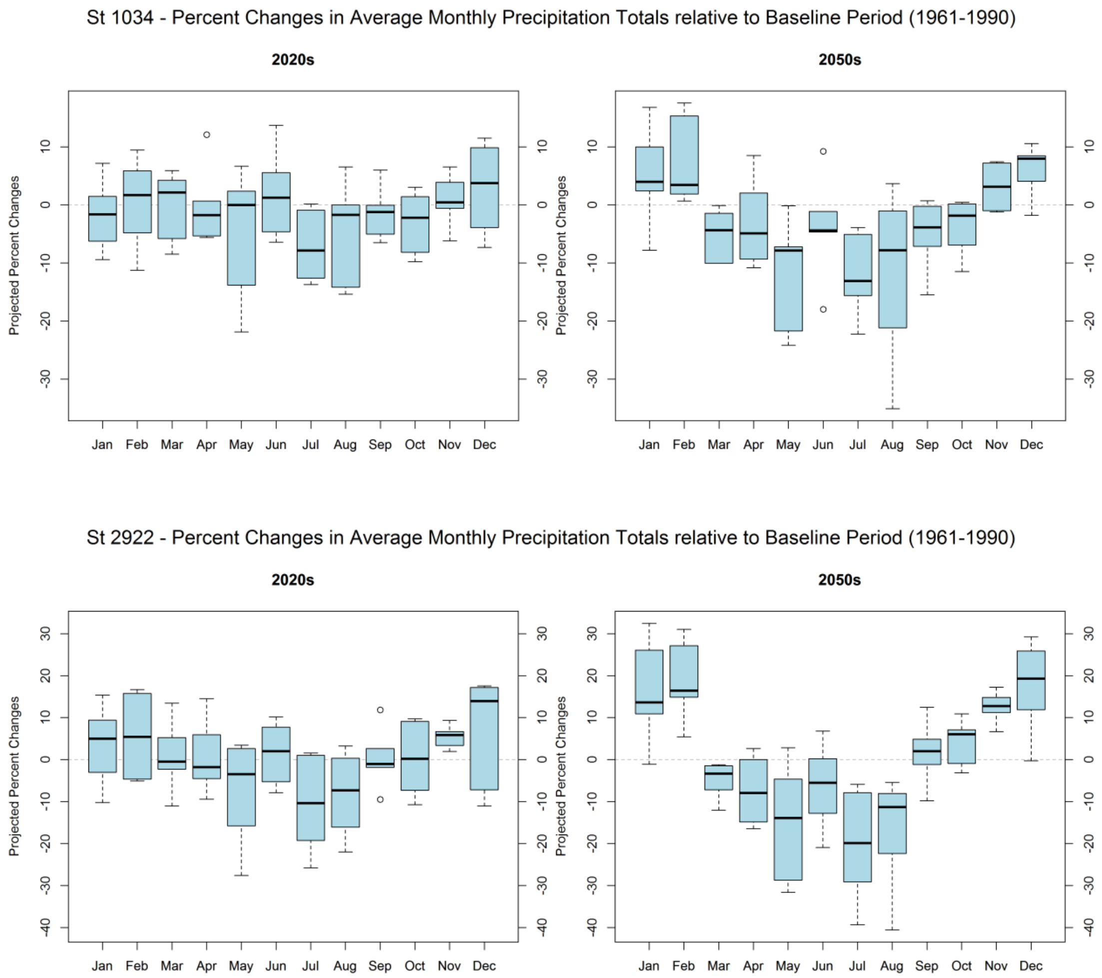


Figure 5.25 Projected changes in average monthly precipitation for the synoptic stations 1034 (top) and 2922 (bottom). Projected changes are relative to the baseline period (1961-1990) for the 2020s (left) and 2050s (right).

5.4.2.2 Projected Future Surface Water Resource Availability

Before employing the scenarios for decision appraisal at each abstraction point, this section provides a brief overview of projected changes in future flows for the case study catchments.

The parameter sets to model the flows at the water abstraction points were obtained through the proxy-basin-split sample approach described previously. The downscaled climate simulations were used to drive HYSIM with the 500 randomly sampled behavioural parameter sets at each water abstraction point.

Simulations were performed for the baseline period (1961-1990) and for two future time periods the 2020s (2010-2039) and the 2050s (2040-2069). Figure 5.26 to Figure 5.31 show ranges of monthly mean flows (95th, 50th and 5th percentile) on the upper panel while the lower panels shows the percent change for monthly stream flow compared to the baseline period for two low flow indicators Q95 (flow equalled or exceeded 95% of the time) and Q75 (flow equalled or exceeded 75% of the time) grouped by month. Q95 is an important indicator for environmental flows to maintain ecosystem functions, below which it is recommended to not abstract any stream flow (Acreman *et al.*, 2008).

The percent change per month between the baseline monthly Q*n* flow and the corresponding future parameter set's monthly Q*n* flow is calculated as:

Percent Change = 100 x (Future indicator– Baseline indicator)/Baseline indicator

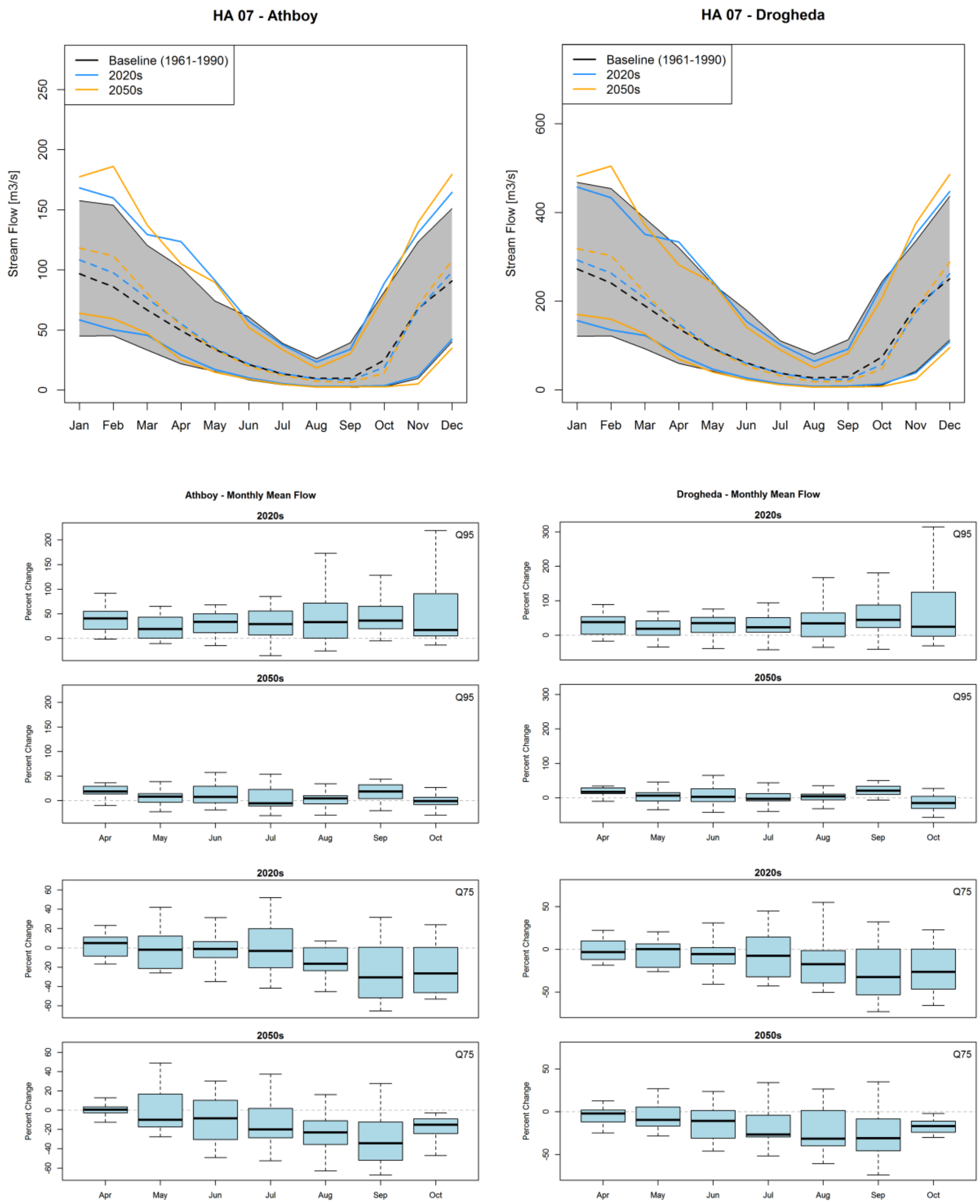


Figure 5.26 Boyne Catchment - HA 07; Stream flow at the water abstraction points Athboy and Drogheda. Upper panels: Modelled monthly mean flow for baseline period (1961-1990) and in blue the 2020s (2010-2039) and in orange the 2050s (2040-2069). Solid lines in their respective colour show the95th and 5th percentiles, dashed lines are the 50th percentile of monthly mean flows. Lower panels: Projected changes in monthly Q75 and Q95 relative to the baseline, for the months April to October. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data

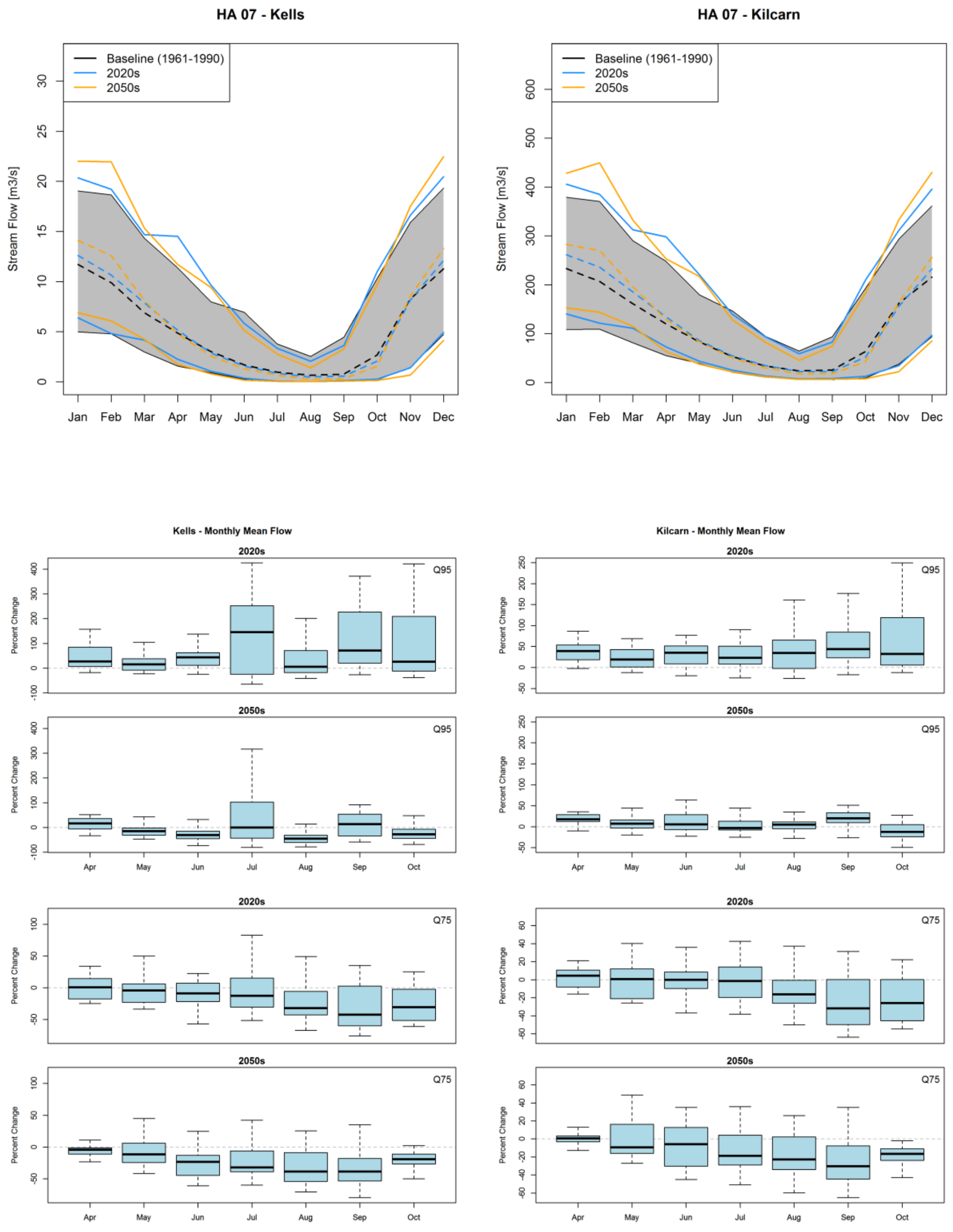


Figure 5.27 Boyne Catchment - HA 07 Stream flow at the water abstraction points Kells and Kilcarn. Upper panels: Modelled monthly mean flow for baseline period (1961-1990) and in blue the 2020s (2010-2039) and in orange the 2050s (2040-2069). Solid lines in their respective colour show the95th and 5th percentiles, dashed lines are the 50th percentile of monthly mean flows. Lower panels: Projected changes in monthly Q75 and Q95 relative to the baseline, for the months April to October. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

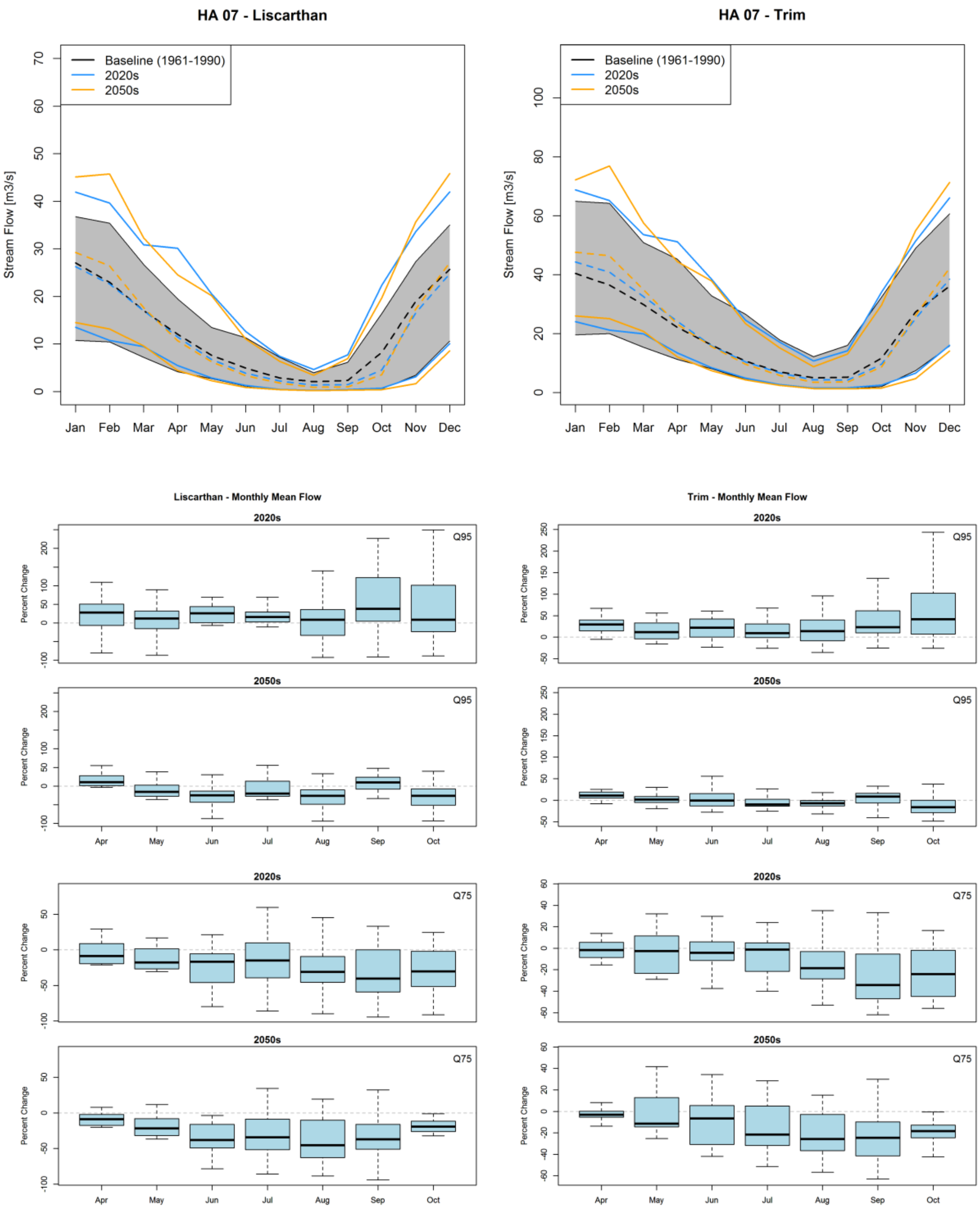


Figure 5.28 Boyne Catchment - HA 07 Stream flow at the water abstraction points Liscarthan and Trim. Upper panels: Modelled monthly mean flow for baseline period (1961-1990) and in blue the 2020s (2010-2039) and in orange the 2050s (2040-2069). Solid lines in their respective colour show the95th and 5th percentiles, dashed lines are the 50th percentile of monthly mean flows. Lower panels: Projected changes in monthly Q75 and Q95 relative to the baseline, for the months April to October. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

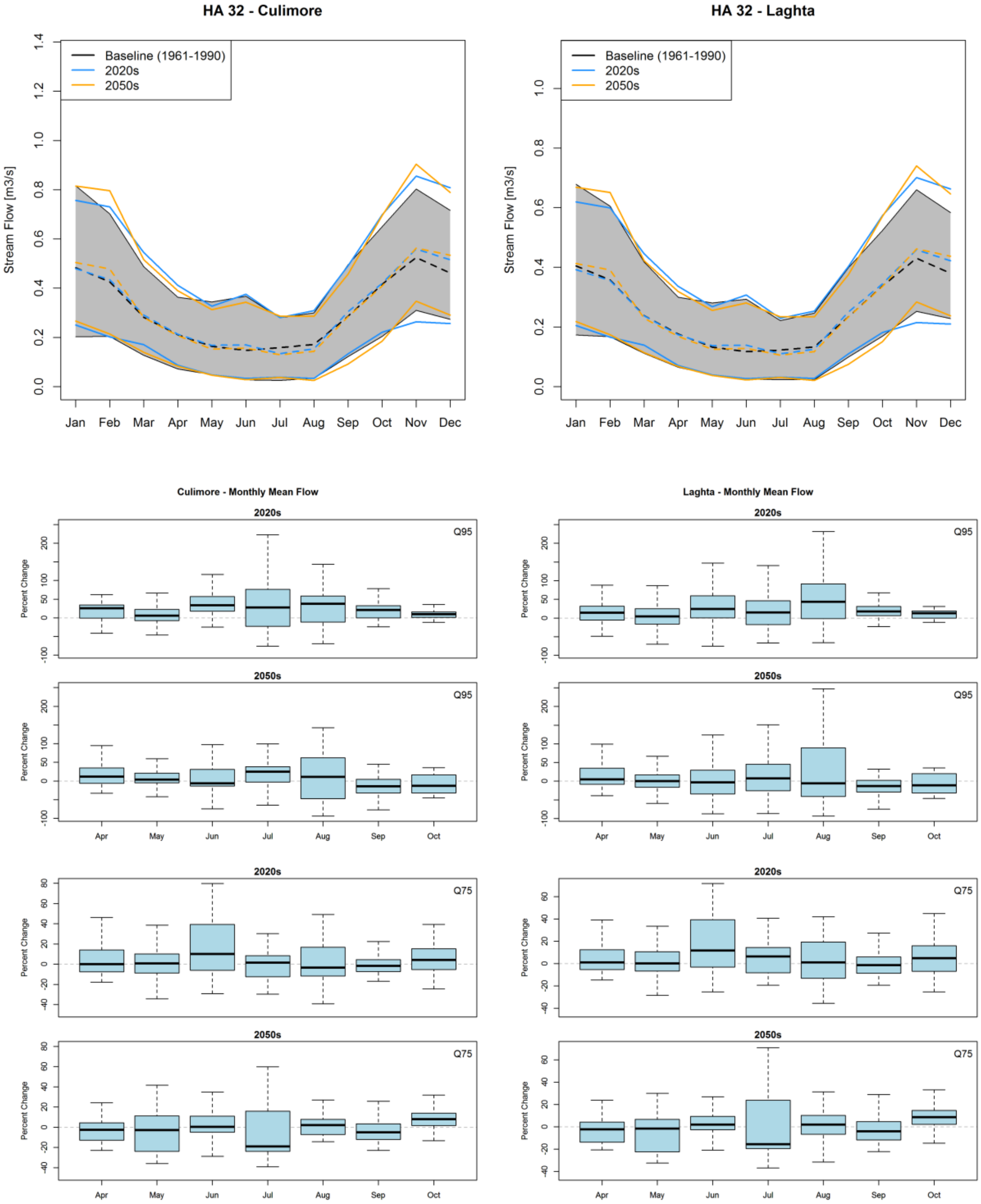


Figure 5.29 Erriff-Clew Bay - HA 32 Stream flow at the water abstraction points Culimore and Laghta. Upper panels: Modelled monthly mean flow for baseline period (1961-1990) and in blue the 2020s (2010-2039) and in orange the 2050s (2040-2069). Solid lines in their respective colour show the95th and 5th percentiles, dashed lines are the 50th percentile of monthly mean flows. Lower panels: Projected changes in monthly Q75 and Q95 relative to the baseline, for the months April to October. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

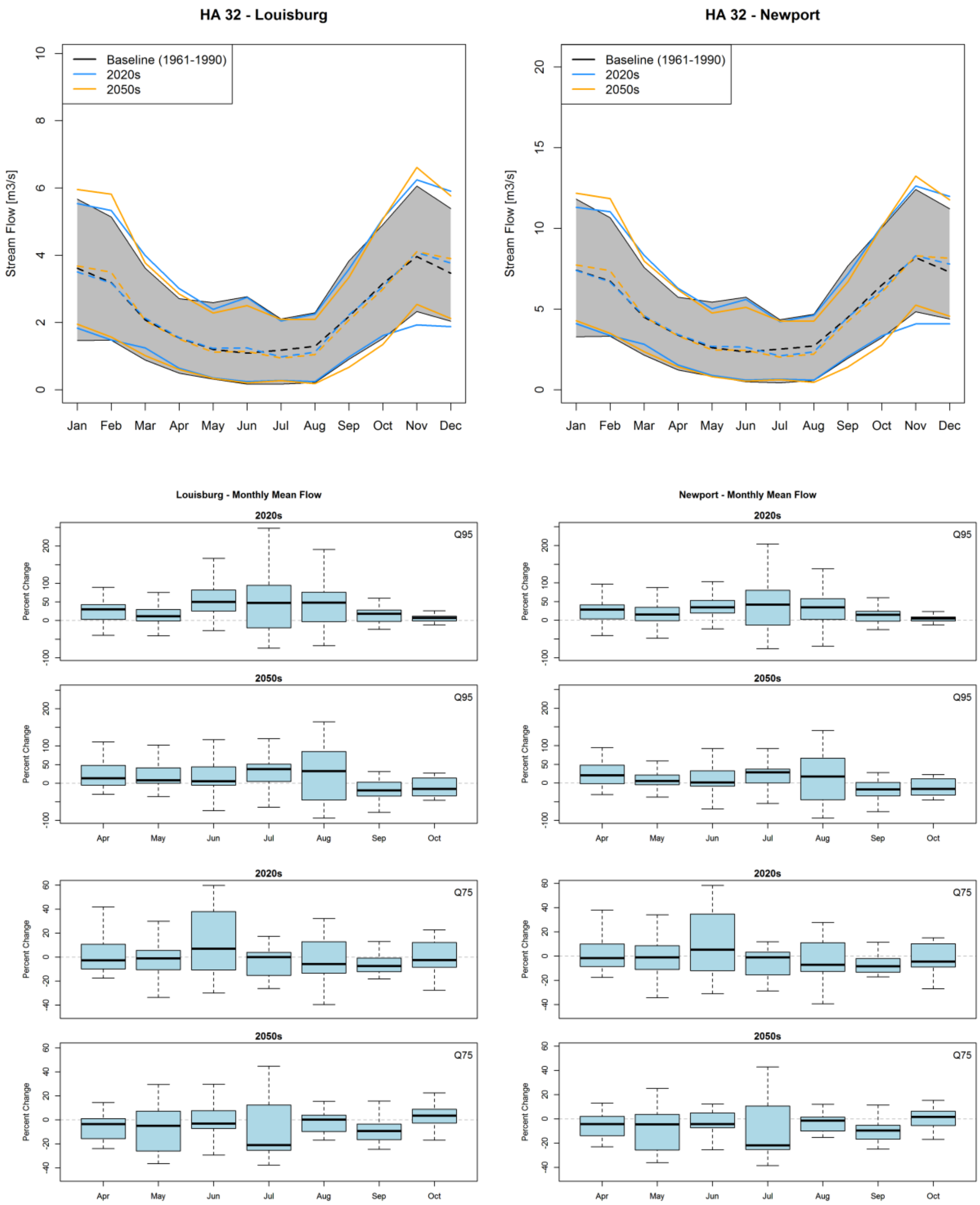


Figure 5.30 Erriff-Clew Bay - HA 32 Stream flow at the water abstraction points Louisburgh and Newport. Upper panels: Modelled monthly mean flow for baseline period (1961-1990) and in blue the 2020s (2010-2039) and in orange the 2050s (2040-2069). Solid lines in their respective colour show the95th and 5th percentiles, dashed lines are the 50th percentile of monthly mean flows. Lower panels: Projected changes in monthly Q75 and Q95 relative to the baseline, for the months April to October. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

