using science to
create a better place

Applying probabilistic climate change information to strategic resource assessment

Climate Change Science programme

Science report: SC050045

The Environment Agency is the leading public body protecting and improving the environment in England and Wales.

It's our job to make sure that air, land and water are looked after by everyone in today's society, so that tomorrow's generations inherit a cleaner, healthier world.

Our work includes tackling flooding and pollution incidents, reducing industry's impacts on the environment, cleaning up rivers, coastal waters and contaminated land, and improving wildlife habitats.

This report is the result of research commissioned and funded by the Environment Agency's Science Programme.

Published by:
Environment Agency, Rio House, Waterside Drive, Aztec West, Almondsbury, Bristol, BS32 4UD
Tel: 01454 624400 Fax: 01454 624409
www.environment-agency.gov.uk

ISBN: 978-1-84911-034-1

Author(s):
Fung, C. Fai
Lopez, Ana
New, Mark

Dissemination Status:
Publicly Available / releaed to all regions

Keywords:
Probabilistic, climate change, water resources, ecology, Itchen, groundwater, LIFE

Research Contractor:
School of Geography and Environment, University of Oxford, OX1 3QY.
01865 285181

Environment Agency's Project Manager:
Harriet Orr, Environment Centre Wales, Deiniol Road, Bangor, LL57 2UW, Wales

Collaborator(s):
Tyndall Centre, School of Geography and Environment, University of Oxford

Science Project Number:
SC050045

Product Code:
SCHO0309BPRH-E-P

Science at the Environment Agency

Science underpins the work of the Environment Agency. It provides an up-to-date understanding of the world about us and helps us to develop monitoring tools and techniques to manage our environment as efficiently and effectively as possible.

The work of the Environment Agency's Science Group is a key ingredient in the partnership between research, policy and operations that enables the Environment Agency to protect and restore our environment.

The science programme focuses on five main areas of activity:

- **Setting the agenda**, by identifying where strategic science can inform our evidence-based policies, advisory and regulatory roles;
- **Funding science**, by supporting programmes, projects and people in response to long-term strategic needs, medium-term policy priorities and shorter-term operational requirements;
- **Managing science**, by ensuring that our programmes and projects are fit for purpose and executed according to international scientific standards;
- **Carrying out science**, by undertaking research – either by contracting it out to research organisations and consultancies or by doing it ourselves;
- **Delivering information, advice, tools and techniques**, by making appropriate products available to our policy and operations staff.

Steve Killeen

Steve Killeen

Head of Science

Executive summary

Through three case studies, the Tyndall Centre for Climate Change Research at the University of Oxford has demonstrated the added value of using large climate model ensembles when assessing climate change impacts on water resources and river ecology and exploring possible adaptation pathways.

The majority of climate change impact and adaptation studies to date have been based on just a few realisations of future climate, using for example one or a few different Global Climate Models and one or more different emissions scenarios. Large ensembles of climate models are currently available either as ensembles of opportunity or perturbed physics ensembles, providing a wealth of additional data that is potentially useful for improving adaptation strategies to climate change by presenting a wider envelope of possible futures.

With the release of the UK Climate Projections by the UK Climate Impacts Programme in spring 2009, users from different sectors will have access to probabilistic projections of climate change for the UK. Due to the novelty of this ensemble-like climate change information, there is little previous experience of practical applications or of the added value of this information for impact and adaptation decision-making. In our work we describe a methodology to perform a top-down approach to impacts assessment using large ensembles of climate change information.

This report presents three case studies which explore the use of the largest perturbed physics ensemble publicly available to date, ClimatePrediction.net. These case studies are:

- Water resources in the Thames River.
- Water supply-demand interaction in the Wimbleball water resource zone.
- River ecology in the River Itchen.

In the River Thames case study, the implications of a probabilistic end-to-end risk-based framework for climate impacts assessment were explored. A probabilistic approach was shown to provide more informative results than if a single realisation of future climate was used, and enabled the potential risk of impacts to be quantified. However, details of the risks are dependent on the approach used in the analysis.

In the Wimbleball water resource zone, river flows simulated using a rainfall-runoff model were used to run a water resource system model designed to analyse the interactions between water supply and demand. This model allows for the exploration of various adaptation paths given the climate change information available. The response of the water resource system when driven by the climate model ensemble data, and operating under different scenarios of demand and supply management, was analysed.

Existing environmental flow thresholds in the River Itchen were assessed in light of the new climate data and showed the limitations of using such tools for climate change impacts assessments. We developed a novel ecological impacts matrix which enables expert opinion and flow statistics to be combined in a way that can be understood by a multi-disciplinary audience, thus facilitating the decision-making process.

Our research shows that the additional information contained in the climate model ensemble provides a better understanding of the possible ranges of future conditions, compared to the use of single model scenarios. Furthermore, with careful presentation, decision-makers will find the results from large ensembles of models more accessible and be able to compare the merits of different management options and the timing of different adaptation measures more easily. The overhead in additional time and expertise needed to carry out the impacts analysis will therefore be justified by the increased quality of the decision-making.

Even though we have focused our study on water resources and river ecology in the UK, our conclusions regarding the added value of climate model ensembles in guiding adaptation decisions can be generalised to other sectors and geographical regions.

Contents

1. Introduction

As part of ongoing work on climate change, the Environment Agency's Climate Change Adaptation Strategy (2008-2011) sets out a systematic approach for embedding climate change adaptation into its core activities. The assessment of risk and adaptation options is key to this strategy, a large component of which involves developing methodological frameworks for the assessment of risk of climate change impacts.

In the past decade, a lot of effort has been placed on water resource and water quality modelling, using a range of climate scenarios. This often resulted in one global climate model (GCM) and a small number of emissions scenarios. However, in order to provide some indication of the uncertainty in the climate modelling, scientists are turning towards multi-model datasets. Recent work in the climate modelling community has included attempts to address the uncertainties inherent in the methodologies for modelling future climate. There has been a move towards large ensembles of climate models in the ClimatePrediction.net (CPDN) experiment, and probabilistic frameworks providing projections of climate change as probability density functions in the UK Climate Impacts Programme's UK Climate Projections project. However, ideas as to how to use the data have been preliminary at best.

In this project, the objective has been to develop a risk-based framework to handle probabilistic climate change information and estimate uncertainties inherent within impact assessments performed by the Environment Agency for strategic planning. The work presented in this report has been carried out in anticipation of the release of the UK Climate Projections (UKCP) later in 2009, and it is hoped that the case studies will provide a basis for the development, uptake and delivery of probabilistic climate change information in the Environment Agency and the wider climate impacts community.

The first of the studies presented in this report attempts to assess the uncertainties associated with climate models using CPDN and how this percolates through to an impacts model, such as a rainfall-runoff model. This work is explored further in two case studies that attempt to develop a methodological framework to use the information from this new large climate model ensemble. The studies have been chosen to reflect some of the core activities carried out by the Environment Agency that are amenable for modelling with large climate ensembles. This includes a water supply case study in the Wimbleball Water Resource Zone and a river ecology case study on the River Itchen.

The report comprises a description of the large ensemble of climate data used (CPDN), and a summary of the key findings in each case study, followed by a closing section summarising the relevance of the case studies to the Environment Agency and possible avenues for future work. Detailed technical descriptions of each of the case studies are given in the appendices: a published paper on the water resources case study in Appendix I (New *et al*., 2007), a preprint of the water supply case study in Appendix II (Lopez, 2009) and a summary of the results of the river ecology case study in Appendix III (for a paper in preparation (Fung *et al*., 2009).

It is highly important to note here that the case studies that have been presented provide a basis to discuss the opportunities that lie in probabilistic climate change information for use in the Environment Agency's portfolio. It will be emphasised throughout the report that the results are by no means predictions of future climate change. The methodologies that have been described indicate how probabilistic information can be used within the context of management of water resources for water supply and river ecology. They are for illustrative purposes only.

2. Large climate model ensembles

Global climate models (GCMs) are our best tools for investigating how the global climate system will respond to future green house gas emissions. We use future scenarios of emissions (Intergovernmental Panel on Climate Change (IPCC), 2000) to drive these GCMs. Most GCMs predict significant changes in the Earth's climate within this century. However, the range in the projections is in some cases very large, in particular at the regional and local scales relevant for the analysis of impacts and adaptation options in the face of climate change. To deal with this problem we need to be able to quantify the uncertainty in GCM projections. Several sources of uncertainty are present in GCM simulations, including uncertainties in the projections of greenhouse gas concentrations that will force change in the climate system in the future, uncertainties in the initial conditions used to initialise the climate model simulations, and uncertainties in the formulation of the climate models themselves. Climate processes that are poorly known or that operate at spatial and temporal scales not resolved by the climate models can be formulated (or parameterised) in a range of plausible ways. Recently, perturbed physics ensembles (PPEs) have been developed in an attempt to quantify initial condition and model formulation uncertainty (Murphy *et al.*, 2004; Stainforth *et al.*, 2005) . These ensembles comprise a large number of runs of a state of the art climate model. Each individual run uses a configuration of the climate model with parameters representing various physical processes set to different values within their acceptable range, as defined by the experts in the relevant parameterisation scheme. For each combination of parameter values an initial condition ensemble is used. PPEs provide a new approach for exploring a wide range of future climates and using this information to assess potential impacts of climate change.

Examples of such experiments are ClimatePrediction.net (CPDN) and the climate change scenarios currently being developed by UK Climate Impacts Programme (UKCIP) (Murphy *et al*., 2004; Stainforth *et al*., 2005).

2.1 ClimatePrediction.net

ClimatePrediction.net is a perturbed physics ensemble (PPE) and ongoing experiment in which individual model simulations are carried out using idle processing capacity on personal computers volunteered by members of the general public. In what follows we describe the two sets of data generated by CPDN that have been used in our case studies.

CPDN first experiment: CO_2 doubling experiment

In this experiment, the PPE is generated by running the Met Office Hadley Centre model HadSM3 with different values for seven of the model parameters. The HadSM3 model consists of an atmospheric model coupled to the simplest possible ocean, a slab ocean model that basically provides the boundary conditions for the atmospheric model (Stainforth *et al*., 2005).

The data from the experiment represent 2,700 individual simulations with the HadSM3 climate model; each simulation comprises three 15-year periods: a calibration phase, followed by a 15-year 1xCO_2 ‘control’ simulation, and a 2xCO_2 simulation. In the 1xCO_2

control simulation the model is run with pre-industrial concentrations of carbon dioxide. In the 2xCO_2 phase, the carbon dioxide atmospheric concentration is instantaneously doubled at the beginning of the simulation and kept fixed afterwards. Therefore, after a period of time during which all the climate variables change as a response to the instantaneous change in atmospheric carbon dioxide concentration, the model moves towards a stationary or equilibrium state since after the initial instantaneous doubling the external forcing (carbon dioxide concentration) remains constant. Thus the goal of this experiment is to investigate the characteristics of the equilibrium state reached by the atmosphere after a sudden doubling of carbon dioxide concentration.

Within the subset of 2,700 individual simulations of the full first experiment, seven physics parameter values are perturbed and there are 449 unique combinations of perturbations. For most perturbations, there is more than one simulation, with each simulation differing only in initial conditions (IC). The total number of simulations in the 449 IC ensembles adds up to 2,700 simulations in the ‘grand ensemble’. The ensemble is therefore large, but limited in a number of ways: it comprises a sampling of only some of the uncertain physics parameters in the HadSM3, and it only samples from a single ‘parent’ model structure, ignoring uncertainties arising from alternative GCM model structures. More importantly, it only aims to study the equilibrium response of the climate system to an instantaneous doubling of carbon dioxide concentration. Even though it might be useful to quantify the sensitivity of the climate system to large changes in atmospheric forcings, this experiment clearly represents an artificial situation that it is very unlikely to occur in the real world. A similar 2xCO_2 experiment is one of the components that are used to generate the probabilistic UK climate projections currently being developed by UKCIP (Murphy *et al*., 2004).