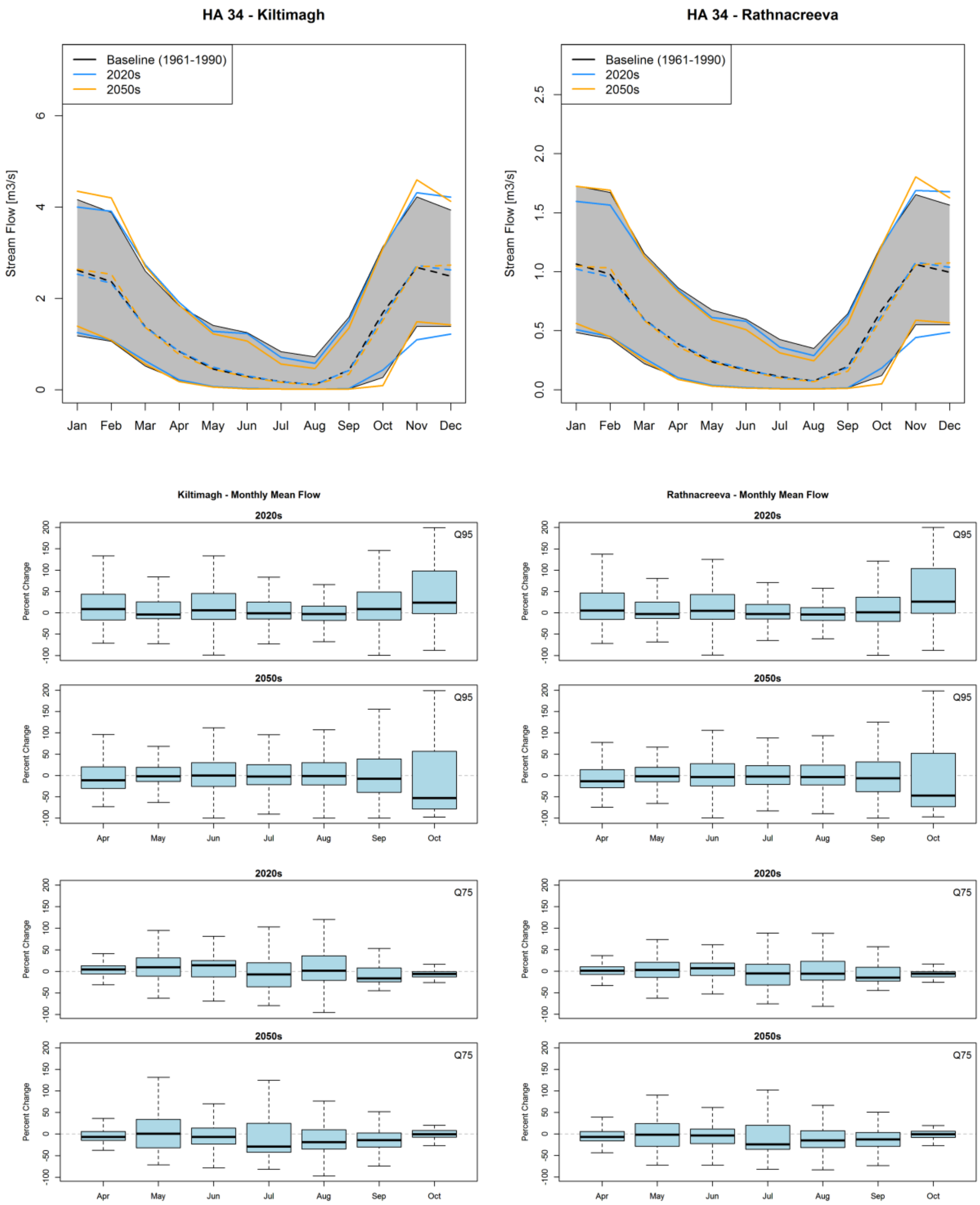


Figure 5.31 Moy Catchment - HA 34 Stream flow at the water abstraction points Kiltimagh and Rathnacreeva. Upper panels: Modelled monthly mean flow for baseline period (1961-1990) and in blue the 2020s (2010-2039) and in orange the 2050s (2040-2069). Solid lines in their respective colour show the95th and 5th percentiles, dashed lines are the 50th percentile of monthly mean flows. Lower panels: Projected changes in monthly Q75 and Q95 relative to the baseline, for the months April to October. Maximum box plot whisker length is 1.5 times the interquartile range, comprising ~ 95% of the data.

The future monthly stream flow simulations for the water abstraction points are presented based on the hydrometric area they are located in. Differences in the pattern of the percentiles result from different catchment areas and differences in hydrological responses resulting from variations in the groundwater, and land surface characteristics expressed in through the physical parameter values. In the figures, these differences are visually mainly apparent in the higher flow percentiles; however, for water management the lower flow percentiles are more important, especially during the months when flows are at their lower levels. Therefore, a detailed analysis of the percentage change for the months April to October for the Q95 and the Q75 of monthly mean flows is shown as box plots in Figure 5.26 to Figure 5.28.

The common characteristics for the two modelled stream flow percentiles (Q75 and Q95) investigated at abstraction points in the Boyne is that the projected percent changes relative to the baseline period (1961-1990) show wide ranges. The percentage changes show high increases in the low flow indicator Q95 for both the 2020s and the 2050s with maximum changes between 200 and 400 % depending on the water abstraction point. But also decreases of 100% are projected for the 2020s. The ranges of percent change get smaller for the 2050s tending towards a negative sign. In particular, catchments with lower discharge, and hence smaller catchment area, show a higher variation in the spread of monthly mean Q95 between the simulations for individual months. During the 2020s the median of the percent change of the monthly mean flows is increasing, whereas for the 2050s no clear pattern of increases or decreases in Q95 emerges.

The other low flow indicator Q75 shows ranges and percentage changes are much smaller and less variable compared to Q95. In July for example at Kells monthly Q95 in the 2020s, the percent changes encompassing 95% of the simulations range from plus 400% to approximately minus 75%, whereas for the Q75 in the same month and time period smaller ranges of plus 75% and minus 50% are projected. Decreases in the median of Q75 are observable for June to October for the 2020s and for all analysed months in the 2050s.

When comparing the results spatially with the Boyne catchment is the East and the Erriff-Clew Bay and the Moy catchment in the West different patterns in hydrological responses emerged from the above analysis. These differences are also apparent in the hydrographs and the ranges of all simulations in the upper panels of Figure 5.26 & Figure 5.31. For example, for Q95, in the East there is a marked reduction in the ranges of percent changes between 2020s and 2050s, the ranges show minor reductions or remain the same in the West. Also for the majority of months the medians of simulations remain positive when moving from the 2020s to the 2050s. When examining the percentage change in the Q75 of monthly mean flows, the spread of the percent changes is lower compared to Q95 for the stream flow in HA 32 but retains a similar spread to Q95 in HA 34. The only strong decrease of the spread of the changes for the abstraction points in HA 34 (i.e. the catchments with grass land cover and little peat), occurs in April, September and October.

5.5 Discussion and Conclusion

This chapter deals with the first two points of the second key research objective by modelling future stream flows at 12 un-gauged illustrative Irish water abstraction points. In doing so the uncertainty ranges derived from national climate scenarios and hydrological modelling are incorporated into future stream flow projections.

Six catchments from the East and from the West of Ireland respectively, were selected to account for different characteristics in the Irish water resources systems. For example, the population served by the individual water abstraction points, in the East is much higher, with large towns, compared to the smaller water schemes in the West with a few hundred people. Additionally, the catchments supplying the water abstraction points in the East have a drier rainfall regime compared to the wetter Western catchments, which also relates into surface water resources availability. The catchments studied also exhibit different hydrological characteristics in terms of grassland and peat land hydrological processes. This diversity in the case study selection ensures a good representation of the typical surface water schemes present in Ireland.

In the typical Irish situation of the water resources system investigated here, most of the water abstraction points are un-gauged. The challenge of assessing future changes in water resources availability in a data scarce context has been addressed using a proxy-basin-split-sample approach. Through the use of proxy-basins with similar physical catchment characteristics it has been shown that this approach can provide flow estimates for such un-gauged catchments. However, this approach requires detailed information on the physical catchment characteristics which might not be available for all un-gauged sites. Additionally, the prerequisite of two proxy-basins with similar characteristics and identical observational flow record, long enough to allow for hydrological model calibration and evaluation is demanding.

The traditional application of the proxy-basin-split-sample approach to estimate hydrological model parameters in un-gauged catchments is extended to account for equifinality in the parameter estimation. Instead of identifying a single behavioural parameter set, this augmentation results in multiple behavioural parameter sets and therefore in multiple future stream flow realisations. This allows incorporating additional uncertainty stemming from the estimation of behavioural parameter sets.

The approach presented here makes the commonly used assumption of time invariant parameter sets, by incorporating an equifinality approach this assumption has lower implications on future outcomes, due to the wide ranges obtained compared to a single future stream flow realisation obtained from an optimum parameter set. Additionally, hydrological model parameters have been shown to be more stable throughout time for low and mean flows compared to high flows (Merz *et al.*, 2011).

The hydrological model output derived from the statistically downscaled (SD) scenarios is consistent and comparable with the output derived from the probabilistic scenarios, for both, the control and the future time period. The six future SD climate scenarios were selected for the case studies in this thesis as they perform comparably with to the probabilistic scenarios and were produced specifically for climate change impact assessment and to support adaptation. The functional objective here is to develop a flexible tool that allows for the incorporation of uncertainty into the adaptation option appraisal. Future application of the tool can be used with updated and/or additional climate scenarios and therefore also allow the inclusion of a wider range of future uncertainty ranges.

In the last section, future stream flow for the water abstraction points is modelled and analysed. The ranges of modelled percent changes compared to the baseline 1961-1990 are large. Large ranges are particularly apparent for Q95 together with high percent-changes for Q75 where the future change signal is much clearer. The large ranges obtained also highlight the importance of hydrological modelling uncertainty, here particularly in regard with the low flow that is sustained by groundwater. These findings highlight the importance of incorporating hydrological modelling uncertainties in such a modelling approach.

The uncertainty ranges obtained for future stream flow at each water abstraction point are large. However, it needs to be highlighted that these uncertainty ranges are highly conditional on assumptions and decision taken throughout the modelling approach. Different input climate scenarios and different hydrological modelling approaches will lead to different outcomes. With the approach taken here it is not expected that the full uncertainty ranges of future stream flow realisations have been sampled. By using other climate projections or an additional hydrological model it is expected that these ranges would further increase.

5.6 Chapter Summary

In this chapter, the 12 illustrative Irish case study water abstraction points are presented together with an approach that allows for the assessment of future stream flow at un-gauged sites. The stream flow scenarios and their associated uncertainty ranges derived in this section, will be used in the following chapter to appraise the effectiveness of selected adaptation options to assist robust assessment, planning and decision-making. This chapter can be summarised as follows:

- The proxy-basin-split sample approach allows deriving future flow projections at un-gauged locations. The approach is complemented by the use of the equifinality concept to allow for uncertainties in parameter set estimation.

- The output of the hydrological model driven by the transient, statistically downscaled scenarios is consistent and comparable with the output derived from the probabilistic scenarios for both the control period and the future time periods.

- The ranges of changes in future stream flow series obtained are large due to the uncertainties related to climatic and non-climatic factors. This highlights the importance of incorporating various sources of uncertainties into the modelling approach particularly when the results are to be used to inform anticipatory adaptation planning.

- The uncertainty ranges obtained for each water abstraction point are highly conditional on assumptions and decision taken throughout the modelling approach. Here only a sample of possible future uncertainty ranges is captured.

In the next chapter, the monthly stream flow series are used as an input into a water resource model to analyse the future performance of the water resource system for each of the illustrative case study water abstraction points under the future uncertainty ranges.

6 Tool Application: Anticipatory Adaptation Option Appraisal

6.1 Introduction

In this chapter, the stream flow for un-gauged water abstraction points generated in the previous chapter is linked to a water resource model, in order to examine the water resources system under the range of future water scenarios generated from the available climate scenarios for adaptation. The main research objective here is to test the effectiveness and robustness to uncertainty of commonly defined robust adaptation options that are represented through four future water resource scenarios specific to Ireland. Based on the adaptation framework presented in Chapter 4, the alternative approach of assessing the potential success of the proposed national low-regret adaptation options is investigated, instead of the traditional top-down approach. In addition, population change is included as an additional non-climatic driver into the adaptation option appraisal.

The chapter is structured as follows; first, the time series of the water resource scenarios are briefly recapitulated (Section 6.2) and then the time series of these scenarios are assessed for each water abstraction point using the water Use-to-Resource Ratio (Section 6.3). In Section 6.4, the threshold-based metrics Reliability, Resilience and Vulnerability indicators are used to appraise the performance of the water resources systems under future water system scenarios at an annual (Section 6.4.1) and decadal (Section 6.4.2) timescale. The chapter closes with a discussion and conclusion (Section 6.5) followed by a chapter summary in Section 6.6.

6.2 Adaptation Scenarios

In a traditional ‘top down’ approach the next step in the modelling chain for impact and adaptation assessment would be to use a water resource model to find the optimum adaptation option to the projected changes on impacts on the water supply system. However, as shown below, the uncertainty ranges derived from the various modelling steps are large and therefore present significant challenges to the traditional approach.

In the framework applied in this study, the water resource model is used not to determine the best or a range of best adaptation option. The aim is to incorporate the uncertainty ranges obtained into the decision-making to investigate if the selected low regret adaptation options are sufficiently robust to the uncertainties, i.e. are functional across the range of simulations considered. Although the future continuous hydrological time series are routed through WEAP; the water resource model is used in this study similar to the traditional approach however, the handling of uncertainties differs. Each of the twelve water abstraction points, from the three case study Hydrometric Areas presented in the previous chapter, is analysed for each of the four water resource scenarios shown and colour coded in Figure 6.1 (Figure 4.16 is provided again to explain the colour coding of the scenarios used in the following sections). For details of the scenarios, see also Section 4.7.

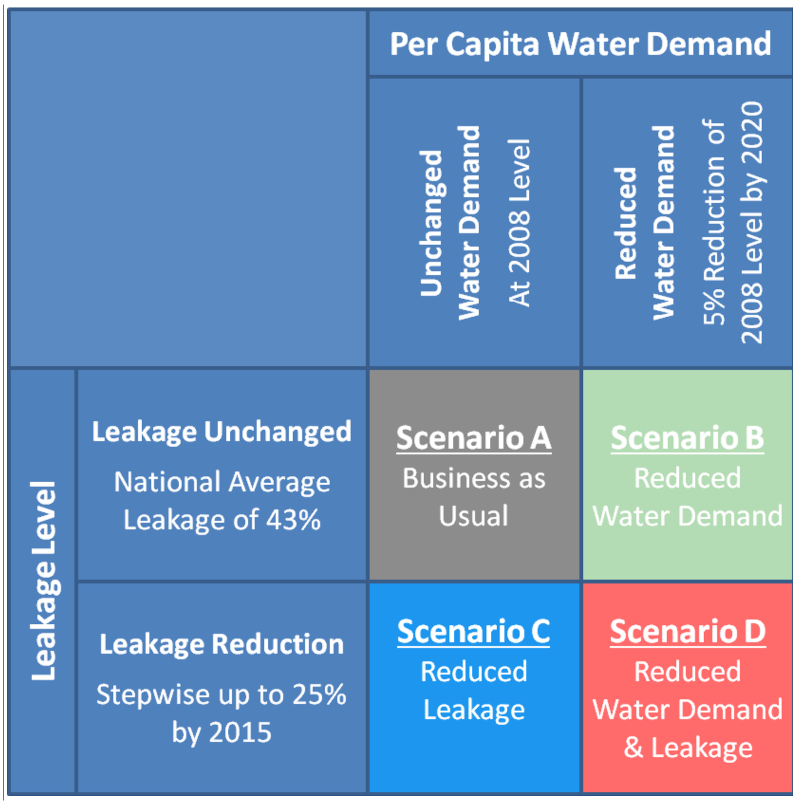


Figure 6.1 Scenario matrix and colour coding of the four investigated adaptation scenarios (A-D).

These future water resource management scenarios are based on plans stated by Irish planning authorities. The four adaptation options shown in the scenario matrix in Figure 6.1, which are assessed against future uncertainty, include no-measures or business as usual (Scenario A), demand side measures (Scenario B), supply side measures (Scenario C) and an integration of supply and demand side measures (Scenario D).

The three examples of alternative management strategies/scenarios presented can be characterised as "low- or no-regrets" and "win-win-strategies", which potentially cope with climate uncertainty and provide benefits, even in absence of climate change (Hallegatte, 2009).

6.3 Time Series Analysis of Future Water Resources

To examine the influence of integrated pressures (climate change and population growth) the time series of stream flow (2010-2069) derived for each water abstraction point in the previous chapter are analysed using the threshold-based approach. The four categories of the water 'Use-to-Resource Ratio' (URR) index are shown in Figure 6.2 (detailed description see Section 4.8 and Table 4.4). The water stress classes are used to assess the water resource system performance and to appraise the successfulness of robust adaptation measures.

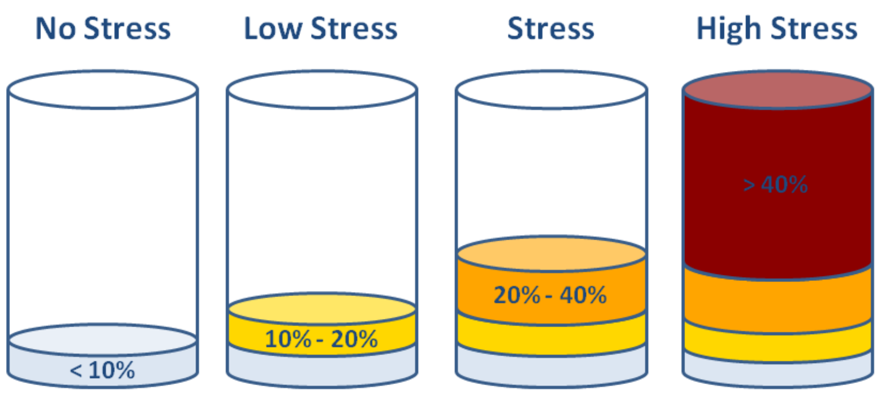


Figure 6.2 Water stress categories based on the Water Use-to-Resource Ratio (URR).

Each water abstraction point with its corresponding stream flow and water demands is modelled on a monthly basis. For an initial analysis the time series of URR are examined for each water resource scenario on a seasonal basis to examine the magnitude of water stress experienced and its frequency of occurrence based on monthly values. The analysis is performed for all water abstractions, seasons and scenarios. For brevity only the water abstraction points and seasons showing a degree of water stress in the 'Business as Usual' Scenario (A) for more than 7 years over the analysis period 2010-2069 are plotted. The water abstraction points showing water stress levels of less than 10% of the simulated years are listed in Table 6.1.

From the 12 investigated water abstraction points, there are four abstraction sites that do not experience any water stress level during any season under the BAU scenario (Athboy, Kilcarn, Trim and Rathnacreeva). Under the investigated index (URR), these water abstractions can be considered as not adversely affected by climate change and population growth. All other abstraction points show a varying number of years with levels of water stress. Liscarthan and Culimore are the only two points, where all seasons show at least 2 years of at least 'Low Water Stress' in the BAU scenario.

For brevity, a full account of all four water resource scenarios is provided for Kells only by examining summer and autumn flows (Figure 6.3 and Figure 6.4). For the other water abstraction points shown, only the BAU scenario is given (Figure 6.5 and Figure 6.6). The seasonal Figures are composed of 9000 data points per year (3 months x 500 parameter sets x 3 GCMs and 2 emission scenarios). Generally, the darker the colour in the plots, the higher the density of data points for a certain Water Use-to-Resource-Ratio.

The analysis of the twelve water abstraction points (Table 6.1) in the East and West of Ireland shows three locations with 'No Water Stress' (Athboy, Kilcarn (both HA07) and Rathnacreeva (HA34)) in the 'Business as Usual' scenario (Scenario A: BAU). The lowest occurrences of water stress are indicated for the winter season, with Liscarthan (HA07) being the only water abstraction indicating for some simulations in the 'Water Stress' categories for two years. Additionally, there are six years with low water stress at Liscarthan and two years for Culimore (HA32) during wintertime.

Table 6.1 Water Abstraction Point and Number of Years per Season and Water Stress Category for Scenario A (BAU) not shown in Figure 6.3 to Figure 6.6.

Water Abstraction	Spring	Summer	Autumn	Winter
Athboy (HA07)	0 yrs	0 yrs	0 yrs	0 yrs
Drogheda (HA07)	0 yrs	shown	Shown	0 yrs
Kells (HA07)	Low WS: 1 yr	shown	Shown	0 yrs
Kilcarn (HA07)	0 yrs	0 yrs	0 yrs	0 yrs
Liscarthan (HA07)	Low WS: 4 yrs	shown	Shown	Low WS: 6 yrs WS: 2 yrs
Trim (HA07)	0 yrs	0 yrs	0 yrs	0 yrs
Culimore (HA32)	shown	shown	Shown	Low WS: 2 yrs
Laghta (HA32)	shown	shown	Low WS: 4yrs	0 yrs
Louisburgh (HA32)	Low WS: 4 yrs WS: 3 yrs	shown	0 yrs	0 yrs
Newport (HA32)	Low WS: 1 yr	shown	0 yrs	0 yrs
Kiltimagh (HA34)	0 yrs	Low WS: 4 yrs	Low WS: 1yr	0 yrs
Rathnacreeva (HA34)	0 yrs	0 yrs	0 yrs	0 yrs

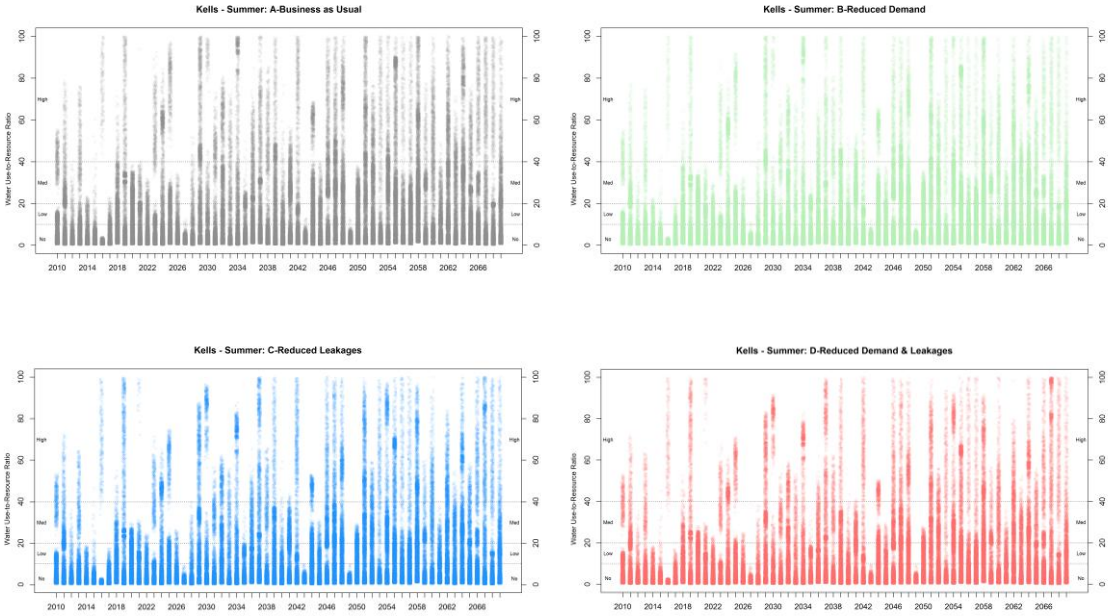


Figure 6.3 Kells – Summer: Water Use-to-Resource-Ratio. Scenario A (grey), B (green), C (blue) and D (red).