Seasonal means from the last eight years of the control and 2xCO_2 runs have been returned by client machines for archival in ClimatePrediction.net data servers, but only for a limited number of variables. We use precipitation, temperature and cloud fraction data to calculate future daily precipitation and potential evaporation to input into the hydrological model used in the first case study.

CPDN second experiment: Transient experiment

The climate data used in our analysis for the second and third case studies has been generated by the second CPDN experiment, launched in February 2006. The GCM used in this case is the HADCM3L, a version of the UK Met Office Unified Model comprising a standard resolution atmospheric model coupled to a lower resolution ocean model. The lower resolution ocean has the same resolution as the atmospheric model, while in the standard HadCM3 model the ocean runs at a higher resolution than the atmospheric model, particularly near the equator.

Contrary to the first CPDN experiment, this is what is known as a transient experiment: an experiment where a comprehensive atmosphere–ocean model such as those contributing to the last IPCC report (Solomon *et al*., 2007) is forced by greenhouse gas concentrations that vary in time following some prescribed scenario and do not reach an equilibrium or stationary state.

The second CPDN experiment explores the effects of perturbing 26 parameters that are relevant to the way radiation, large scale clouds formation, ocean circulation, sulphate cycle, sea ice formation, the land surface and convection are simulated by the GCM.

Each simulation involves a 160-year control run with constant forcing at pre-industrial concentrations and a 160-year transient run. The transient simulations include two phases. In the historical phase from 1920 until 2000, the experiment is forced with historical records of carbon dioxide, volcanic and anthropogenic emissions, and solar forcing. In the second phase, a range of possible future scenarios are used to force the model response between 2000 and 2080.

In our study, we concentrate on a subset of 246 transient simulations first completed, which is now part of the much larger ensemble available to date. Within this subset, all model runs were subjected to the A1B SRES greenhouse gas forcing scenario, which is one of the scenarios described in the Intergovernmental Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (IPCC, 2000). A1B is a 'middle of the road' emissions scenario, representing a world in the twenty-first century with very rapid economic growth, rapid introduction of new and more efficient technologies and a world that does not rely too heavily on one particular energy source.

The CPDN experiment archives a variety of climate variables at different temporal (monthly to decadal means), and spatial scales (grid points to continental averages). Monthly time series are available for several variables, as the global mean, the area average over 22 continental to sub continental regions similar to those defined by Giorgi and Francisco [1] (Giorgi and Francisco, 2000), for six ocean "basins" and for eight individual grid boxes over the United Kingdom. We use monthly time series of temperature, precipitation, and relative humidity for the grid boxes corresponding to the South West of England (48.75N, 5.625W – 51.25N, 1.875W) in the second case study, and the South and South East of England (48.75N, 1.875W – 51.25N, 1.875E) in the third case study.

In our work, we use all ensemble members "as is", without any previous evaluation of their relative skill in simulating the climate system, considering all stable model runs as members of our sample.

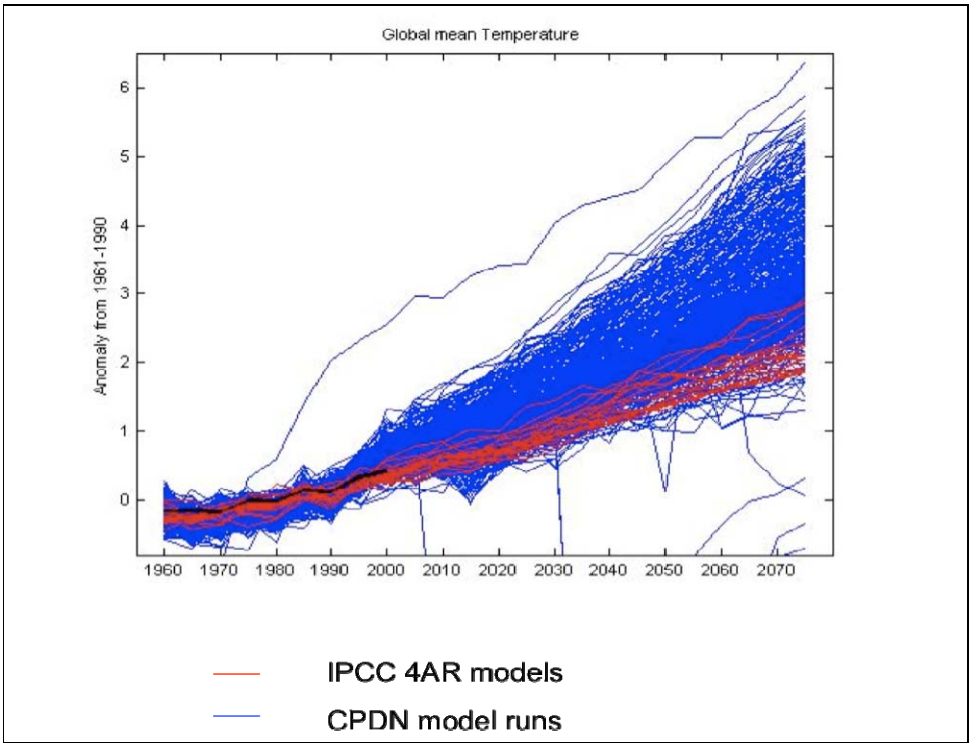


Figure 0.1 Global mean temperature time series for CPDN model runs (blue), IPCC model runs (red) and observations (black). The runs that show rapid cooling in the twenty-first century are unstable and have been discarded from the ensemble.

[1] These regions are defined as rectangles covering the same land area as the Giorgi regions but including the adjacent oceans, and follow the naming convention of the IPCC 4AR (IPCC, 2007; Solomon et al, 2007).

The HadCM3 model generates climate variables at a 2.5° x 3.75° (latitude by longitude) spatial resolution. However, any typical river runoff model needs daily time series of precipitation and potential evaporation at a given location. Therefore, in order to use the climate model information it is necessary to downscale the monthly and spatially averaged time series to daily local time series. Moreover, the model data has biases over the period that observations are available. Details about the downscaling and bias correction techniques used in our work are provided in Appendix II.

3. Case study 1: Water resources in the Thames River

3.1 Introduction

In this case study we explore the implications of this new generation of probabilistic climate information for end-to-end uncertainty analysis in impacts modelling. For a detailed technical description of the work see New *et al*. (2007) in Appendix I.

Data from the carbon dioxide doubling CPDN experiment was used. Even though this is an equilibrium experiment that does not take into account the transient nature of the forced climate system, it allows for an exploration of the relative importance of climate model and impact model uncertainty. We focus on the Thames River in the UK, and use a water balance model (CATCHMOD) to simulate river flows and obtain probabilistic projections of future flow statistics in the Thames.

3.2 Simulated flows: climate model and impact model uncertainties.

CATCHMOD was used to simulate daily discharge in the Thames at Teddington, London. CATCHMOD is a rainfall-runoff model used by the Environment Agency for water resource planning and abstraction licence allocation in England and Wales. It uses daily rainfall (PPT) and potential evapotranspiration (PET) data for input at sub-catchments represented in the model. This requires downscaling of the coarser resolution seasonal mean GCM data. As the archived GCM data do not support either dynamical or statistical downscaling, we use a simple change factor (CF) downscaling approach to produce input for CATCHMOD.

CATCHMOD was set up with three 'sub-catchments', each representing the area of the catchment with a similar hydrological runoff response: urban areas, clay geology and chalk geology. For each sub-catchment, five parameters for CATCHMOD are determined through calibration against observed discharge. This research explores the effects of uncertainty in these parameters by running CATCHMOD with 100 different combinations of parameter values, all of which produce calibration results within predefined goodness of fit limits. The underlying rationale for exploration of parameter uncertainty is similar to the ClimatePrediction.net project; however, unlike ClimatePrediction.net, the set of parameter values used for CATCHMOD is preselected by evaluation against observed discharge.

Figure 0.1 summarises the relative effect of ClimatePredcition.net and CATCHMOD parameter uncertainty on changes in simulated flows. Here, we calculate flow statistics for 44,900 simulations with CATCHMOD, each simulation a unique combination of one of the 449 ClimatePrediction.net IC outputs and one of the 100 CATCHMOD parameterisations. If the standard HadSM3 (the HasSM3 model run with standard values for the parameters) model projections are run through all versions of CATCHMOD (light blue curve), the range of responses in median daily flow (Q50) is -15 to +20 per cent. Similar ranges, with a different central value, arise from combining any one ClimatePrediction.net IC with the 100 CATCHMOD versions (black curves). Thus, the wide spread of ClimatePrediction.net outputs dominate the spread in simulated changes, with different versions of CATCHMOD modulating the

ClimatePrediction.net signal. Nonetheless, if one compares the range of changes in Q50 when using only the standard CATCHMOD (the version of CATCHMOD with parameters as used by the Environment Agency) to those using the full ensemble, CATCHMOD parameter uncertainty adds an additional 23 per cent to the range for Q50.

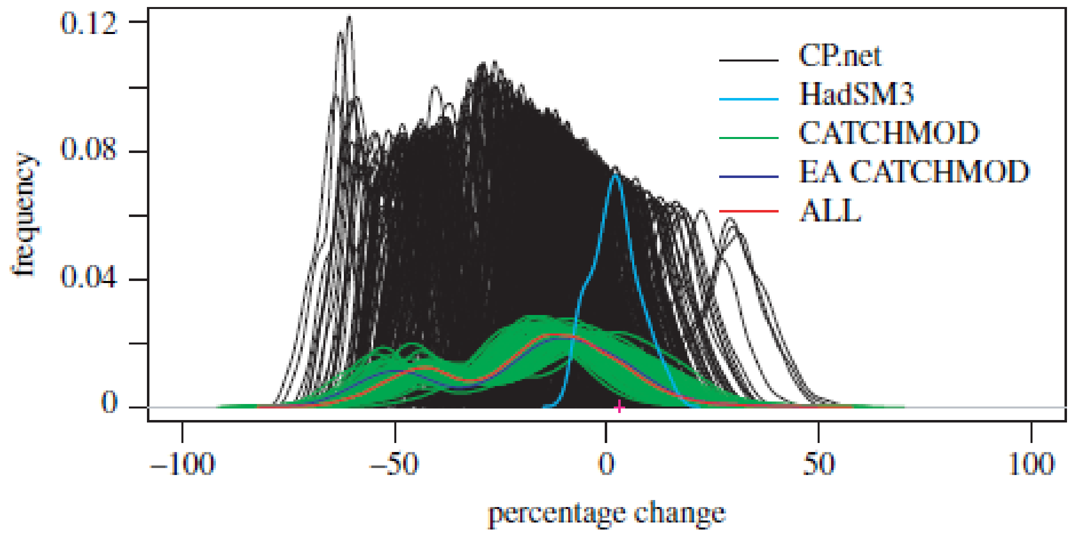


Figure 0.1 Changes in CATCHMOD simulated Q50 (2xCO_2 minus 1xCO_2) when uncertainties in CATCHMOD parameters are combined with the ClimatePrediction.net ensemble. Each black curve is a smoothed frequency histogram obtained by combining one ClimatePrediction.net IC ensemble with 100 CATCHMOD model versions. Green curves show the response of each CATCHMOD version when driven by all ClimatePrediction.net results. The red curve is the frequency distribution from all possible ClimatePrediction.net–CATCHMOD combinations. For reference, the results from (i) the standard HadSM3 model with all CATCHMOD versions (light blue) and (ii) Environment Agency CATCHMOD with all ClimatePrediction.net ICs (dark blue) are also shown. The red cross shows the result of the singular combination of the standard HadSM3 and Environment Agency CATCHMOD.