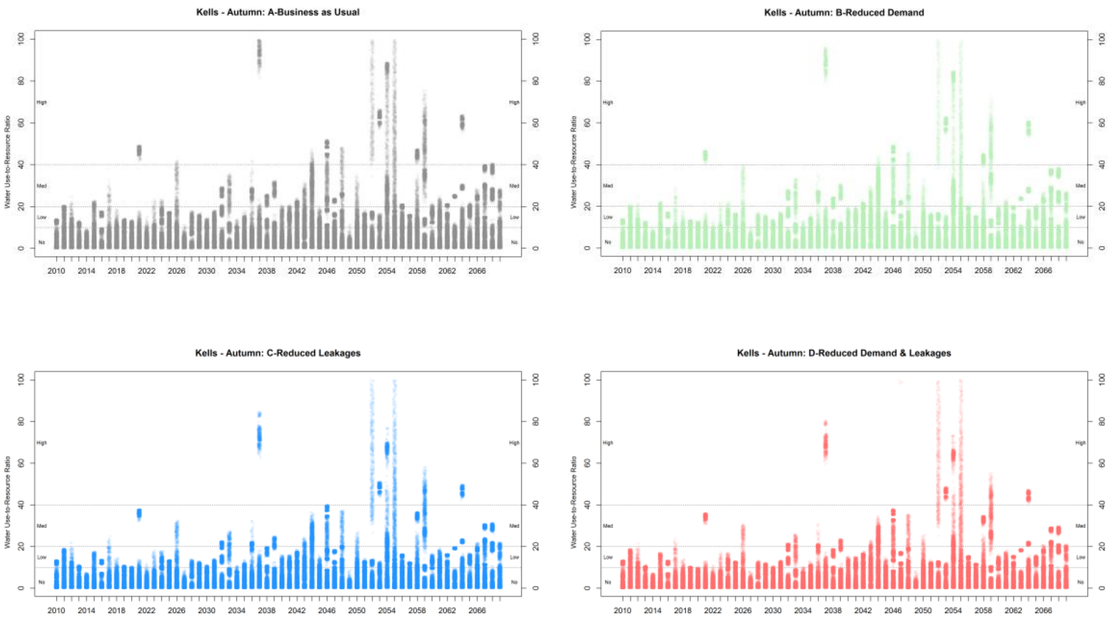


Figure 6.4 Kells - Autumn: Water Use-to-Resource-Ratio. Scenario A (grey), B (green), C (blue) and D (red).

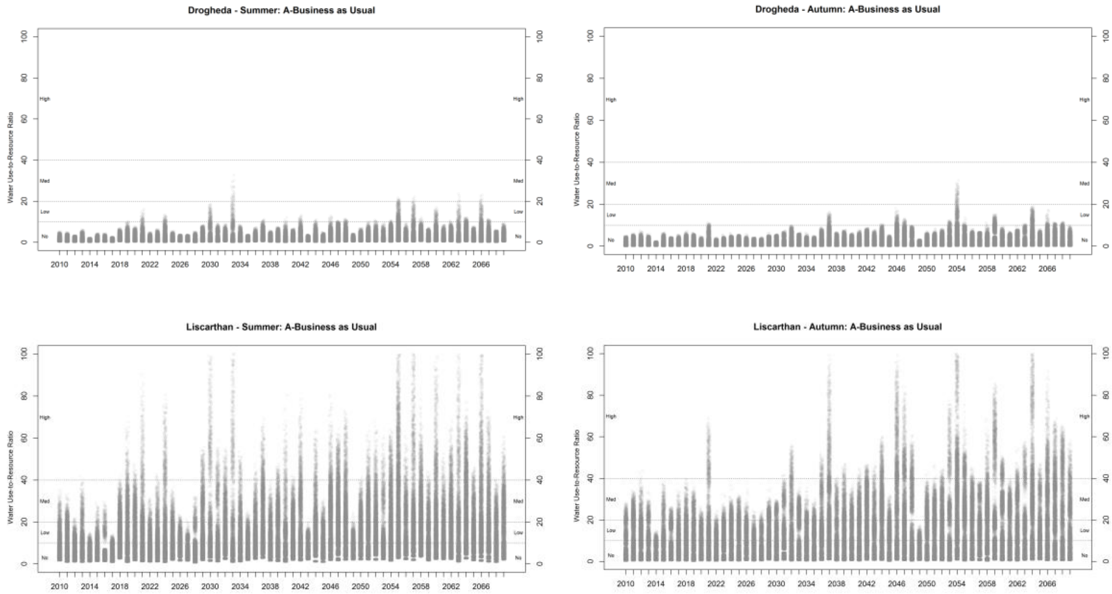


Figure 6.5 HA 07: Water Use-to-Resource Ratio of Scenario A for selected abstraction points and seasons

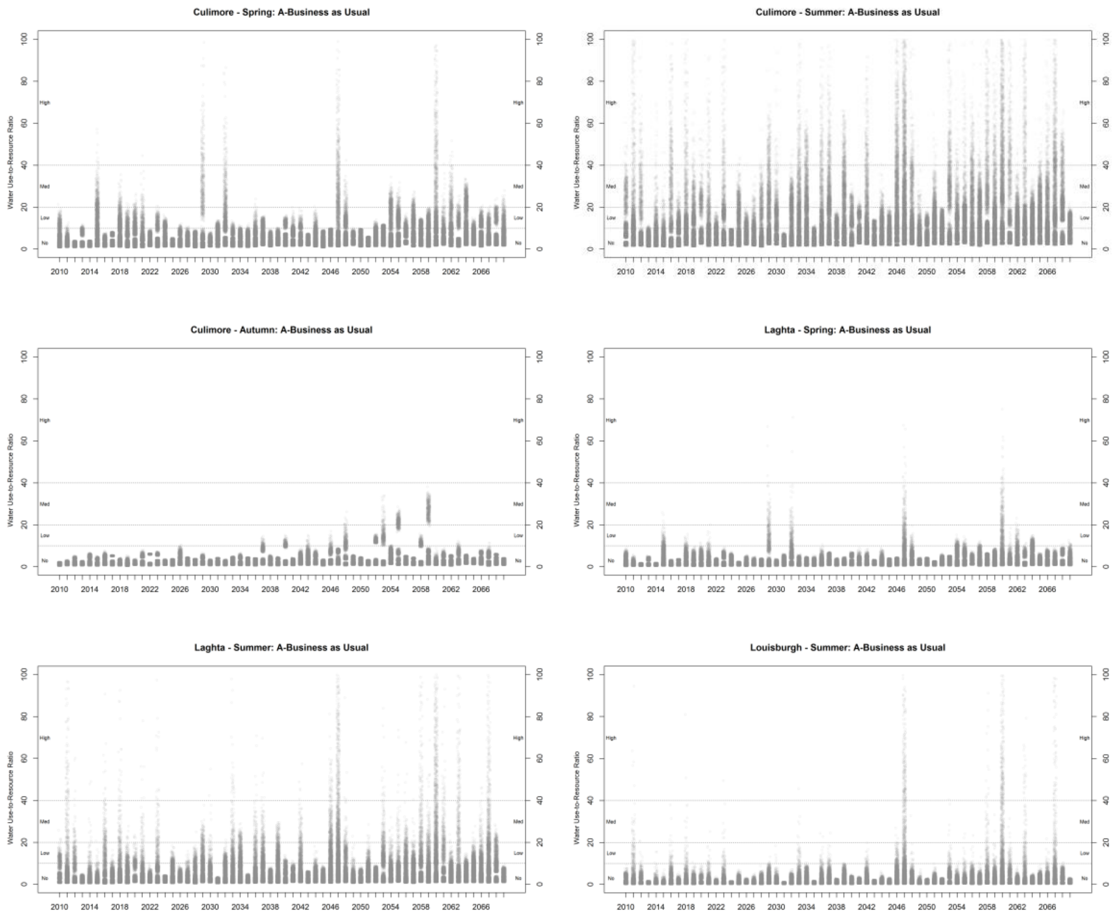


Figure 6.6 HA 32: Water Use-to-Resource-Ratio of Scenario A for selected abstraction points and seasons

In spring eight out of 12 water abstractions experience no or less than 5 years of ‘Low Water Stress’. Only in the West (HA32) three catchments (Culimore, Laghta and Louisburgh (not shown)), indicate ‘Water Stress’ or ‘High Water Stress’. For summer and autumn the number of water abstraction points indicating ‘No Water Stress’ decreases to three and five respectively. Overall, summer and autumn are the months where all ranges of the URR Ratio can be found, for all the water resource scenarios modelled.

The overall picture presented by Figure 6.3 to Figure 6.6 is that with increasing simulation length (more distant future), the spread of the Use-to-Resource-Ratio increases, reflecting the increasing uncertainties in modelling outputs from all previous modelling steps. The BAU scenario has the highest URR, the water use reductions in Scenario B, C and D result in decreasing URR for some individual simulations. However, not all simulations exhibit this decrease, instead remaining at a similar magnitude of URR as in the BAU scenario. In the example of Kells (Figure 6.3 and Figure 6.4) it can be seen that the various water demand reductions (use and leakage) modelled result in decreases of URR in several, though not all, simulations. However, the decreases are not uniform and often result in a downward shift of clusters of certain Use-to-Resource ratios. Overall the spread and the magnitude of some clusters of URR occurrences decrease from Scenario A to D.

To obtain a quantification of the influences of the different adaptation scenarios on the occurrence of different water stress categories, an analysis of the percentage of simulations per water stress category is performed. As a first step, the analysis of changes in ‘High Water Stress’ is carried out across all scenarios as shown in the bar charts in Figure 6.7 for selected water abstraction points and seasons.

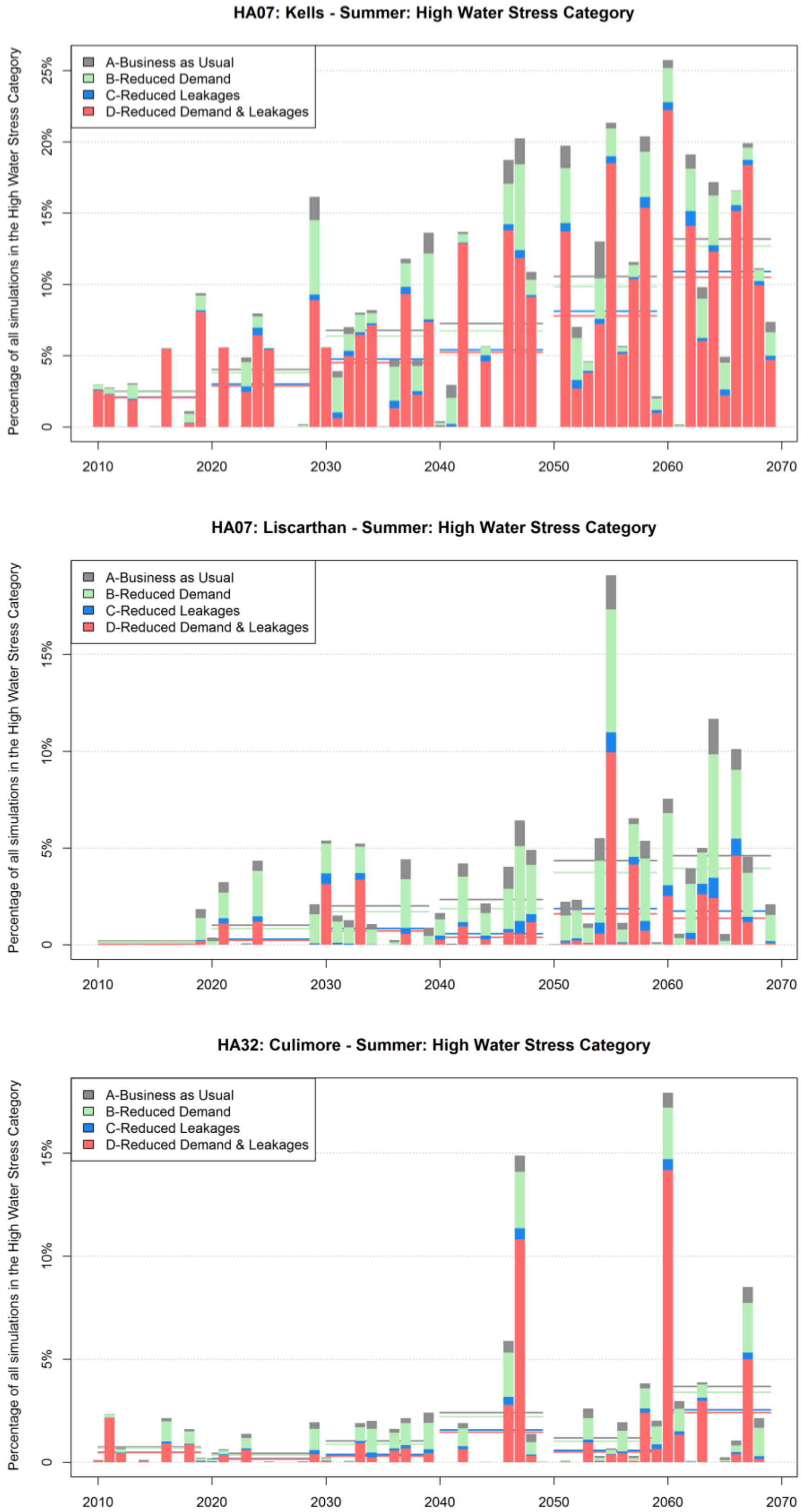


Figure 6.7 Influence of the Scenario on the High Water Stress Category. Bars indicate individual years, the horizontal lines in the background represent the decadal mean for each of the investigated scenarios.

Over time the number and frequency of simulations in the ‘High Water Stress’ Category per year and the 10 year averages increase for all water resource scenarios (Figure 6.7). The adaptation measures reduce the number of simulations in the high water stress categories, but only for a few years are the measures able to completely eliminate the occurrences of ‘High Water Stress’ for all simulations. If the aim of adaptation is to move the system from ‘High Water Stress’ to lower water stress categories, the measures are not enough.

This direct comparison between the individual water resource scenarios is only possible for the highest category of interest, as a reduction in one category by an adaptation option (e.g. from ‘High’ to ‘Water Stress’ category) will result in an increase in the lower category and an over plotting of the BAU scenario in the graph. Therefore, the differences between the individual water resource scenarios in lower categories have to be analysed in separate graphs. Selected plots are shown in Figure 6.8 to Figure 6.14. For Kells all four water resource scenarios are shown for summer (Figure 6.8) for the other water abstraction points and seasons only Scenario A and D are plotted.

Generally, with the adaptation measures in place (Scenario B, C and D), the overall number of simulations falling into a specific water stress category is reduced. This reduction comes about by a shift in the percentage of simulations from higher to lower water stress categories or to ‘No Water Stress’. However, all water abstraction points differ in their responses to the scenarios. For example when a high number of simulations indicate ‘High Water Stress’ only small changes in the overall number of simulations indicating any degree of water stress is achieved in the adaptation scenarios as only the water stress category changes. Whereas if only a low number of simulations indicate ‘Low Water Stress’ then the adaptation measures can be enough to eliminate the occurrence of water stress (e.g. Kiltimagh in summer in Figure 6.14). However, for most of the catchments, the demand and leakage reduction measures are not enough to eliminate the occurrences of any form of water stress

When examining a single water abstraction point the reductions in the water stress categories are not the same from year to year. For example for the water abstractions at Kells, the percentage of simulations showing water stress in the year 2021 only changes by 2 percent (from 24% (Scenario A) to 22% (Scenario. D)), however when examining the year 2047 the percent of simulations with WS in Scenario A account for 58% and are reduced by 7 percent to 51 % in Scenario D.

Similarly, the change in the number of simulations per water stress category is different from year to year. Again Figure 6.9 (Kells) is used as an example where for 2046 in scenario A there are 2 percent of simulations in the 'Low Water Stress' Category, 20% in the 'Water Stress' Category and 19% in the ' High Water Stress' Category resulting in an overall number of water stressed simulations of 41%. In Scenario D this overall number is slightly reduced to 39%, but the 'High Water Stress' is reduced to 14%, 'Water Stress' is reduced to 12% and the percentage in the 'Low Water Stress' Category increased to 13%. For this selected year a general shift to lower water stress category occurred without a marked overall reduction in the number of simulations showing any water stress.

A different situation is presented in the year 2059, where there is no change in the total number of simulations showing water stress, only a shift in 1 percent of simulations is caused by a shift from 'High Water Stress' to 'Water Stress' and from 'Water Stress' to 'Low Water Stress'.

With regard to water management, not only the magnitude and frequency of incidents above a threshold (i.e. water stress category), but also the overall performance of the water abstraction point is of interest. Therefore, in the next section the water resource system performance is analysed using the statistical performance measures of reliability, resilience and vulnerability (RRV) indices described in Chapter 4.

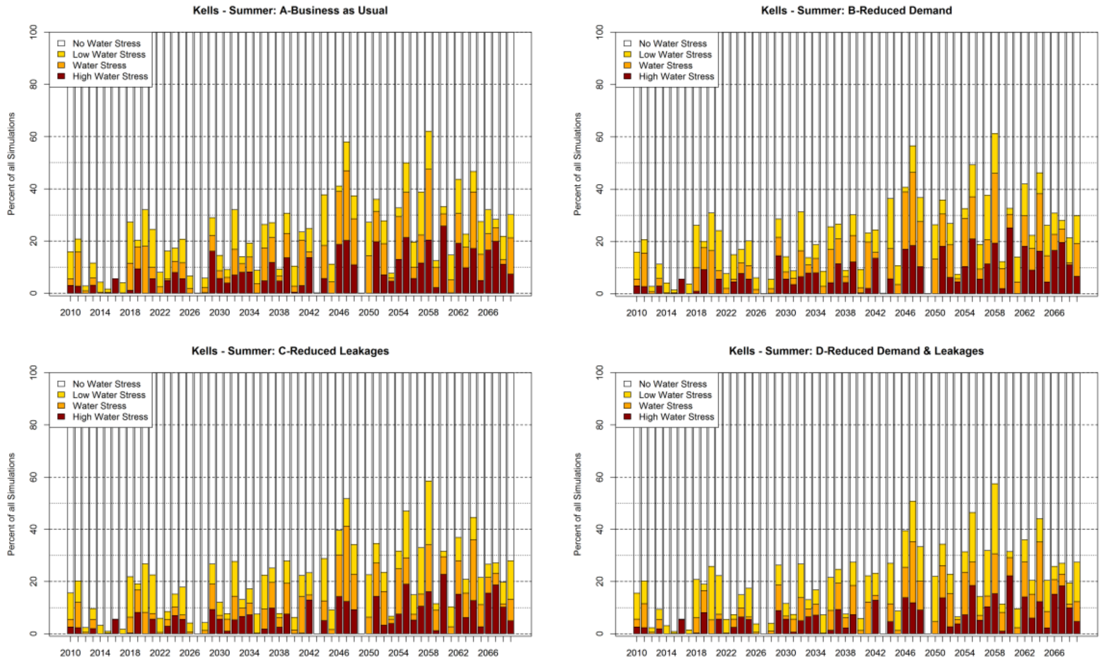


Figure 6.8 Kells – Summer - Percentage of simulations per water stress category. Scenario A, B, C and D.

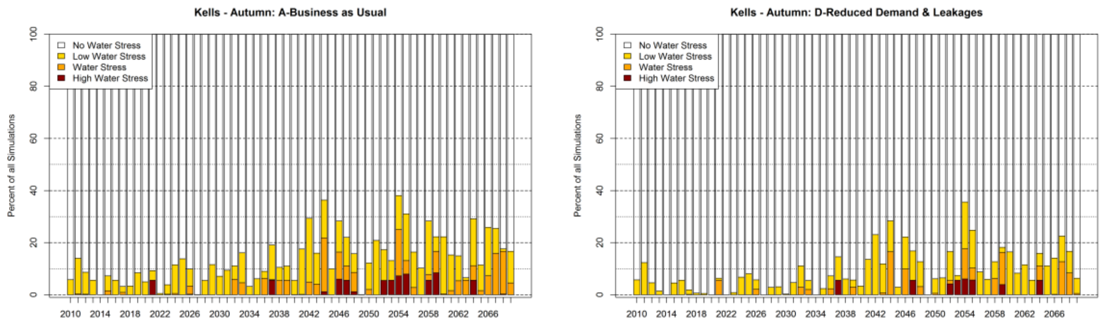


Figure 6.9 Kells – Autumn - Percentage of simulations per water stress category. Scenario A and D.

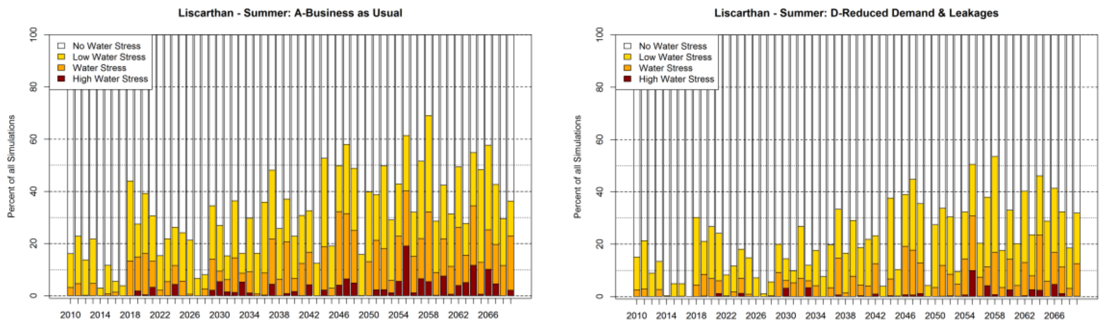


Figure 6.10 Liscarthan – Summer - Percentage of simulations per water stress category. Scenario A and D.

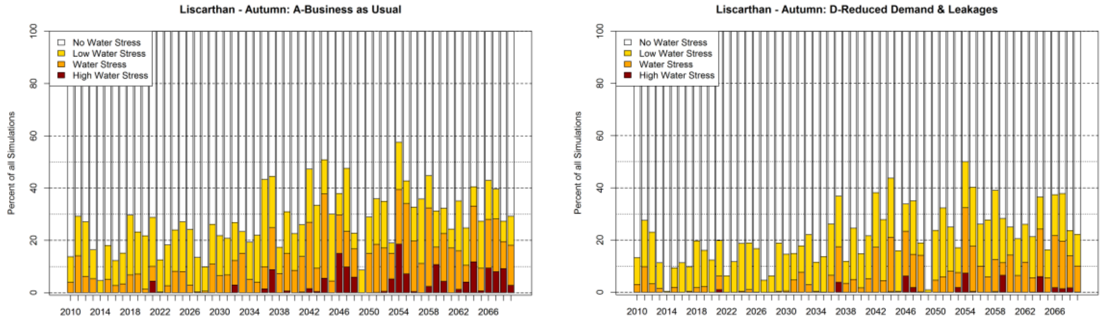


Figure 6.11 Liscarthan – Autumn - Percentage of simulations per water stress category. Scenario A and D.

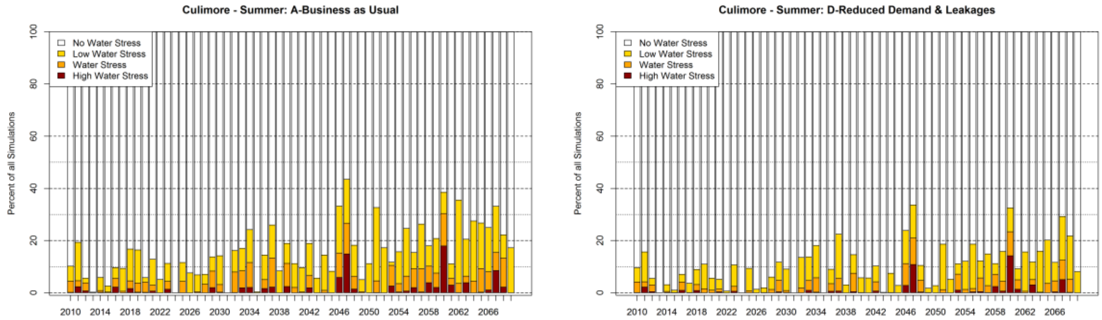


Figure 6.12 Cuilmore –Summer - Percentage of simulations per water stress category. Scenario A and D.

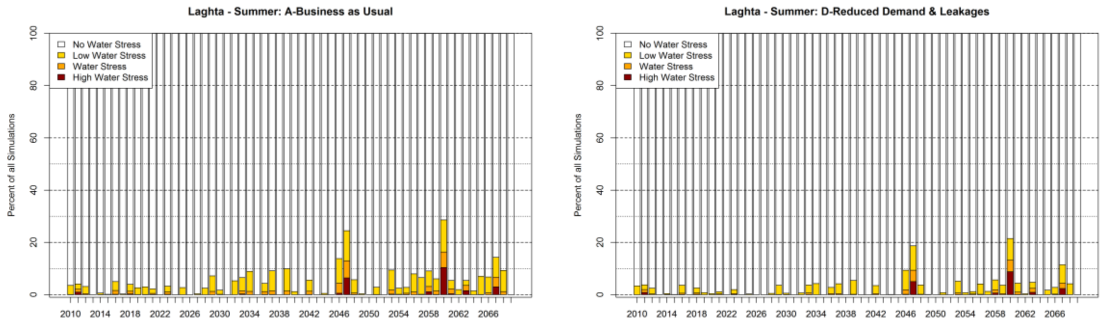


Figure 6.13 Lagtha –Summer - Percentage of simulations per water stress category. Scenario A and D.

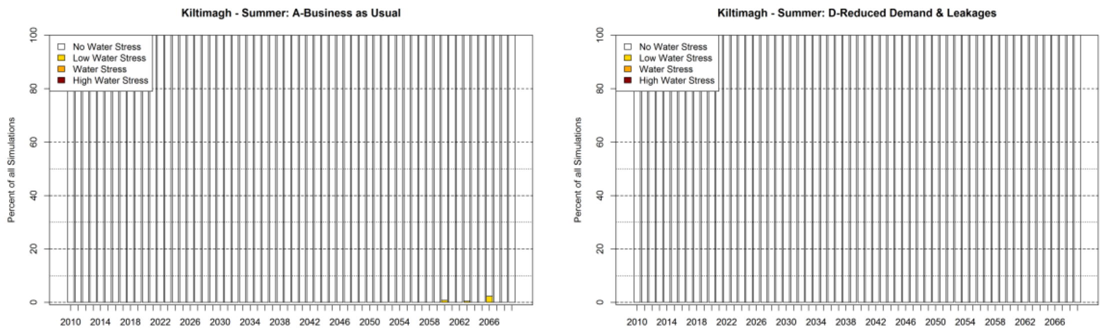


Figure 6.14 Kiltimagh – Summer - Percentage of simulations per water stress category. Scenario A and D.

6.4 Reliability, Resilience and Vulnerability Analysis

In the previous section changes in the levels of water stress over time and for different scenarios has been investigated. However, not only the level of water stress is important but also additional characteristics of change in the water resource system are of importance. System performance indicators can help to identify changes in system characteristics, which are important to the water managers.

Here the water resource system performance is analysed using the reliability, resilience and vulnerability (RRV) indicators. These system performance indicators have been widely used in studies on water resource systems (Hashimoto *et al.*, 1982; Moy *et al.*, 1986; Kundzewicz & Kindler, 1995; Stakhiv, 1998; Fowler *et al.*, 2003; Kjeldsen & Rosbjerg, 2004; Ajami *et al.*, 2008; Sandoval-Solis *et al.*, 2011). The RRV analysis of the water abstraction points is performed based on the upper threshold criterions (UC) (see Section 4.9 and Figure 4.17) provided from the classification system of the water use-to-resource ratio (URR) described in the previous section.

The RRV indices are determined on an annual basis with regard to a 10% Use-to-Resource Ratio indicating at least ‘Low Water Stress’ and a 20% URR representing at least ‘Water Stress’ for the water abstraction points. This approach means that the threshold criteria applied includes all higher water stress classes in the analysis. For example if the threshold criterion is URR >10% (‘Low Water Stress), the analysis includes also ‘Water Stress’ and ‘High Water Stress’, whereas if the UC is URR >20% is applied results will show ‘Water Stress’ and ‘High Water Stress’. Overall, the lower the upper threshold criterion selected, the lower the reliability, resilience, and the greater the vulnerability of the water supply. This highlights the importance of the threshold criteria and levels selected when assessing a water resource system.

The Reliability, Resilience and Vulnerability indices are described in detail in Section 4.9. The time period of analysis is the year with the analysed time steps being months resulting in an annual performance index, for the three RRV indices.

A brief definition of the RRV is given below. Generally the higher the Reliability and the Resilience and the lower the Duration Vulnerability the better the system performance.

Temporal Reliability: Probability of the system being in a satisfactory state. Here, measured as the percentage of months below a threshold, (i.e. no water stress or below selected threshold UC). For example if one month in a year shows unsatisfactory system performance, and consequently the remaining 11 months are satisfactory the reliability for that simulation and that year would be ~0.92. If two months would be unsatisfactory this would result in a reliability of ~0.83.

Resilience: Ability of the system to recover from an unsatisfactory event on average. The resilience values are only calculated for simulations experiencing at least one month in an unsatisfactory state. A resilience of 1 can be achieved if the system recovers from being unsatisfactory to being in a satisfactory state in the next time step, otherwise resilience values of lower than 1 are obtained. For example, if there is a monthly sequence of "... ,S,S,U,S,U,S,S, ..." in this case this means an unsatisfactory month is followed by a satisfactory month twice, therefore the value of 2 is divided by the total number of unsatisfactory months (here 2), resulting in a Resilience of 1. Whereas for the sequence "... ,S,S,U,U,S,S, ...", there is one unsatisfactory month followed by a satisfactory month, divided by two unsatisfactory months. This results in a system resilience value of 0.5. The same resilience value of 0.5 would also be obtained for "... ,S,U,S,U,U,U,S, ...". The resilience values can't directly be attributed to the number of months or individual sequences of U and S as the same resilience value can be obtained from multiple combinations. Possible combinations for resilience values are shown in Table 6.2.

Table 6.2 Resilience value based on monthly simulations and annual analysis with examples of possible combinations of satisfactory (S) and unsatisfactory (U) months.

Resilience Value	Examples of possible combination of S and U
1	...,S,U,S, ... ; ...,S,U,S,U,... ; ...,S,U,S,U,S,U,S,...
~0.67	...,S,U,S,U,U,S,...
0.5	...,S,U,U,S, ... ; ...,S,U,S,U,U,U,S,... ; ...,S,U,U,S,U,U,S,...
0.4	...,S,U,U,S,U,U,U,S,...
~0.33	...,S,U,U,U,S,... ; ...,S,U,U,U,S,U,U,U,S,...
0.25	...,S,U,U,U,U,S,...
0.2	...,S,U,U,U,U,U,S,...
~0.17	...,S,U,U,U,U,U,U,S,...

Average Duration Vulnerability: Average duration (here months) of the water resource system being in an unsatisfactory state per analysis period (here year). This measure can only obtain a value if at least one month indicates unsatisfactory system performance.

6.4.1 Annual Reliability, Resilience and Vulnerability Analysis

When calculating the Reliability, Resilience and Vulnerability measures on an annual basis only certain values for these measures can be obtained, as there is a limited number of monthly combinations of satisfactory and unsatisfactory system performance within a year. This results in distinct categories of values (levels) for the performance measures for Reliability, Resilience or Vulnerability which can be seen when plotting the annual time series.

To illustrate the results of the RRV analysis an annual time series for Kells is shown in Figure 6.15 to Figure 6.17. Each year contains the RRV from 3000 simulations. The blue points in the Figures show the annual reliability, resilience or vulnerability level respectively. The darker and wider the blue points for a particular year, the more simulations fall on that particular RRV level. In addition to showing the spread of the RRV data, the figures also indicate, with colour-coded bars, the percent of simulations falling into each interval. The darker the bars, the higher are the percentage of simulations showing that reliability, resilience or vulnerability level. Five intervals (2.5%, 25%, 50% (dashed outline), 75% and 97.5%) are used to describe the range of simulations. Figure 6.15 to Figure 6.17 show from the top to the bottom the different scenarios with the corresponding colour coding; Scenario A (grey), Scenario B (green), Scenario C (blue) and Scenario D (red) The left hand side of the Figures show the UC Threshold criterion of the Water Use-to-Resource Ratio of 10%; on the right a UUR of 20% is investigated.

Reliability

First, the annual time series of reliability (Figure 6.15) is analysed. For Scenario A ('Business as Usual') it can be seen that the reliability of the system decreases with time with the lowest reliability values of ~0.67 (4 months of unsatisfactory system performance per year) in the first half of the simulated period, down to a minimum reliability of 0.5 (6 unsatisfactory months). In addition to the shift in extreme reliability values, the percent of simulations obtaining lower levels of Reliability also increases -indicated in the plots by the downward shift of darker coloured bars representing a higher percentage of data at this point. When comparing the Business-as-Usual Scenario A (BAU) with the possible adaptation scenarios (B to D), it becomes apparent that measures are able to increase the system reliability through both rising minima and overall increasing reliability values apparent in the BAU scenario.

If the higher threshold value is applied (URR of 20% or at least 'Water Stress') the overall system reliability increases compared to the threshold criterion URR 10%. This is due to the higher threshold for the system performance to be considered as unsatisfactory. Due to the application of a higher threshold, the system is considered to perform better for the same time series, resulting in a apparent more reliable water supply system. The same patterns of decreasing system reliability in both extremes and percent of simulations with increasing time are evident, particularly in Scenario D where 50% of the simulations have a reliability of 1 (no month with unsatisfactory system performance) with the exception of 9 years from 2045 onwards where one month indicates unsatisfactory system performance for 50% of the data.

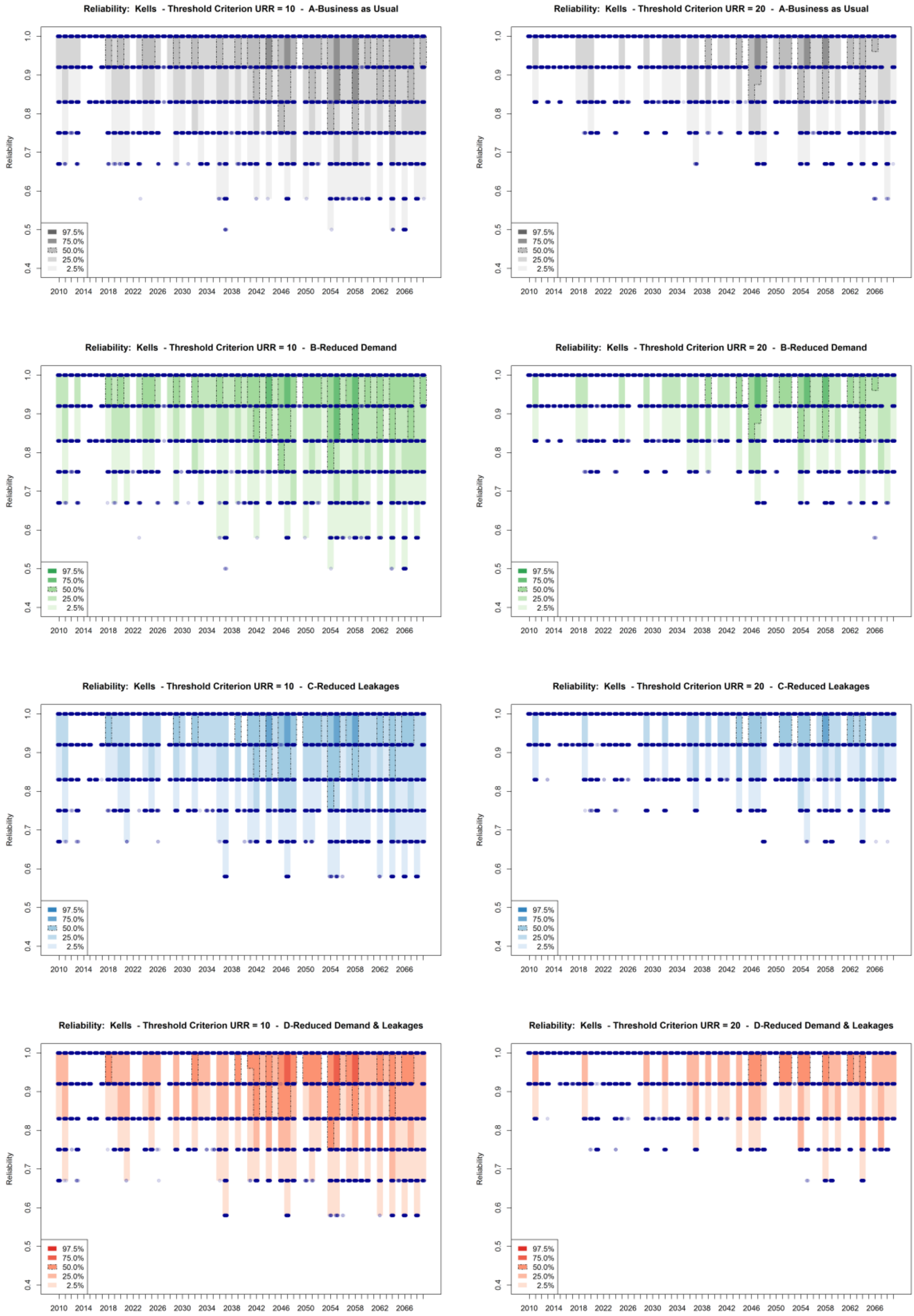


Figure 6.15 Kells Reliability. Blue points show the reliability level per year out of 3000 simulations. From top to bottom Scenario A (grey), Scenario B (green), Scenario C (blue) and Scenario D (red). The darker the bars the higher the percent of simulations showing that reliability level. Threshold: Left URR 10%; Right UUR 20%.

Resilience

Figure 6.16 shows the same features as Figure 6.15 but with regard to the system resilience. When examining the 'Business-as-Usual' Scenario A for URR > 10% and also for URR >20%, there is a tendency towards a decrease in system resilience. This means that the probability of the system recovery decreases overtime for a particular month indicating an unsatisfactory state. For URR > 10% the lowest resilience values decrease from 0.25 (four consecutive unsatisfactory months) in the first third of the investigated time series, down to 0.17 (maximum of six consecutive unsatisfactory months). As with the reliability indicator, not only the low extremes of resilience get worse, but also the percentage of simulations reaching these low values increases (indicated by the darker coloured bars).

When comparing Scenario A (BAU) with the possible adaptation scenarios, of reduced water remand and leakages, it can be seen from the previous section (Figure 6.3 to Figure 6.6) that these measures results in lower URR. A lower URR can result in separation and/or shortening or elimination of unsatisfactory system performance. For example in Scenario C and D (for URR >10%) the occurrences of years with a resilience value of ~0.67 and 0.4 increases (e.g. 2051, 2058 and 2066). Both of these resilience values are derived from sequences of months with unsatisfactory water resource system performance that are broken by at least one month of satisfactory performance. This shows that for some simulations the adaptation measures are able to increase system performance by interruption of continuous series of unsatisfactory system performance. An increase in the overall system performance through the adaptation measures is also evident by an upward shift in resilience values and a higher percentage of simulations in higher resilience categories.

If resilience is analysed using the threshold of URR >20%, the overall resilience values are higher, indicating better system performance for both extremes and the percentages of simulations reaching a certain resilience level. Additionally, the maximum number of continuous unsatisfactory months is lowered to four concurrences per year (resilience value of 0.25). The overall tendency to lower resilience values over time is also evident, with a 50 % chance of recovery at the start of the simulations, down to 25% at the end of 2060) (BAU). With the combined adaptation measures in place (Scenario D) 97.5% of the simulations achieve a resilience value of 1 (recovery in the next month after an unsatisfactory state) for the first nine years. Later in the time series the percentages of simulations obtaining low resilience values also decrease. This indicates that at the start of simulation the adaptation measure are able to balance out the increasing water demand or less water availability that is putting additional pressure on the abstraction point. With increasing time the effectiveness of the measure is reduced resulting in a decreasing resilience. The results suggest that additional adaptation measures would be required in order to maintain the initially high resilience values of the water supply system.

Duration Vulnerability

The average duration vulnerability for Kells is also analysed in Figure 6.17 for URR >10% and >20% for all four water use scenarios. Higher average duration vulnerability corresponds to a higher number of months being in an unsatisfactory state. For Scenario A and the URR >10%, an increase in the average duration of sequences of unsatisfactory events increases with time. For the first 25 years the maximum of the average duration is 4 months, whereas after 2035 the highest duration increases to six months.

Over time, the percentage of simulations reaching a higher duration also increases. For instance at the start of the period for some years a maximum of 2.5% percent of the simulations showed a duration of 4 months whereas at the end of the simulation period 25% percent of the data reaches this level or higher for most of the years. Leakage reductions (Scenario C) and the combined measures to reduce water abstractions (Scenario D) are able to reduce the maximum duration vulnerability from six to five months. Additionally, in these scenarios the number of years increases in which the average duration vulnerability increases by half a month. For example Figure 6.17 for Scenario C and D shows simulations with average duration vulnerability of 1.5 months or 2.5 months from 2050 onwards. This is the result of shortening or splitting of the continuous unsatisfactory month within a year as a result of the adaptation scenarios.

This has implications for water resources management as the adaptation measures result in a reduction of the longer events in which the system is in an unsatisfactory state . With a URR threshold of 20% the overall duration vulnerability is lower, revealing lower extreme values and a lower percentage of simulations in the higher duration levels.

Overall, it can be seen in the detailed examination of the annual RRV indices for the water abstraction point for Kells, that independent of the threshold used the system performance decreases resulting in lower reliability and resilience values and longer average duration vulnerability. The lower the threshold for URR chosen for the analysis, the less satisfactory is the system performance resulting in a less reliable resilient and more vulnerable water resource system on an annual basis. The adaptation measures analysed increase the system performance in all three indicators. This is particularly evident in the Figures for resilience and duration vulnerability, where the adaptation measures are able to split and/or shorten continuous unsatisfactory events.

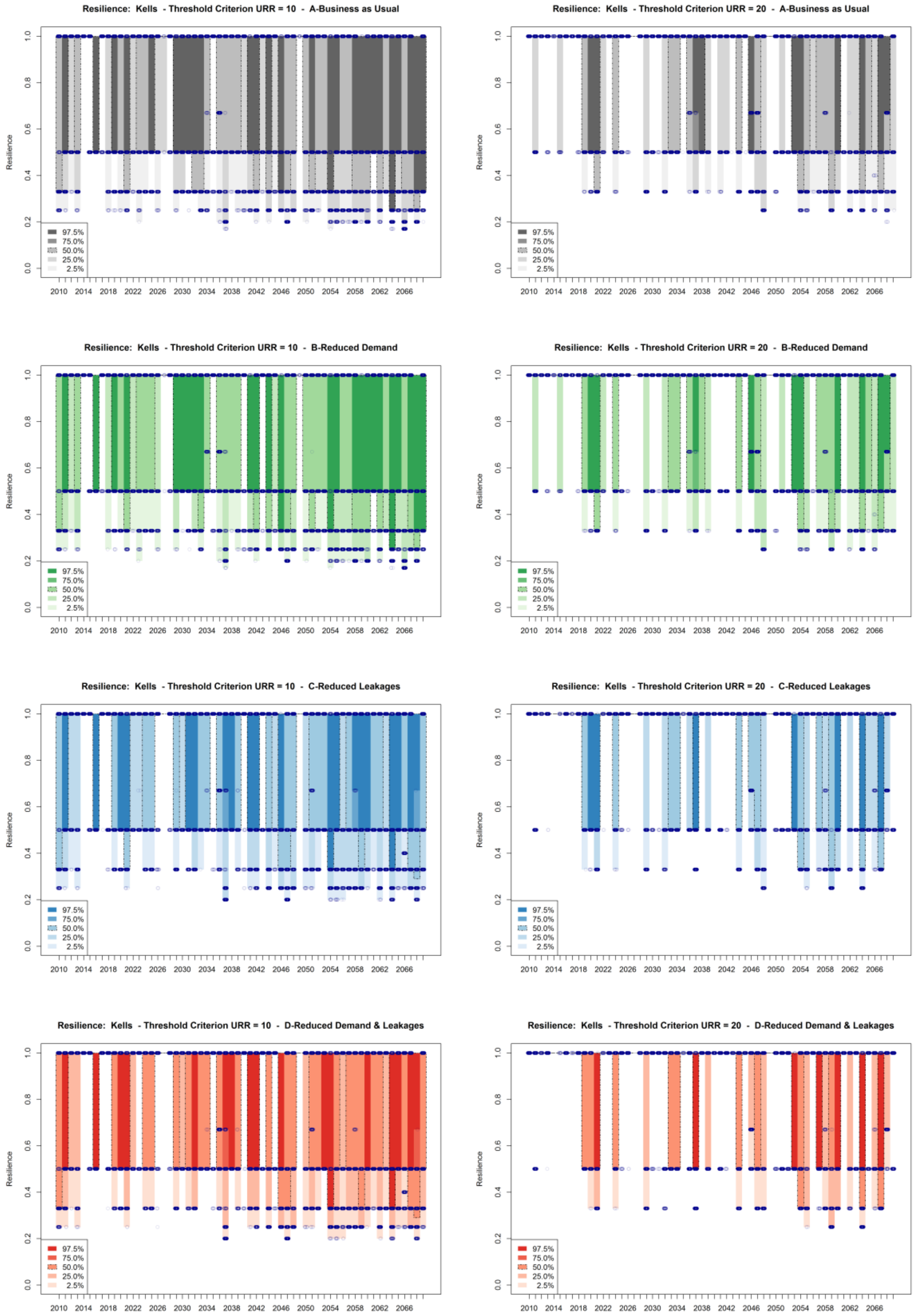


Figure 6.16 Kells Resilience. Blue points show the reliability level per year out of 3000 simulations. From top to bottom Scenario A (grey), Scenario B (green), Scenario C (blue) and Scenario D (red). The darker the bars the higher the percent of simulations showing that resilience level. Threshold: Left URR 10%; Right UUR 20%.

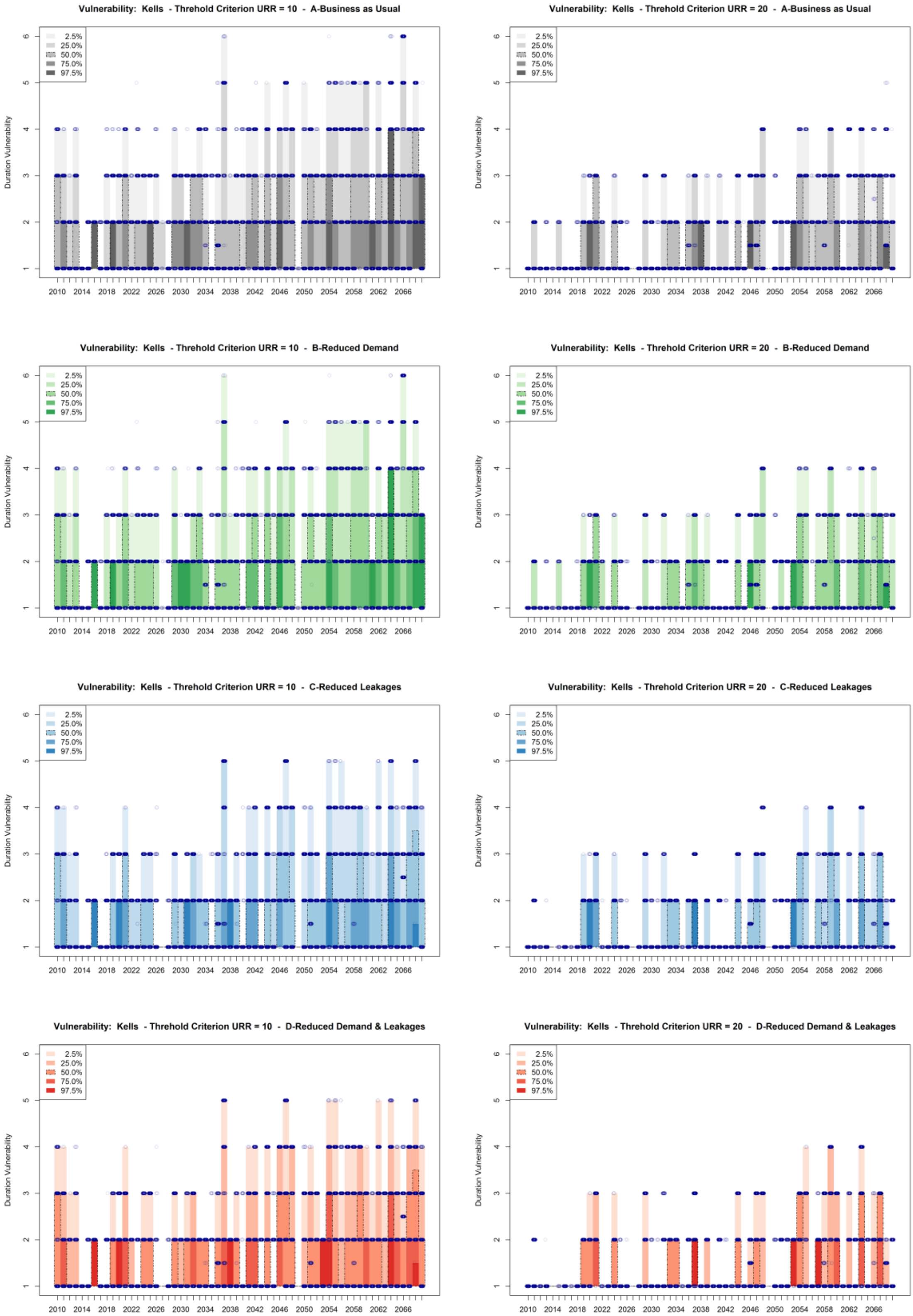


Figure 6.17 Kells Vulnerability. Blue points show the reliability level per year out of 3000 simulations. Top to bottom Scenario A (grey), Scenario B (green), Scenario C (blue) and Scenario D (red). The darker the bars the higher the percent of simulations showing that reliability level. Threshold: Left URR 10%; Right UUR 20%.