This example illustrates the potentially rich information that can be obtained by using large perturbed-physics ensemble outputs in a climate change impact assessment. The approach can clearly provide more information than a scenario-based impact assessment which will only provide the information given by the red cross in Figure 0.1 when using one single GCM, or a series of crosses (one for each model) when using a set of GCMs as those used in the IPCC Fourth assessment report.

On the other hand, with probabilistic climate change information a frequency distribution can be estimated, and the risks of an adverse impact can be calculated and used to make a risk-based judgement.

The following case study moves from this illustrative example to a more complete analysis by using the transient ClimatePrediction.net ensemble. This assesses a wider range of physics perturbations and simulates the transient response to past and future greenhouse gas forcing with a coupled ocean–atmosphere model, and by using a water resource systems model that enables the assessment of the interplay of demand and supply under different socioeconomic and water infrastructure scenarios.

4. Case study 2: Water resources in the South West of England

4.1 Introduction

In this case study the CPDN projections are applied to the Wimbleball water resource zone in the South West of England. This zone has a variety of water sources, which allows some flexibility in the choice of adaptation measures, but at the same time is simple enough to make the analysis transparent. We make use of CATCHMOD and LANCMOD, generic rainfall-runoff and water resource system models used by the Environment Agency for behavioural analysis of water resource supply systems.

The analysis shows that there are basically two advantages in using large ensembles like ClimatePrediction.net data over other sources that provide just change factors at different time slices in the future, or single model scenarios. Firstly, CPDN stores time series of climate variables from each ensemble member, providing time dependent information that is extremely valuable for water resource management. As this time dependent information has been generated by a fully dynamical climate model, we can assume that it provides a range of future possible evolutions of the climate system consistent with current state-of-the-art climate science. This means that we can look at relative changes in time in the frequency of occurrence of different events of interest. This is an important issue given that we are trying to quantify the impacts on water supply infrastructure and management of changes in a non-stationary system.

Secondly, we will see that the use of just one realisation of future climate can give a false sense of security and does not provide the rich picture that the ensemble does. Moreover, our results strongly indicate that the practice of using a single model run, or for that matter ensemble means instead of the individual model runs, can be misleading when analysing impacts of climate change. For a detailed technical description of the work, see Lopez *et al.* (2009) in Appendix II.

4.2 River flows

CATCHMOD is set up to simulate river runoff for the Exe River at Thorverton. The effective catchment area consists of approximately 600km^2 underlain by sandstone. Five hydrological model parameters are determined through calibration against observed discharge. Since in this work we only explore climate model uncertainty, we ran CATCHMOD as calibrated for operational use by the Environment Agency.

We ran the 246 downscaled and bias-corrected precipitation and PET time series through CATCHMOD and obtained an ensemble of flows for the Exe at Thorverton. A large proportion of model runs show substantial reductions in the mean flows during the summer months, 82 per cent, 93 per cent and 91 per cent of runs for June, July and August respectively. This produces large reductions in low flows, illustrated in Figure 0.1, where flow duration curves for daily flows over the period 1961-1990 and over 2020-2039 are shown.

The spread in the range of simulated flows increases with time as members of the PPE diverge in their response to the A1B forcing scenario. For instance, the ensemble range in the simulated flow exceeded 90 per cent of the time (Q90) increases by about 50 per cent between the baseline period (Figure 4.1, top) and 2020-2039 (Figure 4.1, bottom). However, some changes are common to most of the PPE: for instance, driven by a general decrease in summer precipitation, low flows decrease relative to the baseline period as can be seen by the change in the relative position of CPDN low flows with respect to the observed low flows.

Analogously, driven by a general increase in winter precipitation, high flows increase relative to the baseline period except for the highest flows (Q02 and beyond). In this case, simulated peak flows are always smaller than baseline peak observed flows, perhaps due to the fact that CATCHMOD was not calibrated for high flows. Further work is required to confirm whether this is a real result or a consequence of the hydrological model or downscaling errors.

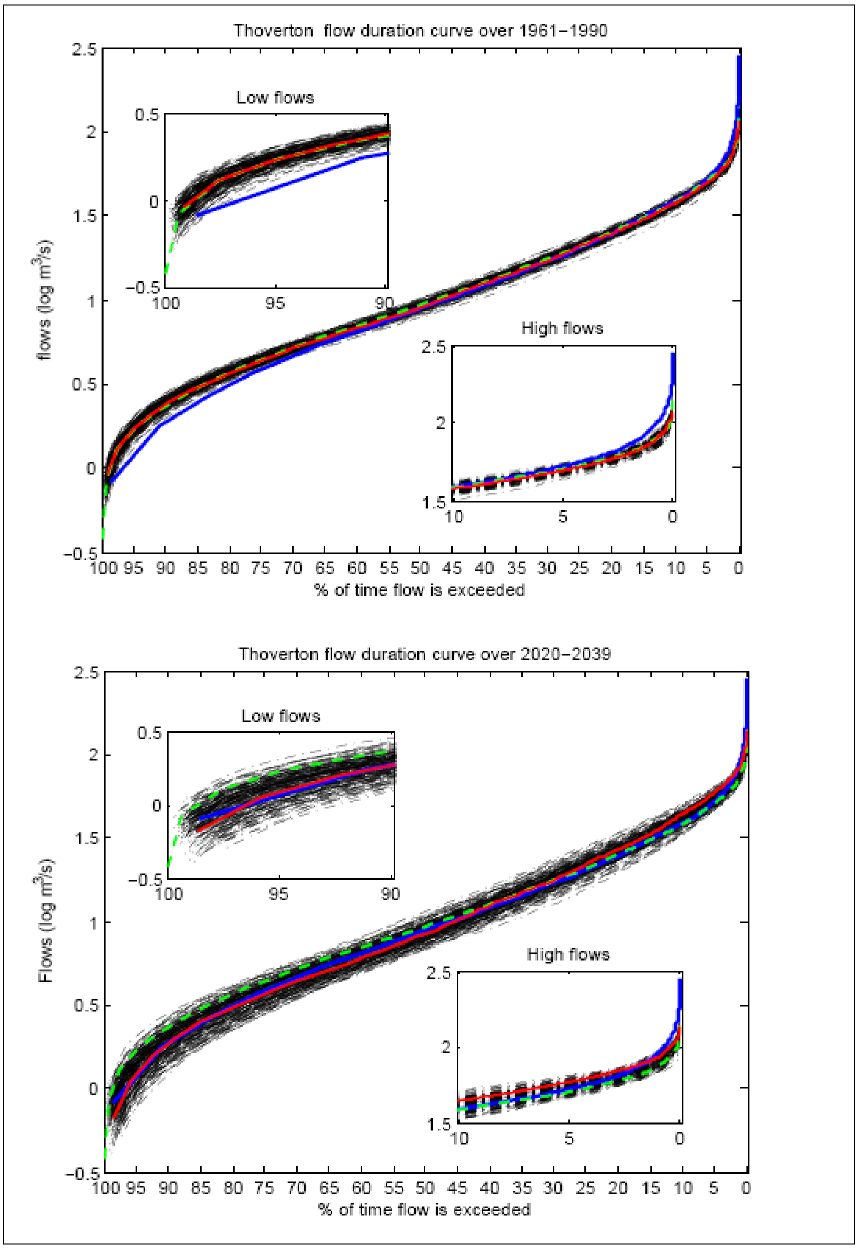


Figure 0.1 Flow duration curve for daily flows at Thorverton over the period 1961-1990 (top) and 2020-2039 (bottom). The blue lines correspond to observed flows, green dashed lines to simulated flows using observed precipitation and PET, black dashed to CPDN model runs, and the red lines to the CPDN model run with standard values of the physical parameters. The blue and green lines are included for reference in the bottom panel.

4.3 Water resource management system

The Wimbleball water resource zone is situated in South West England and supplies water to the counties of Devon and Somerset. In our simplified version of the zone simulated using LANCMOD (see Figure 5 in Appendix II), water is supplied by two reservoirs (Wimbleball and Clatworthy), the river Exe (at two abstraction points, Exebridge and Thorverton,) and from a sandstone groundwater source. The largest demands are East Devon (which includes the city of Exeter), Somerset and Peak. The latter two represent transfers out of the catchment to a neighbouring water utility, Wessex Water. There is also “pumped storage”, which is water that is available to be transferred from the river Exe at Exebridge to Wimbleball to refill the reservoir during the winter months.

Using the transient climate change information provided by CPDN we can explore how the reservoir storage level across the ensemble changes over time under a business as usual scenario, for example under current demand profiles . Figure 0.2 represents the storage level for a single month as a function of time between 1960 and 2079 - we show September as one crucial month towards the end of the summer, when the reservoir level becomes particularly low. This figure shows that the storage levels associated with any fraction of the ClimatePrediction.net ensemble decrease slowly from the present to about the 2020s, and more rapidly later on. For instance, the 50th percentile goes from nearly 60 per cent of full capacity to about 50 per cent by the 2020s, and ends up at nearly 30 per cent by the end of the simulation period. Notice that individual model runs have large variability (red crosses for instance), while percentiles across the ensemble are smooth curves. The fraction of model runs that fall below the critical reservoir level in any one year increases from around 4 per cent in the present day to 25 per cent by 2080. Thus, the evolving risk of the reservoir reaching critically low levels under current operating rules and for this particular climate model ensemble can be quantified.