6.4.2 Decadal Reliability, Resilience and Vulnerability Analysis

From the water managers point of view a condensed summary of the results of RRV analysis is desirable to be able to more readily compare the evolution of the individual RRV values over time and across different scenarios. In addition to the changes in the percentage of simulations per RRV indicator and indicator level it is also important to know whether the relative changes in the indicator levels happen in the extremes of the indicators (minimum performance) and how lower values shift, to be able to meaningfully interpret the ensemble of future performance indicators.

Figure 6.18 to Figure 6.20 summarises individual time series over the four investigated scenarios for selected water abstraction points. The 60 years of data are combined to six decadal sub periods and the RRV indicators are analysed separately per decade and for each water use scenario. By analysing decadal time series the influences and possible changes caused by inter-annual variability are reduced and provide a more conclusive overall picture of chnage.

In the original definition, the resilience indicator is calculated if there is at least one unsatisfactory month in the analysis period. Similarly, the average duration vulnerability is based on the time of the system being in an unsatisfactory state. For both indicators the years that do not have any unsatisfactory system performance are neglected in the original indicator definition. In this analysis, to be able to relate Resilience and Vulnerability to the total amount of simulations, the simulations without unsatisfactory months need to be incorporated to allow the percentages of simulations to be calculated based on the same number of future simulations (here 3000 per scenario). In the case of Resilience, this means that all years that do not experience any unsatisfactory state are classified as having a resilience of 1, together with the simulations that immediately recover from a failure (which also classifies a system for being resilient). For Vulnerability, an additional duration class with the value of zero is added to the analysis to allow for the incorporation of simulations with no unsatisfactory month. In the Figures, all the RRV levels shown in the legend for the particular RRV indicator are present in the data, even as small percentages, which are too small to be visible as bars.

The decadal analysis of four selected water abstraction points (Kells, Liscarthan (both HA07), Culimore and Laghta both (HA32)) is shown in Figure 6.18 to Figure 6.20 (other stations are shown in Appendix II).

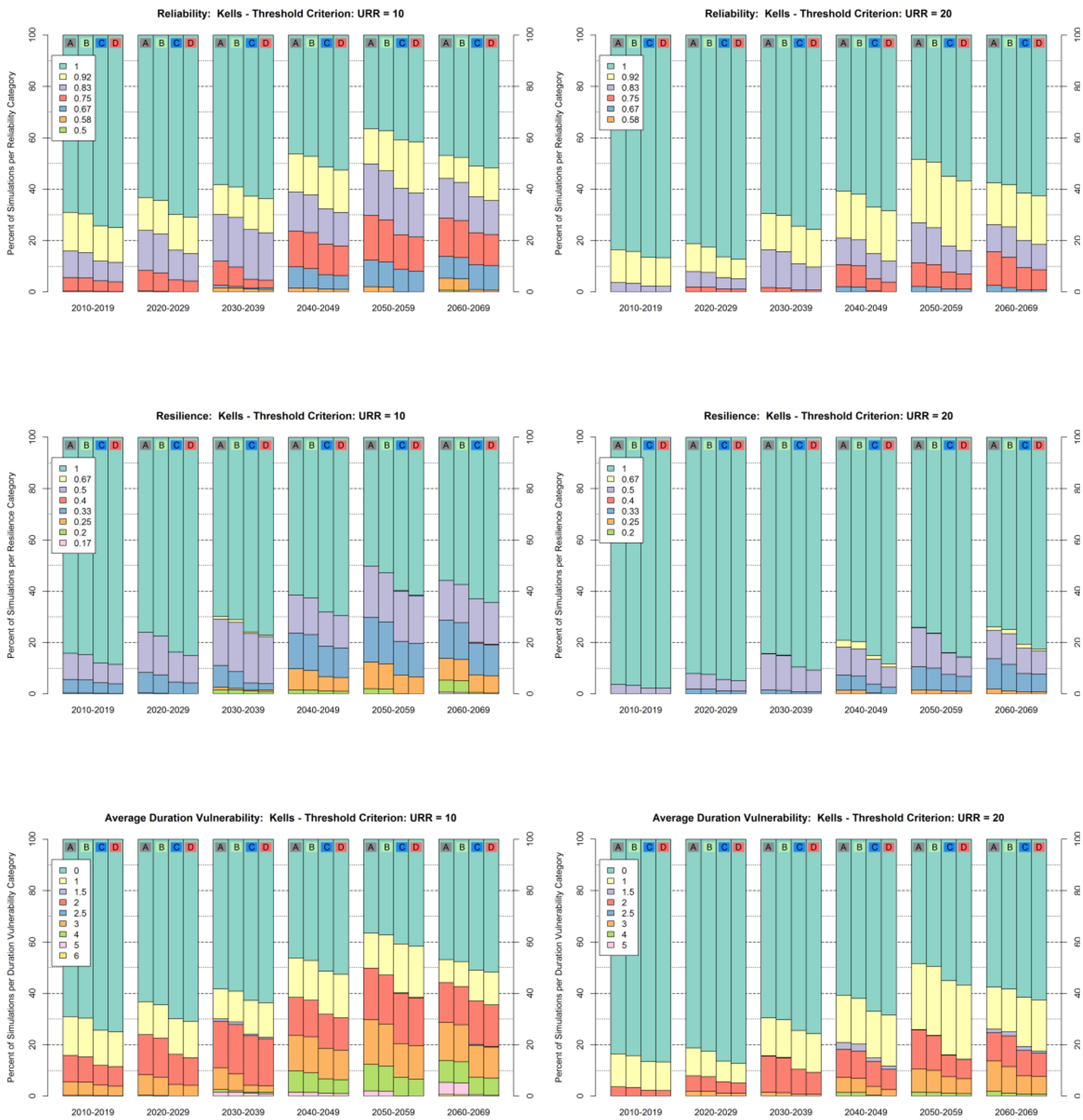


Figure 6.18 Kells: RRV analysis for 10 year windows for Scenario A, B, C and D showing the percent of simulations in each Reliability, Resilience and Duration Vulnerability category. UUR >%10 (left,) >20% (right).

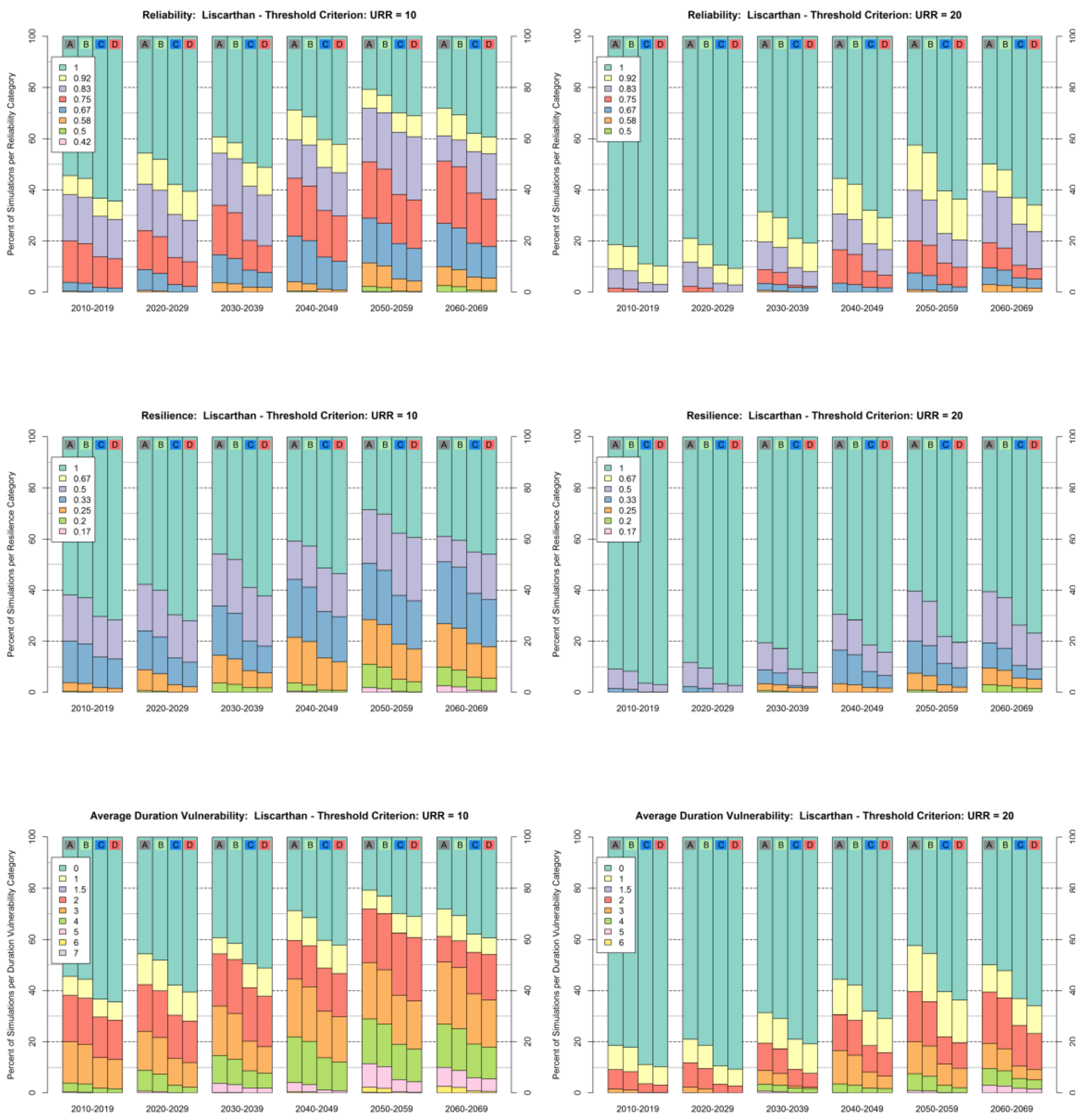


Figure 6.19 Liscarthan: RRV analysis for 10 year windows for Scenario A, B, C and D showing the percent of simulations in each Reliability, Resilience and Duration Vulnerability category. UUR >%10 (left,) >20% (right).

Figure 6.20 Culimore (right) and Laghta (left) with a UUR threshold >10%. RRV analysis is based on 10 year windows for Scenario A, B, C and D showing the percent of simulations in each Reliability, Resilience and Duration Vulnerability category.

For the decadal analysis of RRV for Kells (Figure 6.18), for both URR thresholds of 10% and 20%, the same pattern of poorer RRV values with time emerges that has been documented in the annual analysis before. Over time, the percentage of simulations in each RRV level also increase. An exception to this pattern is the last decade analysed (2060-2069), in which the total number of simulations in the best RRV level (Reliability=1, Resilience=1 and Vulnerability=0) decreases. For instance, in Scenario A for 2050-2059 63% of simulations do not obtain a Reliability of 1, this percentage decreases for 2060-2069 to 52%. This apparent decrease could be interpreted as an increase in system performance; however although the overall percentage of simulations decreases, the reductions are caused by shifts in the less severe levels. The more severe levels, (e.g. reliability values of 0.75 and lower or vulnerability values of 3 and higher) remain proportionately similar between 2050 and 2069 for the URR of 10% and the more extreme levels increase their percentages (e.g. duration vulnerability of 5) or new levels are added (e.g. vulnerability of 6 months). However, for URR of 20%, the percentage of simulations with a lower resilience levels of 0.33 increases over the period 2050-2059 to 2060-2069 (particularly for Scenario A and B). These different response signatures apparent in the URR (10% versus 20%) and the analysed RRV indicators highlight the importance of the use of multiple threshold criteria and levels of criteria in the evaluation of water supply systems. If only a single threshold and a single performance indicator would have been analysed the change signature of a lower system resilience could have been missed and lead to erroneous water management decisions.

Eastern Ireland

When assessing the effectiveness of different robust adaptation options it can be seen that all options are able to increase the overall percentage of simulations with the highest system performance (RRV). The increase in performance occurs particularly in the reduction of occurrences of extreme low values for reliability and resilience and high duration vulnerability. For example, at Kells with a URR threshold of 10% for the period 2060-2069, for Scenario A there are 2 % of simulations with a duration vulnerability of 6 months and 5% of 5 months. The combined water demand and leakage reduction measures in Scenario D are able to eliminate the occurrence of 6 month long vulnerabilities and reduce the vulnerability of 5 months down to 1%. If lower duration vulnerabilities are aspired, additional adaptation strategies need to be sought.

The patterns described above for the water abstractions at Kells are also apparent in the overall pattern revealed at Liscarthan (Figure 6.19). However, the Liscarthan results have a higher percentage of simulations falling into lower RRV classification level (indicate lower system performance) compared to Kells, although Liscarthan water supply indicated visually better performance in the URR assessment. For instance when comparing Scenario A with an URR threshold of 10% for the period of 2050-2059 only 21% of the simulations were fully reliable at Liscarthan, whereas at Kells the lowest percentage of full reliability is 37%. Additionally, the maximum duration vulnerability in Liscarthan is 7 months compared to Kells with a maximum of 6 months. At Liscarthan the Reliability and Vulnerability indicators are similar. This is caused by the low presence of interrupted sequences of unsatisfactory months; therefore the average duration vulnerability is directly linked to the overall reliability.

The adaptation measures, particularly leakage reduction, (Scenario C and D) have a higher effect in Liscarthan compared to Kells. For example, for URR of 10% for the period 2030-2039 Scenario A indicates 54% of simulations with a resilience of lower than 1 which is reduced to 41% (Scenario C) and 38% (Scenario D), a reduction in 13% and 16% of the simulations respectively. At Kells, the reductions over the same time period are only 6% and 7% respectively. At Liscarthan, the strong reductions (>10%) in the percentages of simulations between Scenario A and Scenario C and D are apparent for all decades, RRV indicators and both URR thresholds from 2020 onwards. With a URR threshold of 20%, reductions in the RRV values between Scenario A and D can even account for 20% of all simulations for the two decades 2050-2059 and 2060-2069. Overall, the system performance increases when the higher URR threshold is applied.

Western Ireland

Figure 6.20 shows the RRV analysis at a threshold of URR 10% for two water abstraction points in the West of Ireland (URR 20% is in Appendix II). For both water abstraction points, the first three decades do not show much change in the system performance. The effect of water demand and leakages reductions in reducing the percentages of simulations per category are visible for Reliability and duration Vulnerability. For these three decades at Laghta, the Resilience is 1 for all simulations indicating that the simulations that are experiencing an unsatisfactory month revert back to satisfactory system performance in the next month. The water resource system at Culimore experiences a rapid decrease of system performance between the decades 2030-2039 and 2040-2049. For instance for Scenario A the Reliability of 1 decreases form 81% to 63% and Resilience of 1 also decreases form 95% to 81% of all simulations. From 2030 onwards, the system performance decreases over time. This indicates that if a system improvement or a system performance at the pre 2030 level is aspired with the help of additional adaptation options, the measures need to be timed to counteract the indicated decrease in system performance.

The adaptation measures are effective in Culimore and Laghta in reducing the overall percentage of simulations which do not achieve the best RRV levels. However, care is needed when analysing the graphs. For example for the Reliability indicator in Culimore for the decade of 2040-2049 and at Laghta for the decade 2060-2069, the adaptation measures reduce the overall percentage of simulations with lower reliability. Comparing Scenario A with Scenario C and D, the occurrences of a reliability of 0.83 are eliminated and a lower reliability of 0.75 is detected. This could be considered to be a decrease in system performance (lower reliability). However, the appearance of a reliability of 0.75 is caused by an increase in system performance and through simulations improving from a resilience level of 0.67. The same applies also to Resilience and Duration vulnerability, where an apparent decrease of system performance is actually caused by the elimination of one higher level and a better performance in another level. This highlights the need of combined interpretation of the RRV levels instead of focusing on a single category, without also analysing changes in other levels.

6.5 Discussion and Conclusions

The modelling tool developed in this research allows the identification of vulnerability within water supply systems and the assessment of robust adaptation options through an exploratory scenario-based modelling approach. Ranges of possible future outcomes are explored by the incorporation of uncertainties stemming from climate and hydrological models. This enables an assessment of robustness to possible futures and departs from the traditional ‘predict, provide and optimise’ approach to a single outcome approach. The tool derived is flexible and can be used with different threshold criteria and can be updated as new information and projections become available.

The differences in the results between the two URR threshold criteria investigated highlight the importance of the selection of the threshold criterion or the need to use multiple criterions for the analysis of the sensitivity and sustainability of the water resource system and the selection of robust adaptation options. Nevertheless, through the flexibility in the selection of the threshold criteria, a wide range of additional criteria could be investigated in future work. Additionally, the different responses in the RRV indices, which represent changes in the system characteristics to different adaptation options highlights the need for an assessment of multiple criteria (here critical thresholds used) to evaluate the performance of water supply systems with multiple performance measures. These critical thresholds are water resource system specific and expert knowledge is required to determine these.

For the case studies employed, climate change in combination with population growth is likely to result in a reduction in the reliability and resilience and an increase in the vulnerability of water supply. In many cases, the reduction in leakage and demand is successful in reducing the occurrence or the level of water stress. However, each water abstraction point responds differently to such adaptation measures, resulting in different response signatures in relation to the RRV performance indices analysed. The adaptation measures proposed for Ireland are able to increase system performance for some future simulations particularly by interrupting continuous series of unsatisfactory system performance and therefore increasing the overall water resource performance.

For example, in Western Ireland for the water abstractions at Culimore and Laghta (with a UUR threshold of >10%), the RRV analysis identified a tipping point between the decades 2030-2039 and 2040-2049. Up to 2030-2039 the water resources systems where able to cope with the changes; however from 2040-2049 onwards a rapid decrease of system performance is indicated by the RRV indicators. However, when adaptation measures are applied the system performance decrease is less pronounced.

The example of performance changes in Western Ireland highlight the utility of the tool and analysis framework in identifying when and where vulnerability threshold are being approached. By identifying such thresholds, water managers are able to identify when changes in water management or adaptation procedures might become necessary.

The effects of the adaptation options are mainly evident in the reductions in the low system performance. This is particularly important when aiming to manage these extremes and a detailed analysis such as the RRV analysis employed here can provide valuable information. However, for some abstractions, the investigated soft strategies alone will not be sufficient to avoid the occurrence of high water stress and alterative supply sources or additional adaptation measures may be required. Within this context, consideration will need to be given to what is an acceptable level of residual risk once demand management options have been exhausted.

6.6 Chapter Summary

In this chapter the adaptation information appraisal tool, developed in Chapter 4, is applied to 12 illustrative Irish cases study water abstraction points. Nationally proposed low-regret, 'win-win' adaptation options are assessed for their performance in relation to uncertainty ranges obtained from projected future hydrological changes in Ireland. A framework based on the assessment of critical system thresholds and system performance indicators is used to test the functionality of these adaptation options under multiple future stream flow realisations.

The modelling tool is applied in a process-oriented 'assess-risk-of-policy' framework instead of a scenario-led, top-down 'impacts-thinking' approach to adaptation. The framework within which the modelling tool is applied here to test and explore adaptation options, combines flexibility with planning over long time horizons and monitoring, as well as adaptive management, recognising the uncertainty in projected hydrological changes.

The main findings of this chapter can be summarised as follows:

- The modelling tool developed can be used to test the functionality of adaptation options and analyse the system performance across a range of future scenarios. It also allows the identification of when and where critical thresholds in specific water resources systems might emerge. Thus, it is important not to focus only on a single level of a system performance metric, but to analyse levels together to identify changes of the system characteristics.
- The illustrative case studies show various degrees of responses to projected future changes and the proposed adaptation measures. Therefore, the sensitivity of the system and the effectiveness of such measures are highly dependent on the characteristics of the water resources system.
- Due to the differences in responses of individual water abstraction points the assessment of system performance should be based on multiple critical threshold indicators and multiple performance matrices to ensure that the system response to the investigated adaptation measures is appraised in detail. In applying the

techniques presented here, the outcomes from multiple future realisations can be summarised and presented in a meaningful manner.

- The proposed Irish ‘low-regret’ adaptation options are able to increase the water resources system performance. However, the proposed measures are not sufficient in some cases to eliminate the occurrence of water stress in the entire range of future projections and can therefore not be considered as the only options needed to reduce potential future vulnerabilities. Such cases will have to be assessed in conjunction with stakeholders.
- Due to the flexibility of the tool, the input data and the assessment of adaptation options can be readily updated, as soon as new information becomes available. Therefore, the developed tool can help to inform anticipatory adaptation decision planning.

This chapter provides an illustrative sample application of the first attempt to use uncertain climate information in a tool developed for anticipatory decision appraisal in Ireland. In the next chapter, the overall findings of the possible information sources in providing information for future planning and management of Irish water resources are summarised and discussed to conclude this thesis.

7 Discussion and Conclusion

7.1 Introduction

Future water resources planning and management is challenged by the anticipated impact of climate change on the natural stream flow regime. In order to prepare water resources systems, information is required to support decision-making on anticipatory adaptation. This thesis sets out to explore possible information sources to aid future planning and management of Irish water resources. To date, limited information about future changes can be extracted from observational hydrological data using traditional trend techniques, due to high variability of Irish low flow indicators. Therefore, in this thesis, a tool for the Irish water sector is developed to facilitate the transition from the traditional top-down, predict-and-provide approach to the use of future climate scenarios for decision appraisal.

In this final chapter, Section 7.2 provides a summary of the thesis. This is followed by a summary (Section 7.3) and a discussion (Section 7.4) of the main research findings of this thesis. In Section 7.5 the limitations of work are presented and followed by suggestions for a future research agenda. The thesis finishes with the concluding remarks in Section 7.6.

7.2 Thesis Summary

Observational hydrological records and future stream flow projections are the two key sources to information for informing anticipatory adaptation. The two main aims of this thesis are built around the analysis of historical records and the development of a modelling and decision-support tool to inform anticipatory adaptation to climate change in the Irish water resources sector.

The thesis has investigated the utility of observational data and modelled projections of future stream flow in providing information for anticipatory decision-making. An analysis of trends in historical stream flow records for selected indices relevant to water resources management has been conducted in Chapter 3. This was followed by the development of a tool to inform adaptation decisions based on future projections in a framework for anticipatory adaptation in Chapter 4. The tool developed is applied in an Irish context in Chapter 5 using 12 illustrative case study water abstraction points. In applying the tool, the uncertainties stemming from various sources are incorporated into the modelling framework. Uncertainty sources integrated into the framework include uncertainties associated with future climate scenarios, hydrological model parameter uncertainties and uncertainties related to the need of estimating stream flows at un-gauged water abstraction sites. Finally, in Chapter 6, recommended adaptation options are examined with regard to their effectiveness in reducing water stress based on uncertainty ranges in stream flow obtained in Chapter 5, by analysing the potential changes in the water resources system performance and characteristics.

7.3 Summary of Main Research Findings

In the first part of this thesis, the utility of trend analysis in river flow observations for informing decision-making for anticipatory climate change adaptation in the Irish water sector was examined. Results of the trend analysis highlight the danger of over interpreting trends derived from short fixed period, as these are highly dependent on the study period selected. Trends obtained from long observational datasets in the Irish Hydrometric Reference Network are important to put shorter flow records into context. However, due to the relatively low number of long record stations with near-natural low flow records, it is difficult to distinguish between real long-term changes and medium-term and long-term natural variability. Further research is required to understand the increasing trends in low flow indicators in summer. The increases found in low flows are contradictory to what is projected by future scenarios and calls the representativeness of the selected period (1976-2009) into question.

In addition to the challenges to trend detection described above, high inter-annual variability and a low signal-to-noise-ratio amongst others, makes it difficult to extract a robust anthropogenic climate change signal from hydrological records, particularly for the low flow indicators investigated here. This makes it difficult to detect trends with a high statistical significance using traditional statistical trend detection techniques in an Irish context. The length of time or magnitude of change required for detecting linear changes in such highly variable indicators is too long and respectively too high to be able to wait until a robust climate change signal can be statistically detected. Therefore, it is suggested that anticipatory adaptation has to take place with this limited information available from observational data, highlighting the need for flexible or reversible, non -path dependant measures.

The key aim of the second part of this thesis is to develop a tool for informing anticipatory planning and adaptation in the water sector in Ireland. This tool is developed to provide a starting point for further investigation into how climate scenarios can be used for decision appraisal. The development of the tool and its application here marks the first attempt in Ireland to go beyond the top-down, predict-and-provide-approach that has been the basis of climate policy development so far. This is the first work in Ireland that goes beyond the first order impact assessment and explores how observed and projected climate information can be used to inform water resource management and planning.

The tool developed here couples a conceptual rainfall-runoff model (HYSIM) with a water resource model (WEAP). Nationally available climate scenarios are integrated to generate future stream flow projections and appraise identified adaptation options for the Irish water resources sector in the context of uncertainty. While it is recognised that the climate scenarios used do not represent a large sample of the uncertainties from Global Climate Models, this work is important to initiate the transition to the alternative use of climate scenarios for decision appraisal in the Irish context. Further work, as discussed below should continue to tackle the challenges identified and incorporate the suggestions for future research that are outlined.

Unlike many applications of such decision-making tools in the literature, the tool developed particularly for the structural conditions of the Irish water resources systems, allows deriving future stream flow projections at un-gauged water abstraction points. This is an important feature for Irish water resources as many of the abstraction points do not have hydrometric gauges in their vicinity. This is also likely to be the case in other regions of the world. The uncertainties that are associated with modelling flow at un-gauged locations are large and should be considered more comprehensively in future application of such tools. The future stream flow information obtained in the modelling framework incorporates uncertainty ranges stemming from both climate scenarios and hydrological modelling.

The ranges of future stream flow information are used to appraise the utility of nationally identified adaptation options in conjunction with population growth as non-climatic pressure. Overall, the tool developed is fit for purpose and provides a methodology to appraise and compare anticipatory adaptation options under projected future uncertainty ranges by analysing potential changes in water resource system performance through a threshold-based analysis of system performance indicators.

The catchments and their associated water abstraction points represent different hydro-climatic environments, which are representative of Irish conditions. The stream flow series for the un-gauged water abstraction points were obtained using proxy-basin-split-sample approach. This widely applied approach has been augmented in this thesis to account for the concept of equifinality in accounting for the uncertainties associated with the estimation of hydrological model parameters. Parameter uncertainties have a strong influence on the lower part of the flow regime, which is of particular interest to water resources management.

The selection of the future climate scenarios, used to drive the hydrological model to obtain future stream flow projections, influences the range and variability of change under which adaptation options are appraised. Therefore, the results obtained are strongly dependant on the choice of such scenarios. Here a set of six statistically downscaled climate scenarios is chosen. While this is a relatively small sample of possible changes in climate, the comparison of these scenarios with national probabilistic scenarios, and indirectly with a wider range of CMIP3 scenarios suggest that the scenarios used here fall within the more extreme low flow range. Nonetheless, a priority of future work will be to expand the scenarios available.

Here, to the best of knowledge, for the first time, the Water Evaluation and Planning System (WEAP) is coupled with a strongly physically based rainfall runoff model (HYSIM), to allow for the appraisal of adaptation options. In doing so envisaged adaptation options for un-gauged catchments can be analysed within WEAP with regard to future uncertainty ranges. Therefore, WEAP is used with the aim of appraising changes in the water resource system performance under a wide range of uncertainties and not as a simple climate change impacts assessment or optimisation tool, which is different to the traditional application of WEAP (Höllermann *et al.*, 2010; Ingol-Blanco & McKinney, 2010; Sandoval-Solis *et al.*, 2011; Harma *et al.*, 2012).

Within the analysis framework, the performance and the responses to suggested anticipatory adaptation options of the water resource systems was investigated. The results show that when applying a threshold-based approach combined with different system performance indices that each water abstraction point responds differently to both climate change impacts and adaptations options. The results show that depending on the system capacity projected changes can result in variable vulnerabilities and a ‘one-size-fits-all’ approach to anticipatory adaptation is not realistic. Small changes can have a significant impact when water supply systems operate close to their system capacity. However, other water abstraction points do show little or no vulnerabilities to the most extreme future stream flow simulations, with regard to the employed critical thresholds. Vulnerability and response to adaptation measures are site specific. Therefore, to ensure a best possible assessment of the system, thresholds and indicators need to be selected for each water resource system explicitly, preferably with strong stakeholder engagement.

7.4 Discussion of Main Research Findings

The analysis of trend in the first part of the thesis highlighted the challenges involved in detecting climate-driven trends in Irish hydrological records. High natural inter-annual and inter-decadal variability of analysed indicators makes it difficult to discern monotonic trends from and long-term oscillations. Additionally, if a series of unusual extremes is present at the end of the investigated record, it cannot be decided whether these extremes are outliers in the time series, or present an actual change in the regime, such as the wet recent summers in Ireland. Only when sufficiently long time after the commencement of such a potential change will be available, change detection will be possible. However, even when changes in hydro-climatological records cannot be statistically detected, this does not prove the absence of a trend. Trend test can fail to detect weak changes or changes which have occurred only recently (Radziejewski, 2009).

Furthermore, in the case of Ireland, the relatively low number of near-natural, good quality, long hydrological records makes is particularly difficult to extract information that can guide planning and decision-making with regard to specific options for anticipatory decision-making. However, the shortage of suitable observational hydrometric data for change analysis is a commonly encountered problem internationally (Whitfield *et al.*, 2012).

Additionally, it needs to be considered whether the spatial distribution and sampling frequency in a network such as the Hydrometric Irish Reference Network are appropriate to detect climate-driven trends. Near-natural catchments are often small upstream catchments which might not be representative of the entire hydrometric conditions in a country. Particularly the streams that are used for abstracting surface water are often located in the downward reaches of a catchment close to the sea. Additionally, Blöschl & Sivapalan (1997) have shown that in smaller catchments the coefficient of variations (CV) is particularly high compared to large catchments. This makes it even more difficult to detect changes in the IRN, and results in long detection times and high change magnitudes to be able detect changes that are statistically significant.

However, without the use of specifically approved stations within a reference network the quest for trends in hydrological data becomes even more difficult. Due to multiple possible drivers of change such as land use change, or changes induced by artificial hydraulic changes in addition to changes in climate, attribution of any detected changes becomes even more difficult. Attribution of processes and key drivers that result in changes in hydrometric records is currently an area attracting the interest of the scientific community (Merz *et al.*, 2012). Until drivers and physical processes of change are identified and better understood, observational hydrological data can only provide limited information for long-term planning in the water sector, as observed changes cannot simply be extrapolated into the future.

For water resources planning and management, it is important to assess hydrological records for statistically significant trends in magnitude and timing, and attribute these changes (if present) to certain drivers. However, it is also important to assess in which parts of the flow regime; and when and where changes will occur (Ziegler *et al.*, 2005). The analysis of low flow indicators suggest, that the number of years or trend magnitudes required until trends become statistically significant (α=0.05) will be too large to provide practical guidance to anticipatory adaptation. A less conservative approach to risk (e.g. α=0.1) results in an increased detectability, however, the detection times still remain long.

Nevertheless, waiting until changes in hydro-climatological records can be identified and attributed is not an option for the water resources sector due to long planning horizons and design life of water supply infrastructure (Murphy *et al.*, 2011). However, climate change impacts on future stream flow is highly uncertain and is unlikely to become constrained within the timeframe required for adaptation. Future climatic and non-climatic uncertainties influence the assessment of future water resource system performances and if future planning is based on projections, the assessment has to account for these uncertainties.

Therefore, tools are needed that are able to extract information content from the uncertainty ranges derived. Exploratory modelling where outcomes of an ensemble of multiple future simulations are used to explore the implications of a wider range of assumptions can provide a tool to appraise adaptation and policy decisions with regard to their robustness to future climate change uncertainties (Samaniego & Bárdossy, 2008).

However, an exploratory modelling approach becomes challenging when applying it to actual water resources systems. In the case of Ireland, difficulties are encountered in areas with limited data availability, such as un-gauged sites. In such settings, the uncertainties in the approaches and models used to generate future scenarios become increasingly important. For example, the selection of the hydrological model or how hydrological modelling uncertainties such as parameter uncertainties are treated, will determine the overall system performance. HYSIM, a physically based conceptual rainfall-runoff model, in combination with the proxy-basin-split-sample-approach, extended using equifinal parameter sets, is used to address these challenges. However, it is acknowledged that by using a different hydrological model or different regionalisation approaches to derive flows, it is likely that different future stream flow scenario ranges would have been obtained.

Modelling future hydrology is ad difficult process, due to the complex feedbacks between climate change, human actions and catchment responses, which are difficult to represent in models. Therefore, large assumptions are made that land-use and hydrological model parameters remain unchanged over the period considered (for example Poulin *et al.* (2011)). However, in reality these simplifications, assuming future stationarity, are not likely as land-use will change in response to external divers such a climate and population growth. It can also be expected that the hydrological model would need to be adjusted due to the co-evolution of catchment characteristics (e.g. rate of infiltration and flow pathways) and dominant climatic regime. The inability to represent such feedback mechanisms introduces another layer of uncertainty and is to date not commonly accounted for in future scenarios.

As shown above, water supply system performances are highly dependent on each of the decisions in study design taken throughout (e.g. selection of future climate scenarios) and modelling steps involved to generate the future stream flow scenarios, performance metrics and critical thresholds used for the analysis.

One focus of this thesis was the development of a tool that can support anticipatory adaptation in the water resources sector. The 12 illustrative case study water abstraction points are a first-pass application of the tool. Through the incorporation of multiple future hydrological time series, the tool facilitates awareness raising of where and when potential vulnerabilities to climate change could arise. Here a limited sample of possible future adaptation options was modelled; however, the future application of the model allows examining multiple options and operation rules under wide uncertainty ranges.

The flexible setup of the tool permits the user of the tool to update climatic scenarios or other characteristics of the water supply system such as population growth. Additionally, depending on the end-users needs, different assessment criteria and performance measures can be employed within WEAP; for instance constraining the amount of abstractions depending on specific in stream flow requirements, when exploring the performance of adaptation or management options. This is particularly important as the responses of water supply systems to thresholds and measures vary considerably and are therefore site specific. If for a particular indicator the water system indicates no unsatisfactory performance this does not necessarily mean that the systems are not vulnerable with regard to other indicators. It could just be the case that the system has little or no sensitivity to the selected critical thresholds, performance measures of climate scenarios. Here it is found that for some abstraction points, robust adaptation options such as demand and leakage reduction will not be sufficient in reducing vulnerability to future change. In such cases, further adaptation options will need to be considered, preferably with stakeholder engagement.

In this first application of the tool, the critical thresholds used to appraise the water resources system performance are assumed to be constant over time. However, it is likely that over time, with each iteration of the decision-support loop described in Chapter 4, the system requirements and therefore the thresholds selected will need to be adjusted depending on new information, altered requirements or changed management objectives. The system performance and the responses to set strategies will therefore also change, as might the thresholds change dynamically over time.

A key constraint in modelling future stream flow and exploring the performance of future adaptation options is that the changes in natural variability are not taken into account in future climate scenarios. To date climate models are not able to fully capture the processes that influence natural variability (Ledbetter *et al.*, 2012). This has strong implications for future water resources planning and management, as particularly the sequences of periods with low water availability, i.e. droughts have the highest potential to affect water direct abstractions from streams if no storage is available, as it is typical for smaller water supply schemes in Ireland.

The tool developed here can provide information on the water resources system performance and robustness of adaptation options under the ranges of future scenarios explored and thresholds investigated here. However, when practically aiming to adapt water supply systems to climate change, their robustness to uncertainty will only be one amongst other assessment criteria employed. A successful adaptation option or a set of adaptation options will always involve trade-offs between robustness, economic efficiency and social preferences and equity amongst others (Adger *et al.*, 2005).

Overall, in the thesis presented here only planned anticipatory adaptation to the modelled scenarios is considered. Additionally, the modelling framework presented is not able to incorporate autonomous adaptation. It has not been possible to incorporate direct human responses into the modelling approach, such as for example short term water use restrictions put into place as a result of drought conditions, or increasing water demands due to higher temperatures.

7.5 Current Limitations and Suggestions for Future Research

In this thesis, trends are analysed using methods for detecting monotonic changes in time series. However, hydro-climatic data is often spatially poorly sampled and have a low signal-to-noise ratio. Additionally, changes in hydrological variables cannot only be expected to occur as linear changes, but might also take place as step changes or oscillations. Therefore, future studies should also focus on extracting signals from the observed time series that are different to linear changes, such as long-term oscillations and quasi-periodic signals.

Generally, long detection times were found for trends to become statistically significant. However, certain stations and indicators indicated lower detection times than others due to less variability or a stronger change signal. To maximise the potential of being able to detect changes in the hydrological record, it is important to identify and further investigate the characteristics of such catchments. This also applies to the selection of indicators investigated, as some indicators showed in this study to have lower detection times than others. Future work would benefit by identifying hydro-climatic indicators that are specifically sensitive to changes in the climate driver. Further work could also consider that the relevance and sensitivity of indicators might change over time, as the climate and hydrological system co-evolve.

While the future climate scenarios used here were found to fall within the lower end of the ranges of comparatively larger samples, they represent a partial sample of the possible uncertainty space. As a priority, future application of the tool should incorporate a much greater selection of future climate scenarios, derived from, for example, the use of different climate models and perturbed physics ensembles, to obtain a more representative sample of the possible uncertainty ranges obtained from climate model uncertainty.

The stream flow series, generated here to provide information input into the water resources model, are derived using a single hydrological model. Although the modelling approach employed here takes into account parameter uncertainty, the uncertainty space related to hydrological model structure uncertainty is not being fully addressed. A future application of the modelling framework should include hydrological model uncertainty as an additional source of uncertainty by incorporating a multi-model approach. However, this is secondary to the incorporation of a greater sample of Global Climate Models.

The work presented here primarily focuses on providing water managers with information on the volumetric raw surface water availability, based on observed and modelled data. However, climate change can also to affect surface waters not only by changing volumetric availability. Amongst others, for example, an increase in the magnitude of rainfall events has the potential to cause damaging floods or increased erosion and might in this way adversely affect water supply systems and water abstraction due to decreased water quality, high turbidity and disrupted systems, or by increasing cost of water treatment. Another effect of a changing climate on water resources might for example happen through increased water demand due to higher temperatures. When planning for future anticipatory adaptation of the water sector to climate change, the possibility of such additional climate change related effects will have to be also taken into account. Additional future uncertainties also exist in relation with other non-climate related changes and challenges, such as changing legislation frameworks in the water resources sectors, which can potentially affect both water availability and demand.

7.6 Concluding Remarks

Adapting future water resources systems to potential climatic and non-climatic changes is challenging due to the wide range of future uncertainties involved.

Observational information from near-natural, long, good quality hydrological time series are regarded as a valuable source of information for future water resources planning and management. However, internationally there are only a low number of stations fulfilling these criteria. In practice, as shown for Ireland, only relatively short records that are dominated by natural variability are available, which makes it difficult to detect a long-term change signal in hydrological data. Therefore, until key driver and processes of change in hydrological time series are deciphered, only limited information about future hydrological changes can be extracted to be potentially used to inform water resources planning in Ireland. For that reason, additional sources of information and tools are required to allow the appraisal of future management options, to facilitate anticipatory adaptation in the water resources sector.

Decision information tools that are developed to provide alternative approaches such as exploratory modelling to test the robustness of future measures can offer a way forward. However, in line with the framework on anticipatory adaptation as an iterative process presented in Chapter 4, such assessments will not be a once-off task, but will rather require continuous monitoring and adjustments of the strategies to bring and keep the water resources systems into a desired state. Therefore, flexible and reversible strategies are advocated, when faced with such an uncertain future, to minimise the risk of becoming locked into a single future trajectory (path dependency) that could require disproportional effort and investment to adapt.

This thesis marks the first attempt to move beyond first order climate change impacts assessment on hydrology in Ireland toward the development of methods forming a tool for exploratory modelling and 'stress-testing' the potential performance of specific scenarios and adaptation options. The tool developed is aimed at application at a catchment and or local authority level in Ireland and can be used to inform water resources planning. Tools that support robust decision-making by combining multi-scenario approaches with exploratory modelling will play an important role in supporting successful adaptation of water resources under conditions of uncertainty. The tool developed here marks the first attempt in transitioning towards using climate scenarios and associated uncertainties, to explore potential policy directions, rather than relying on the traditional top-down, predict-and-provide approach to inform decision-making for adaptation.

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I. Appendix I

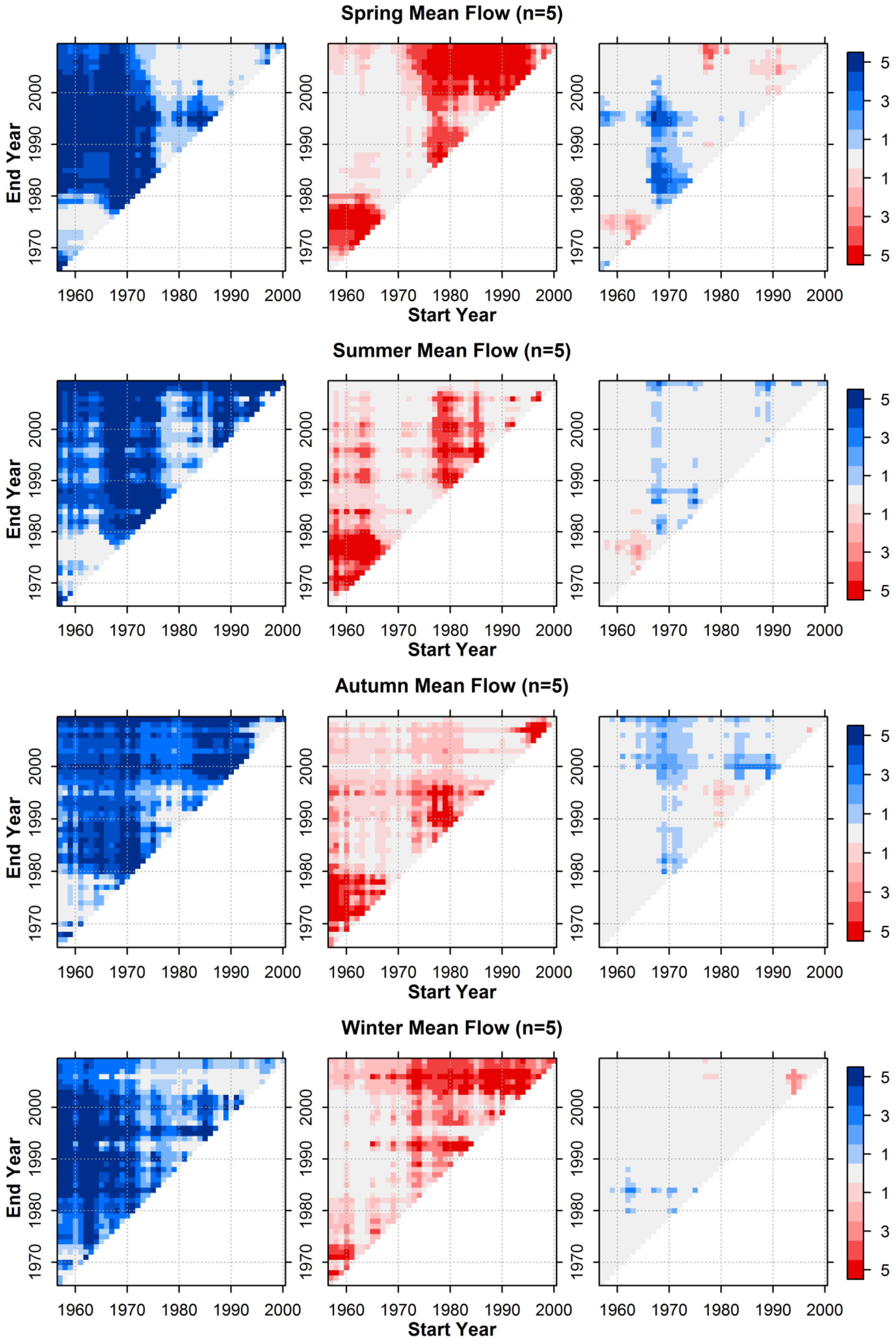

Figure I.1 Trends in seasonal Q50 Flows for five stations with long records, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

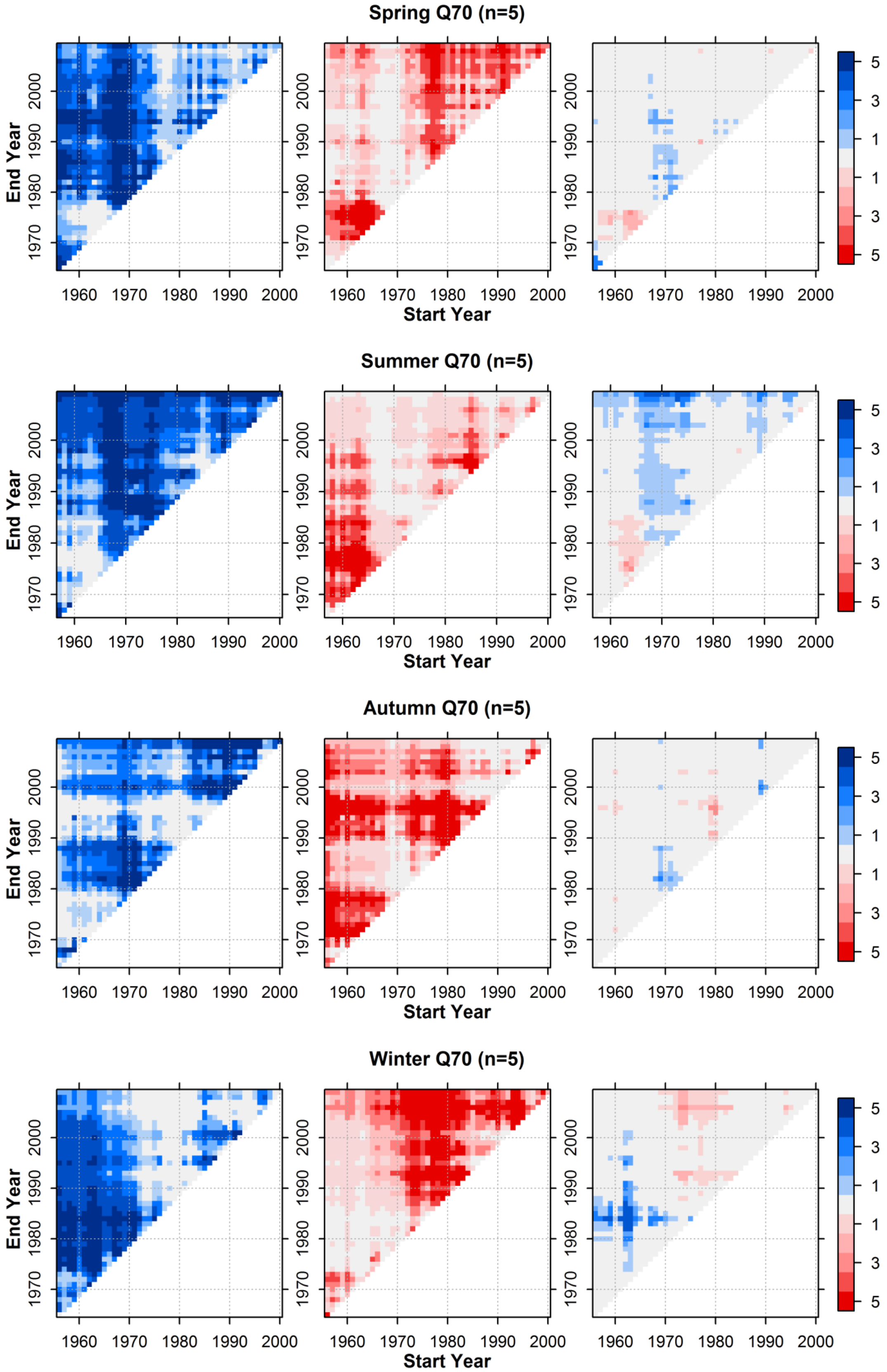

Figure I.2 Trends in seasonal Q70 Flows for five stations with long records, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