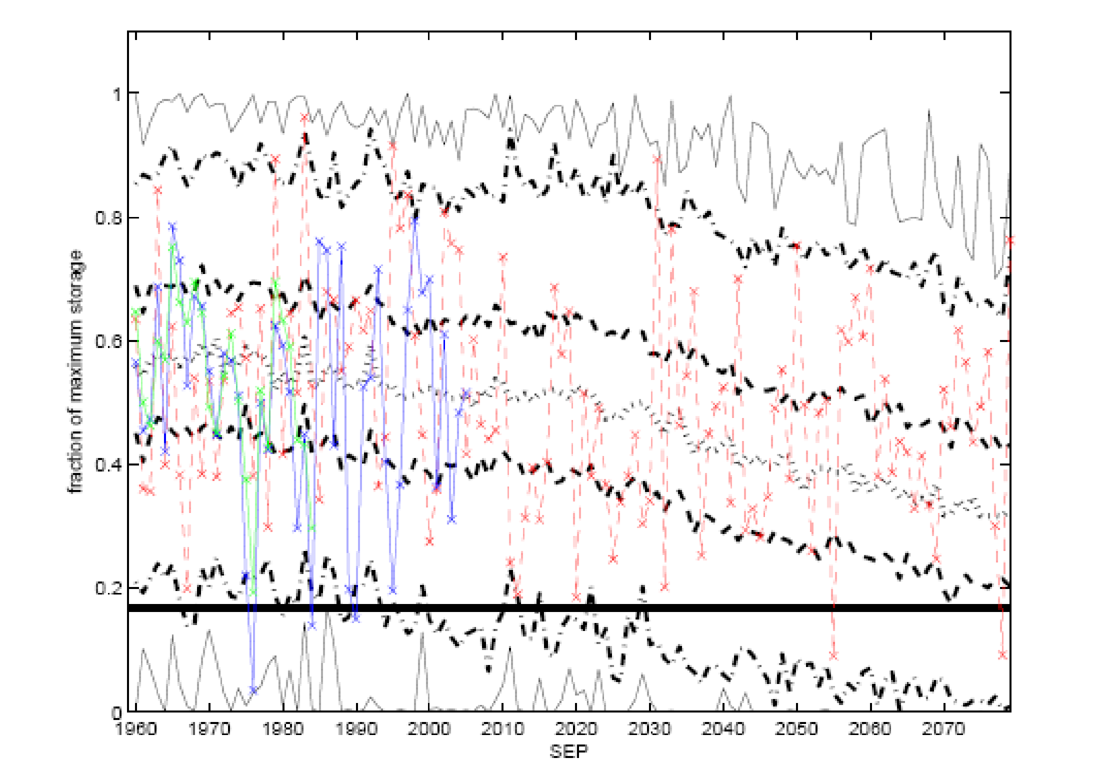


Figure 0.2 Mean monthly fraction of maximum storage level for September between 1960 and 2079. The black lines represent from top to bottom: maximum values (solid), 97.5% (dotted-dashed), 75% (dashed), 50% (dotted), 25% (dashed), 2.5% (dotted-dashed), minimum values (solid), across the climate model ensemble. The thick solid line corresponds to the control rule described in the text. Blue and green crosses indicate storage levels simulated by LANCMOD using observed flows and simulated historical flows respectively. Red crosses correspond to storage levels for the CPDN model run with standard values of the physical parameters.

4.4 Adaptation and management options under climate change

Various changes can be made to the water resource model set-up to explore how different adaptation strategies can decrease the risk of supply failure in the future, and thus make the system more resilient to climate change. Options include reducing demands to comply with water saving policies, increasing the volume of water available in the reservoirs, reducing the transfer of water outside the catchment, increasing the pumping rate to the reservoir, and changing the control rules that govern the river abstractions reducing the flows maintained for the environment.

The above is simply a list of changes that could be simulated given our water resource model. In a real situation, the path chosen to adapt to possible impacts of climate change will depend on many factors that include, but are not limited to, the climate information. In particular, issues such as the cost of the different options, their impacts on the environment, public response, technical feasibility, as well as demographic and water use changes, will play important roles in the decision.

Here we show the results for two different scenarios that can be simulated by making minor changes to LANCMOD set-up, one based on consumption reduction, one on increasing supply. Other management possibilities are discussed in the paper by Lopez *et al*. (2009) in Appendix II.

For the purposes of this study, we have assumed that the baseline household demand in the area is 150 l/h/d, the current average for England and Wales. The recent UK government water strategy (Defra (Department for Environment, Food and Rural Affairs), 2008) aims for this to reduce to 130l/h/d, suggesting that a reasonable scenario for demand reduction would be about 15 per cent less than the current figures. In this scenario, we are implicitly assuming that non-household and other demands also fall by the same proportion.

Since the two most significant demands through the year are East Devon and Somerset combined with Peak demand, we devise a scenario in which these are reduced by 15 per cent, amounting to an annual average reduction of about 28Ml/d. This approach assumes that a water saving strategy is put in place, and other factors, such as population changes, remain constant.

If demand reduction alone is implemented, much of the effect of drier summers can be alleviated: many more models exceed any given storage threshold compared to the business as usual scenario. For example, the storage level exceeded by half the models in the 2070s shifts from 30 per cent under business as usual to 40 per cent when the demand reduction is implemented. Furthermore, the risk of occurrence of very low reservoir levels across the ensemble, as indicated by the 2.5 percentile, is delayed from the 2030s under business as usual until the 2070s under demand reduction.

An alternative to reducing demand is to add another source of water. One way to do this in LANCMOD is to increase the size of the reservoir. Although this may not be feasible in practice for Wimbleball, increasing reservoir size is often an option, as it is relatively uncontroversial and often cost-effective. It is also an easy way to represent an additional source of water within the current model set-up. Increasing the depth of the reservoir by one metre augments the storage from 21,320Ml to 25,075Ml, an increase of 18 per cent in the volume of water stored. Since we do not change any other parameter in the model, such as link capacities or control rules, the limitations in the amount of water that can be released into the system will still be controlled by these factors. However, the fact that the reservoir can store more water during the periods of high flows changes the behaviour of the reservoir in relation to other scenarios.

When the reservoir capacity is increased without reducing demand, we see that the behaviour of the 50th percentile is similar to the demand reduction case (Figure 0.3 top), improving the chances of having the reservoir half full as compared with the business as usual scenario. However, the risk of very low reservoir levels as indicated by the 2.5 percentile does not change significantly compared to the demand reduction scenario, suggesting that even though there is more storage capacity within the system, river flows across the ensemble are not enough to make use of this greater capacity in the driest years.