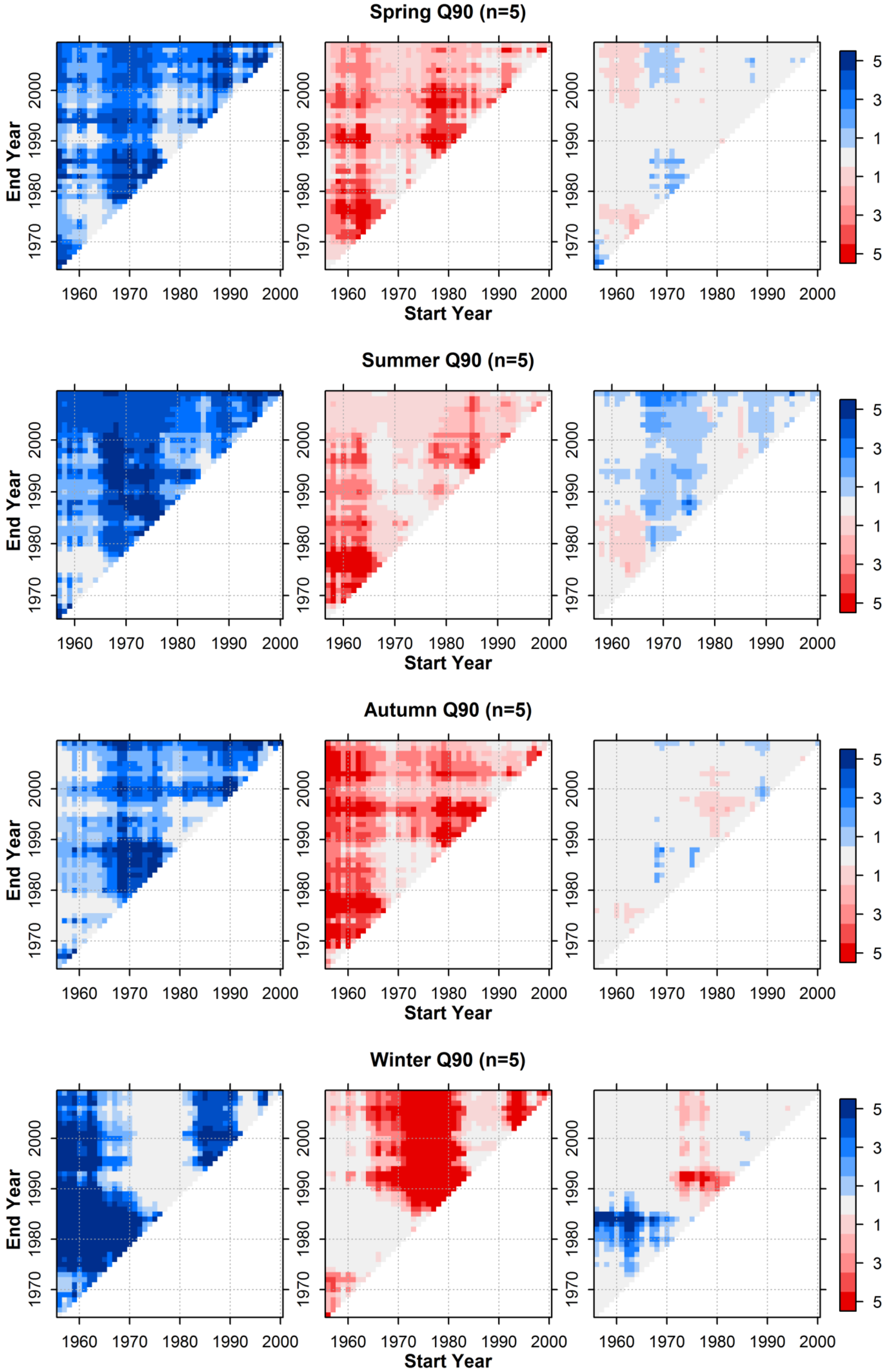

Figure I.3 Trends in seasonal Q90 Flows for five stations with long records, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

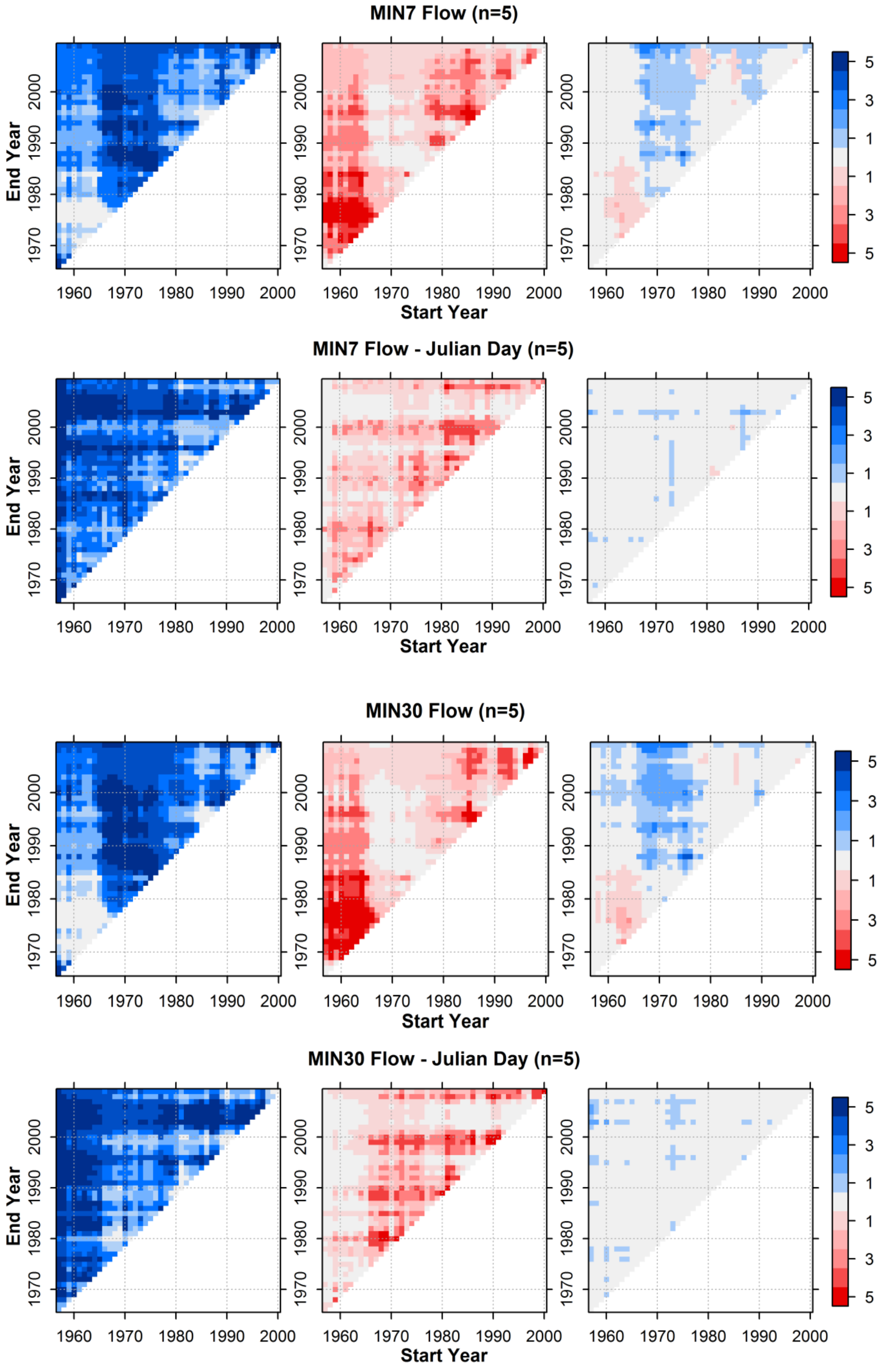

Figure I.4 Trends in Magnitude and Timing for 7-day and 30-day Sustained Lows, for all possible start and end dates. Number of positive trends (left), negative trends (middle) and significant trends at 5% level (right).

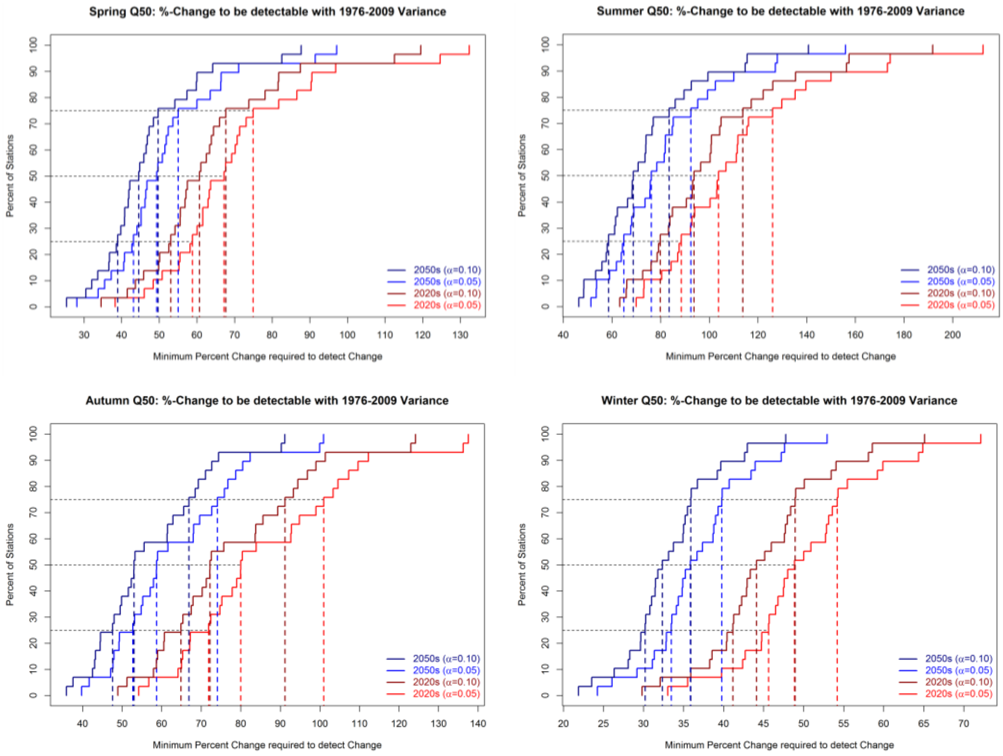

Figure I.5 Minimum change magnitude required for seasonal Q50. Changes occurring by mid 2020s (2050s) are plotted in red (blue). Light (dark) colours represent a significance level of α=0.05 (α=0.1).Dashed horizontal lines show from bottom to top 25%, 50% and 75% of the investigated stations.

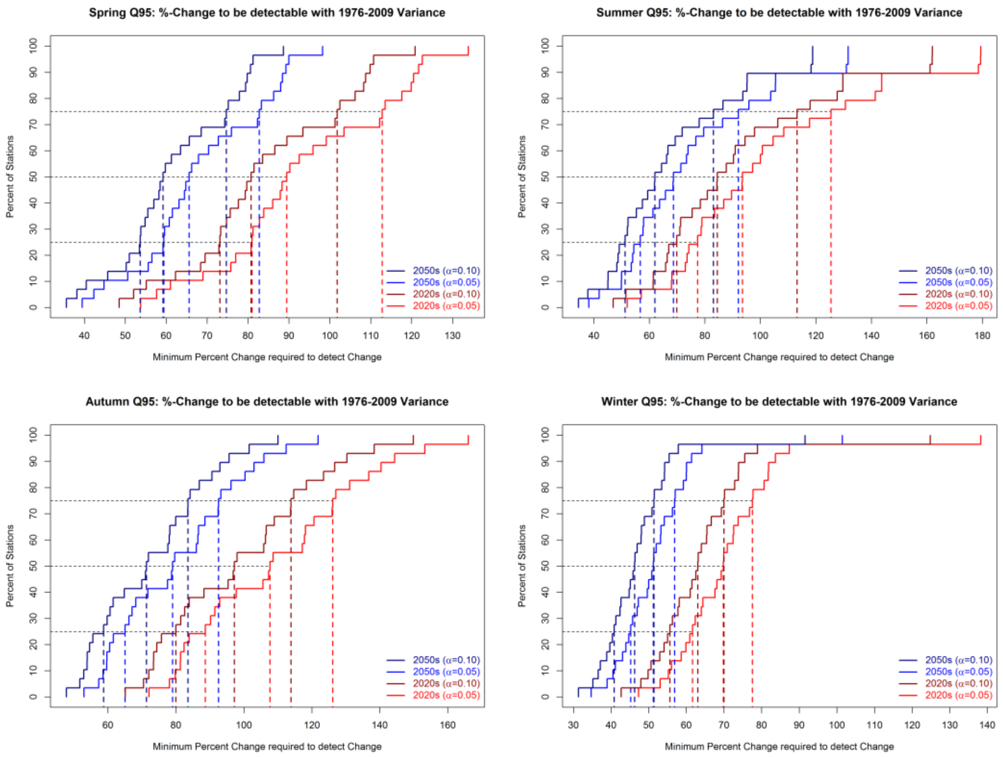

Figure I.6 Minimum change magnitude required for seasonal Q95. Changes occurring by mid 2020s (2050s) are plotted in red (blue). Light (dark) colours represent a significance level of α=0.05 (α=0.1).Dashed horizontal lines show from bottom to top 25%, 50% and 75% of the investigated stations.

II. Appendix II

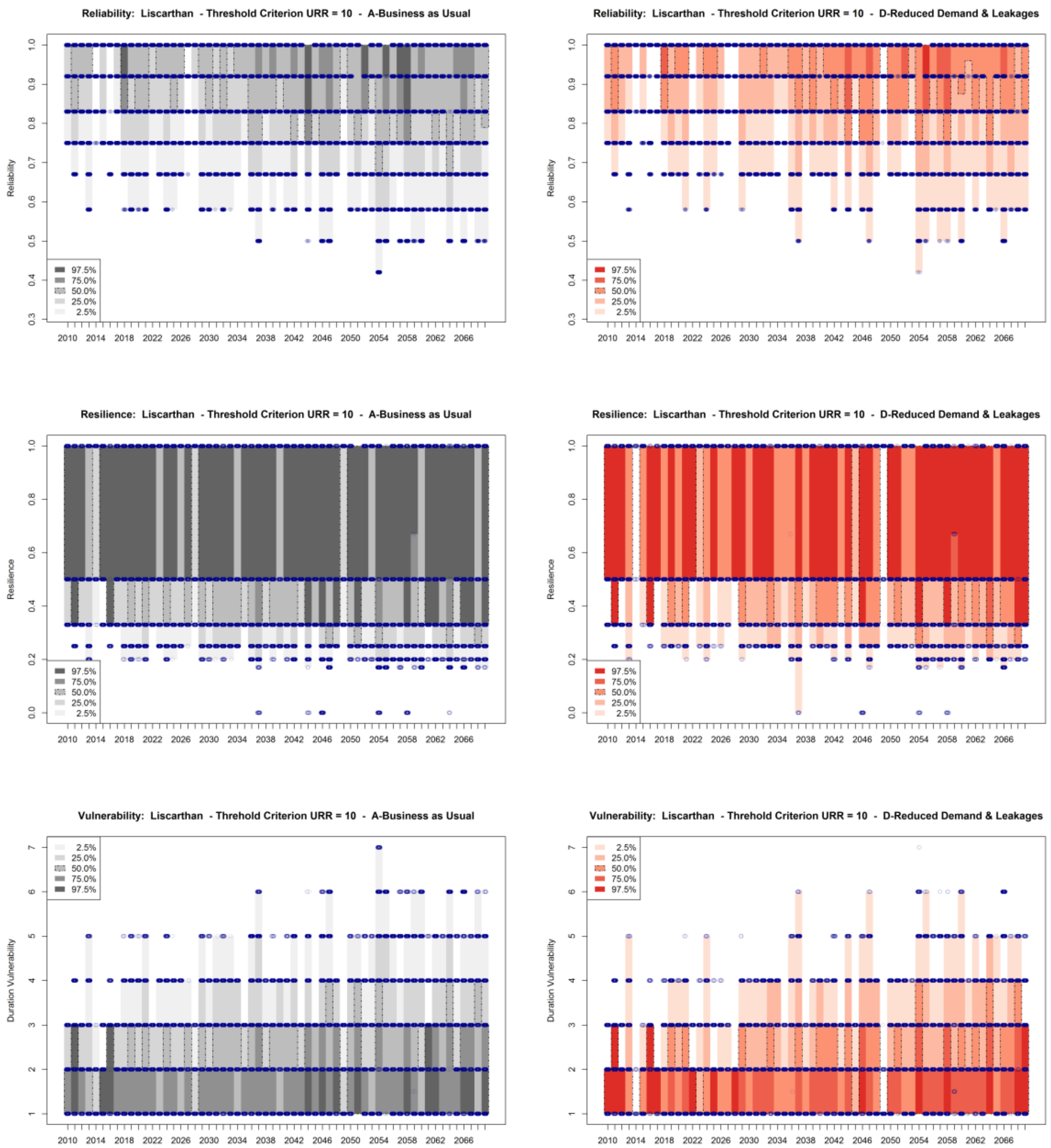

Figure II.1 Liscarthan: RRV analysis for Scenario A (grey), and D (red) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 10%;

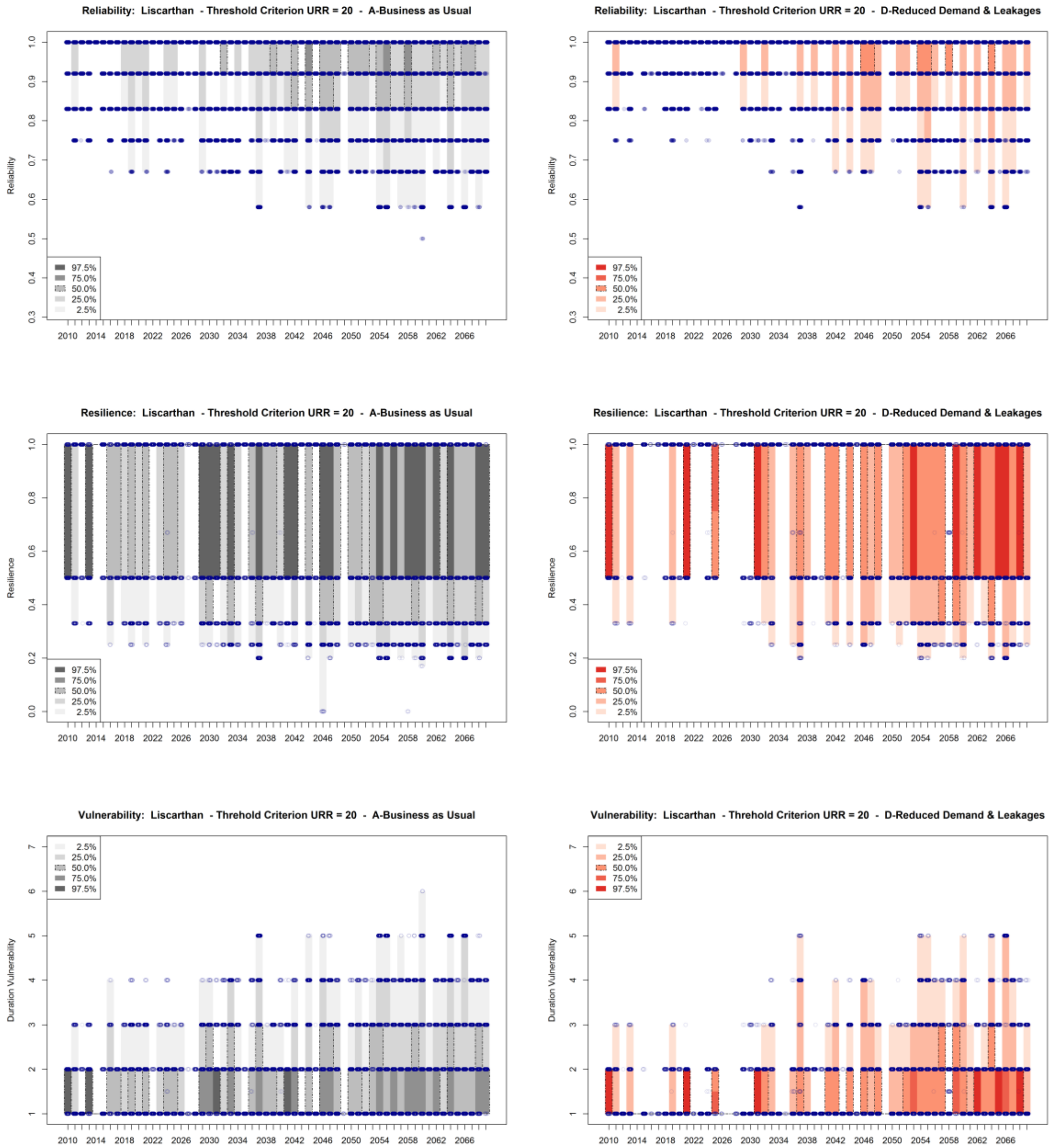

Figure II.2 Liscarthan: RRV analysis for Scenario A (grey), and D (red) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 20%;

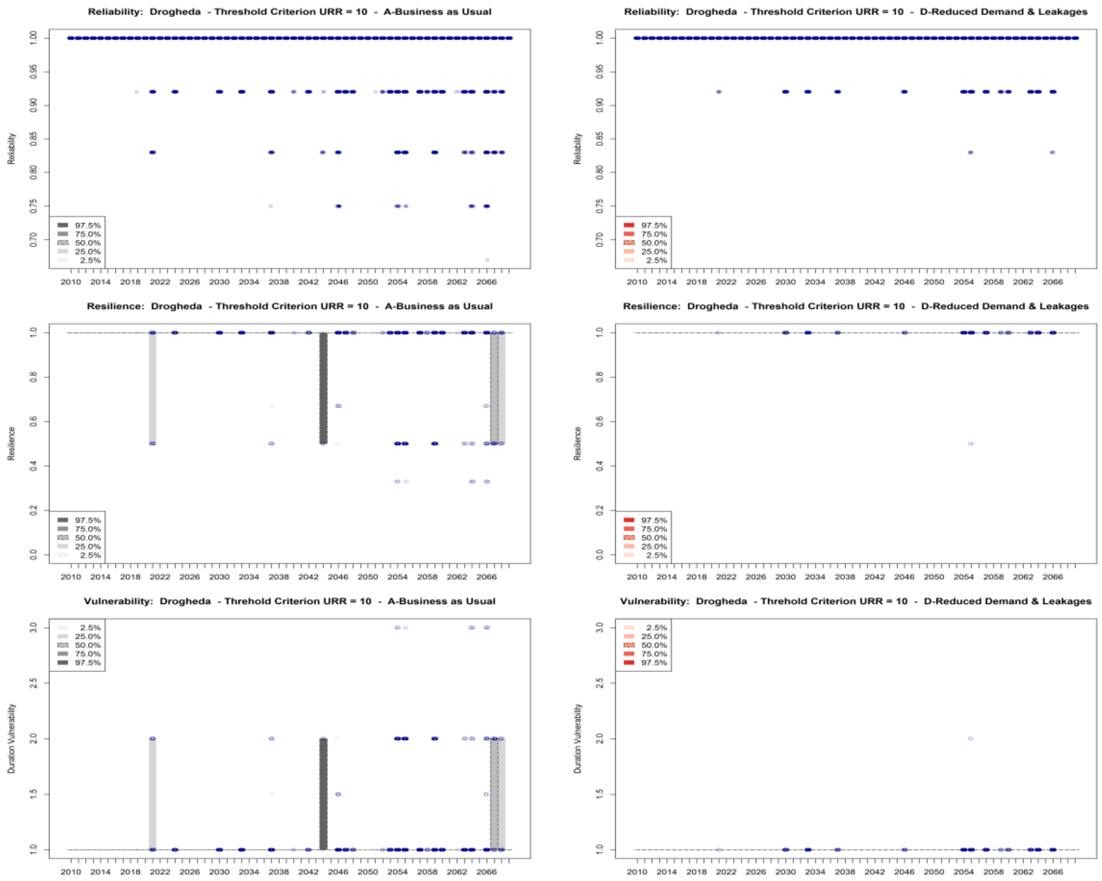

Figure II.3 Drogheda: RRV analysis for Scenario A (left), and D (right) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 10%.

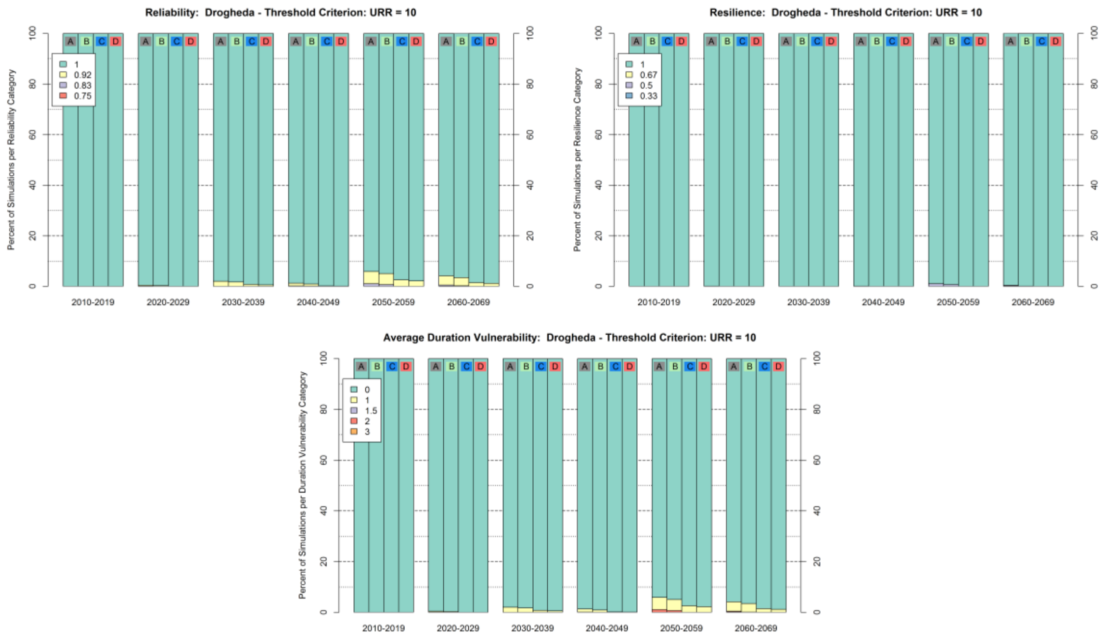

Figure II.4 Drogheda: RRV analysis for 10 year windows for Scenario A, B, C and D showing the percent of simulations in each Reliability, Resilience and Duration Vulnerability category. UUR >%10.

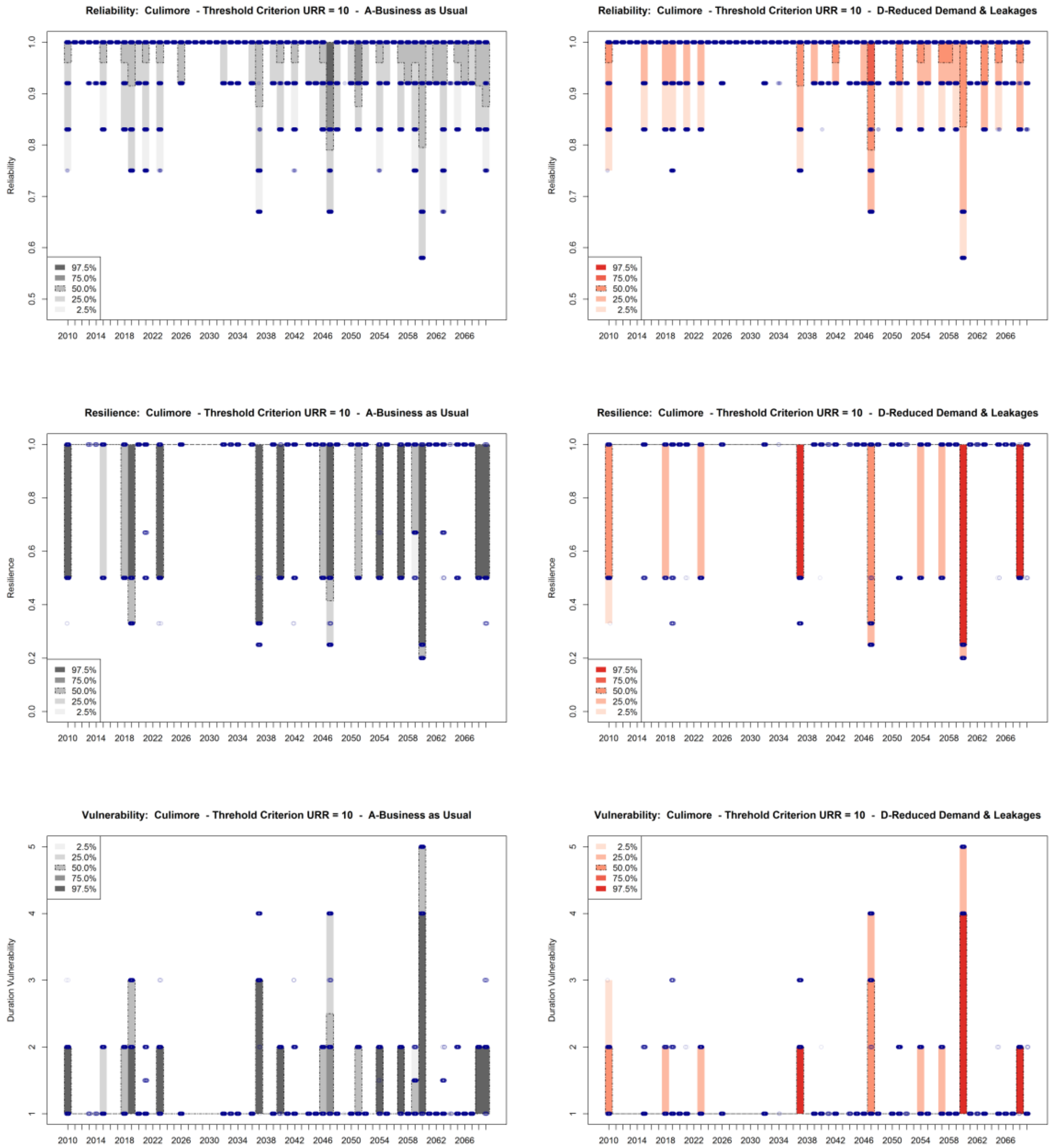

Figure II.5 Culimore: RRV analysis for Scenario A (grey), and D (red) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 10%;

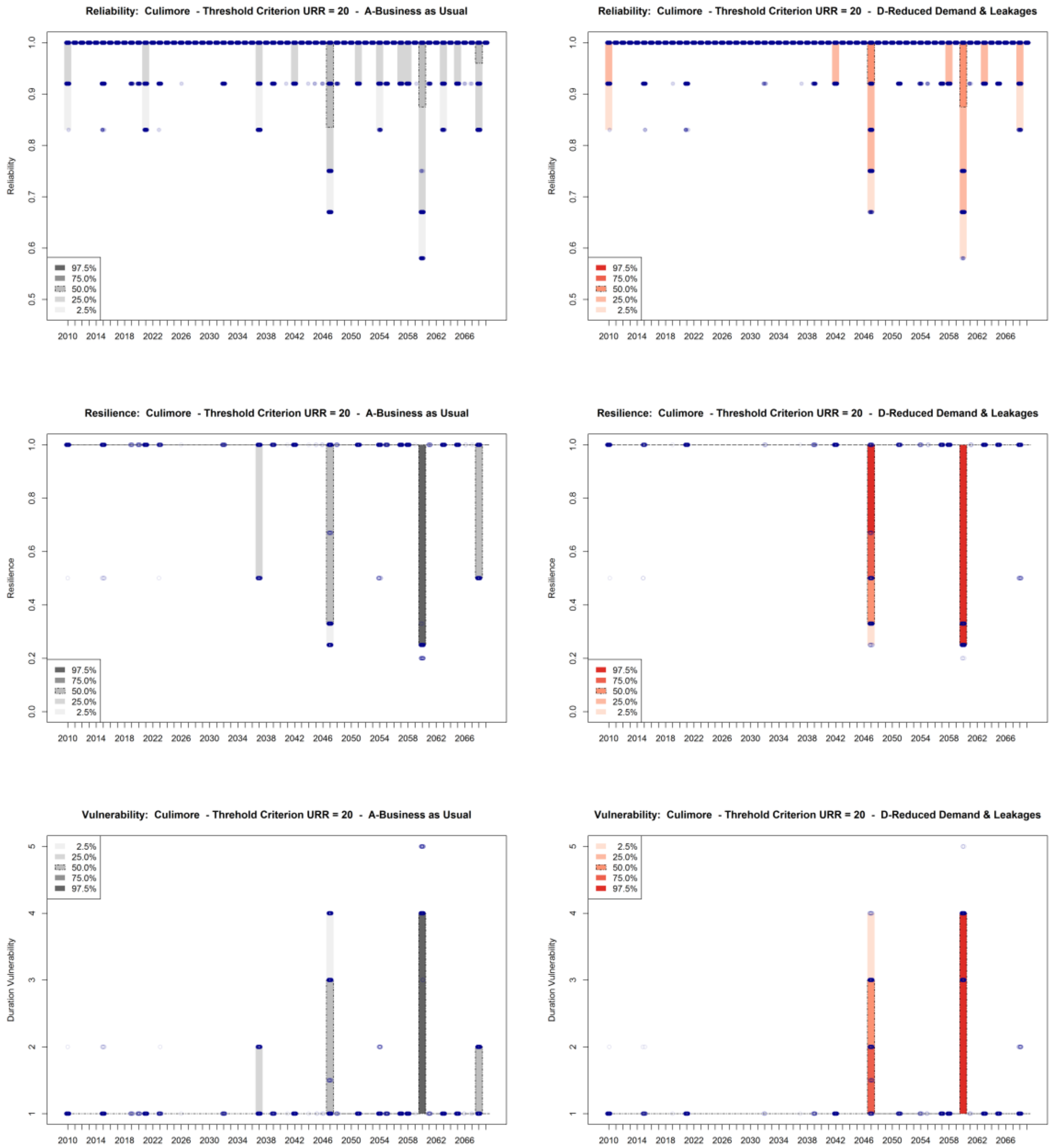

Figure II.6 Culimore: RRV analysis for Scenario A (grey), and D (red) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 20%;

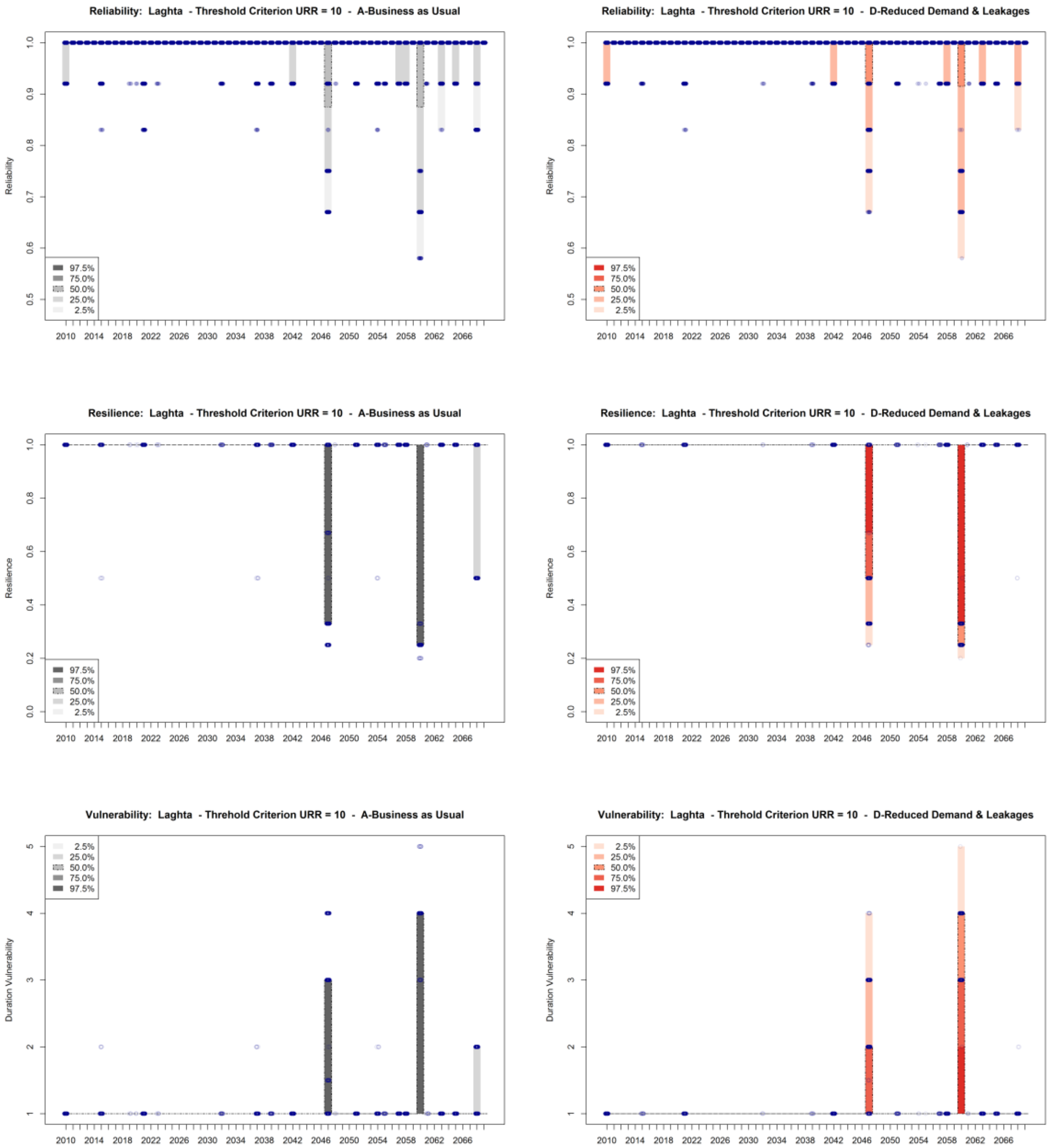

Figure II.7 Laghta: RRV analysis for Scenario A (grey), and D (red) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 10%;

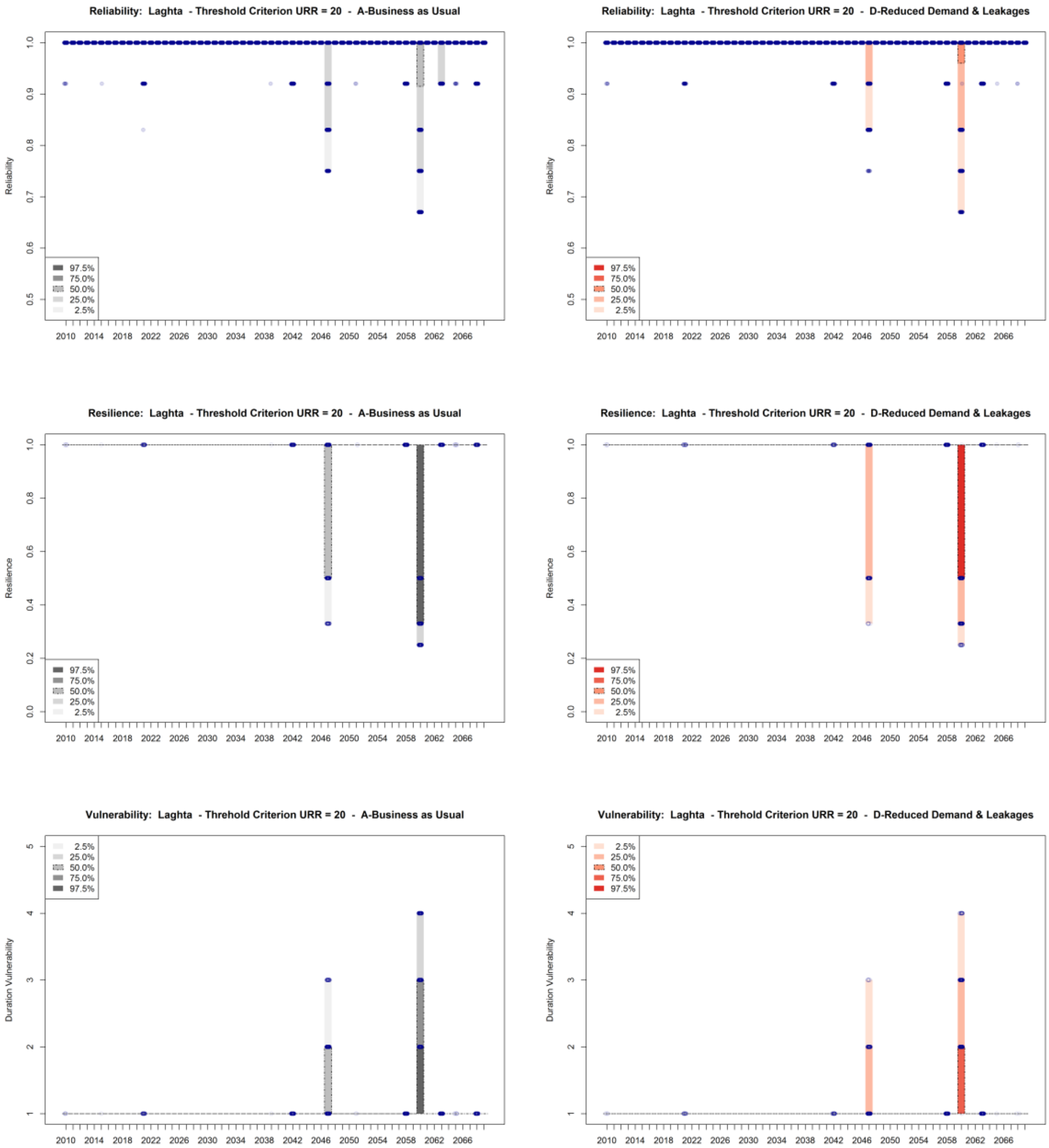

Figure II.8 Laghta: RRV analysis for Scenario A (grey), and D (red) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 20%;

Figure II.9 Culimore (right) and Laghta (left) with UUR threshold >20%. RRV analysis is based on 10 year windows for Scenario A, B, C and D showing the percent of simulations in each Reliability, Resilience and Duration Vulnerability category.

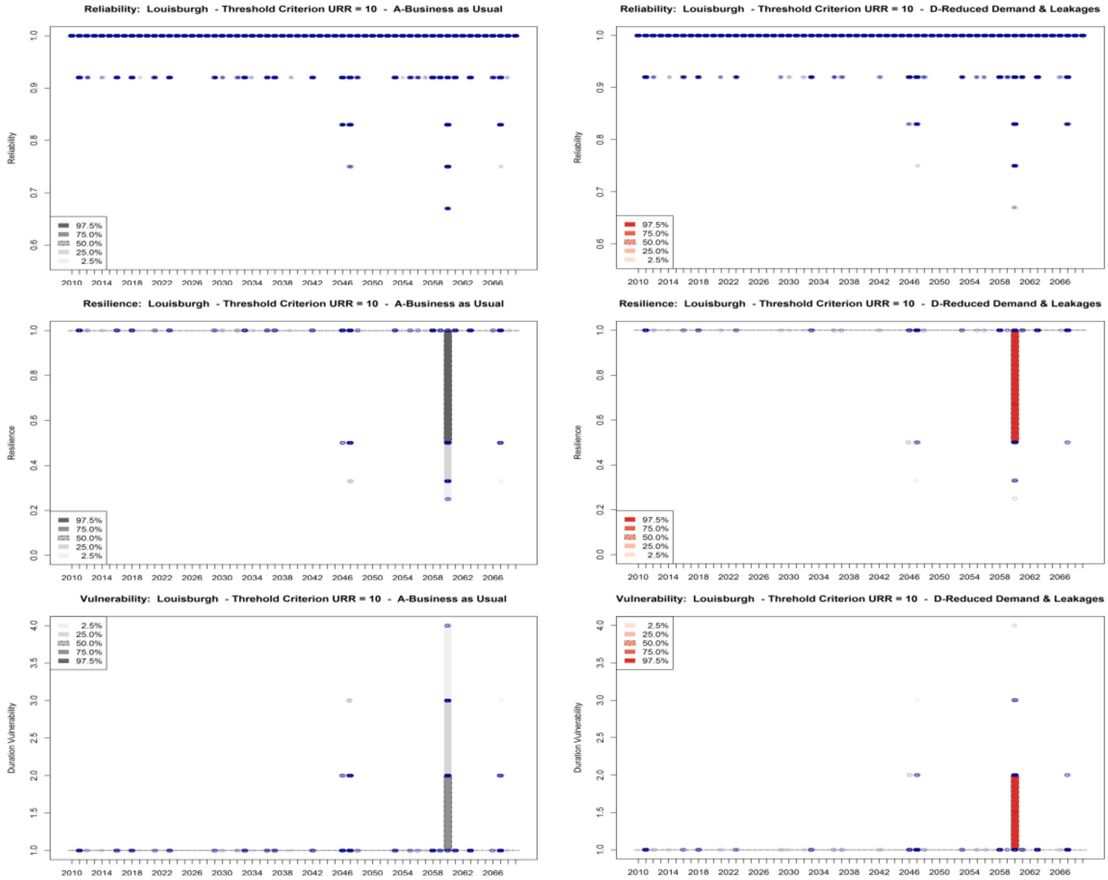

Figure II.10 Louisburgh: RRV analysis for Scenario A (left), and D (right) Vulnerability. Blue points show the RRV levels per year out of 3000 simulations. The darker the bars the higher the percent of simulations showing a RRV level. Threshold: URR 10%.

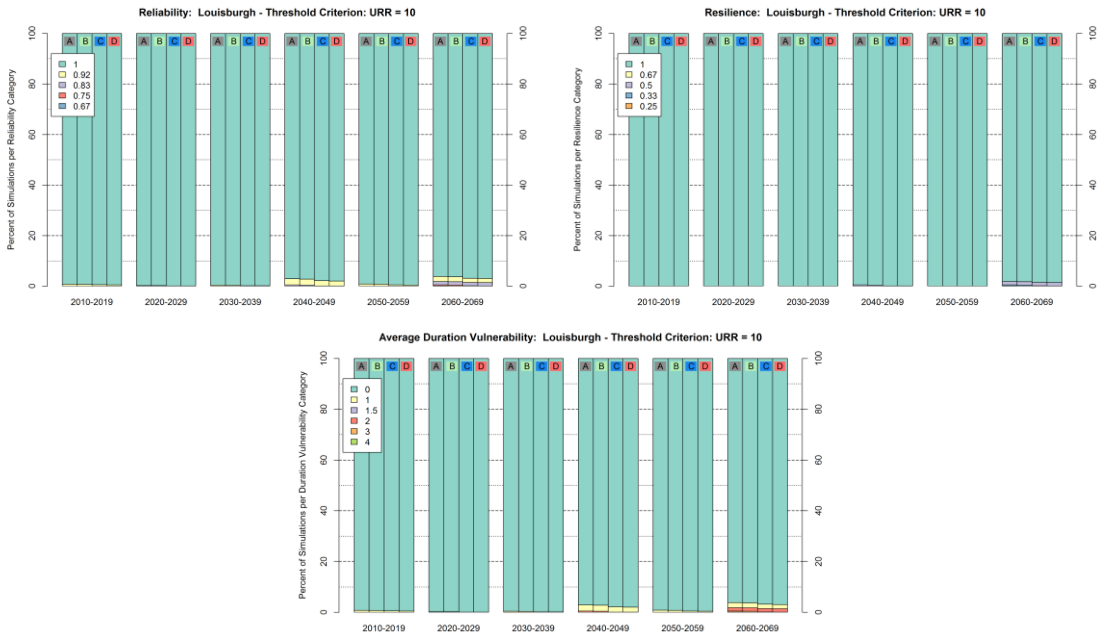

Figure II.11 Louisburgh: RRV analysis for 10 year windows for Scenario A, B, C and D showing the percent of simulations in each Reliability, Resilience and Duration Vulnerability category. UUR >%10.