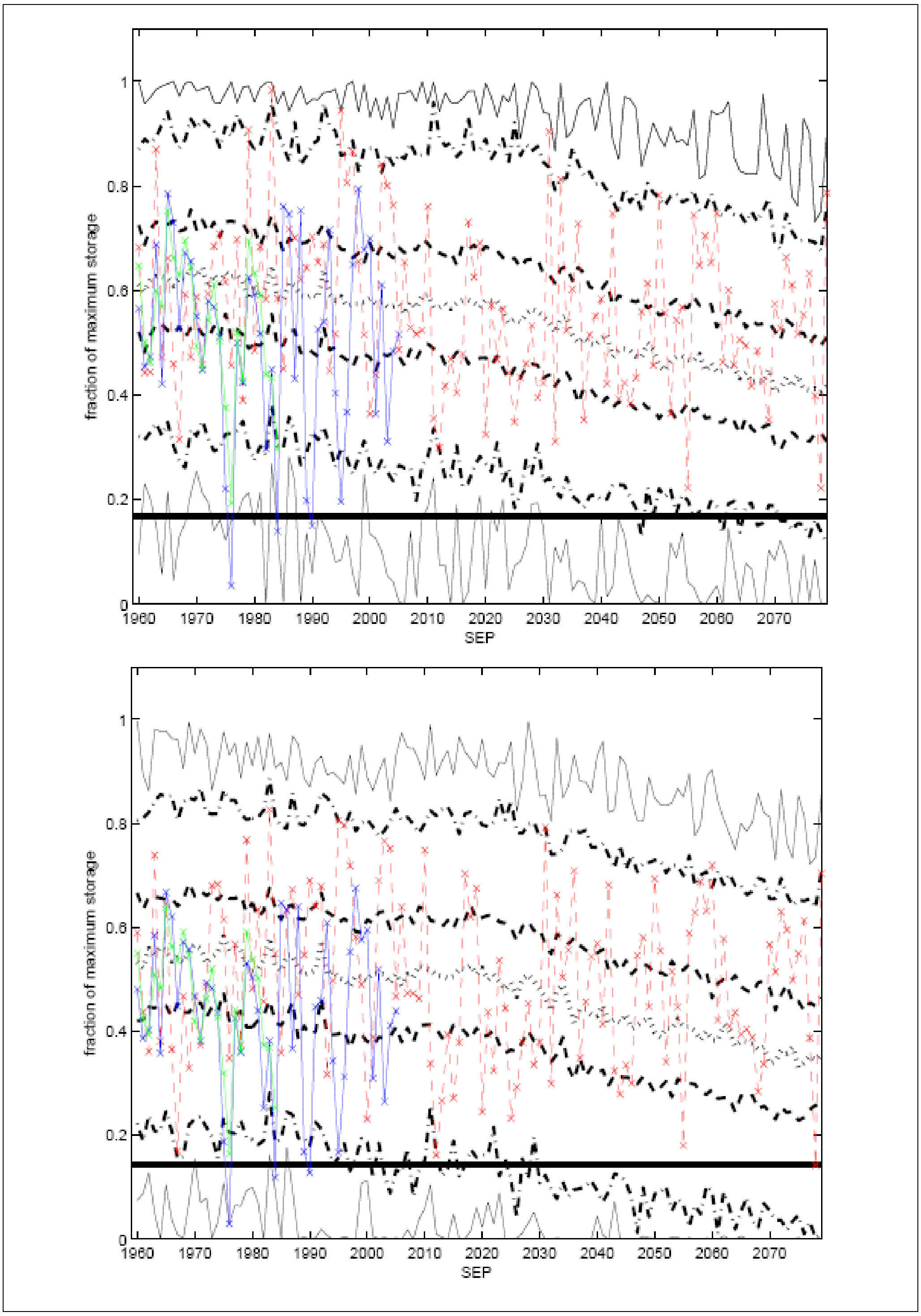


Figure 0.3 Wimbleball storage levels as a function of time (September) for main demands reduced by 15% (top), and Wimbleball storage increased by 18%(bottom) management scenarios. The black lines represent from top to bottom: maximum values (solid), 97.5% (dotted-dashed), 75% (dashed), 50% (dotted), 25% (dashed), 2.5% (dotted-dashed), minimum values (solid), across the climate model ensemble. The thick solid line corresponds to Wimbleball control rule. Blue and green crosses indicate storage levels simulated by LANCMOD using observed flows and simulated historical flows respectively, and are included here for reference. Red crosses correspond to storage levels for the CPDN model run with standard values of the physical parameters.

The scenarios proposed here are simple options that can be easily implemented with LANCMOD, and allow us to describe how the system responds and whether there are any physical limitations imposed by, for instance, lack of water available to be stored in the system. In a more realistic situation the path chosen to adapt to possible impacts of climate change will depend on many other factors that include the climate information, but are not limited to that. This will require an integrated assessment of possible adaptation strategies, taking into account issues such as the cost of the different options, their impacts on the environment, public response, technical feasibility, population and water use changes.

This study demonstrates the value added by the use of large climate model ensembles as opposed to a small number of scenarios used in impact studies to date. It is clear that a single HADCM3 model run fails to capture the full range of climate possibilities and might lead to false confidence, suggesting in our case that there is no need for intervention while the full ensemble indicates the need for adaptive management. Moreover, the ensemble information provides a particularly effective way to consider the benefit of different management options in a way that a limited number of scenarios would not. We expect that the overhead in additional time and expertise needed to carry out the impact analyses will be justified by the increased quality of the decision making process.

It is clear that adaptation to climate change is often context-specific. Different sectors will have different climate information needs and more or less sophisticated approaches to using this information for impact analysis. In this sense, the UK water sector is perhaps better prepared than other industries to undertake the challenge of using large ensembles of climate models since it already possesses hydrological and water resource management models potentially adaptable to the novel climate data. However, even though our case study is specific to the water sector, the key conclusions regarding the value added by the use of large climate model ensembles in impacts studies can be generalised to other sectors.

5. Case study 3: The role of climate model ensemble information in river ecology management

5.1 Introduction

This case study attempts to use tools that already exist within the Environment Agency to provide some indication on how probabilistic climate scenarios can be used in the realm of river ecology. The River Itchen was chosen as the case study catchment on the strength of having a relatively long-term ecological and flow dataset (from 1978 to 2002) and having been an area of intensive study in the past. It is a chalk stream located in the south of England and a candidate Special Area of Conservation (SAC). It has also been designated a Site of Special Scientific Interest (SSSI), achieved due to the number of rare species and the richness of the macro-invertebrate community in the river catchment.

The same transient ClimatePrediction.net simulations desrcibed in the Wimbleball case study, were used to drive CATCHMOD and test the effect on LIFE score thresholds (Extence *et al.*, 1999). Environmental thresholds had previously been derived during the development of the Catchment Abstraction Management Strategy (CAMS). A new form of representing the results is presented that allows expert opinion to be canvassed, and adaptation measures have been explored.

5.2 CAMS ecological threshold tests

One of the CAMS targets is based on the observed long-term averaged summer Q95 averaged over the period of 1970 to 2002. In Figure 0.1, the grey lines represent the mean summer Q95 averaged over the previous 30 years and each line is calculated from the flow generated by a single CATCHMOD run using climate data from one member of the CPDN climate ensemble. Therefore the grey plume represents the whole 246 member ensemble of CATCHMOD runs. The black lines summarise the distribution across the ensemble: the bottom line is the 95th percentile, indicating the flow which 95 per cent of all runs exceed. To demonstrate the added-value of the information provided by the ensemble, the standard run is represented by the green line. This is the run that uses climate parameters from the GCM model that has an unperturbed parameter set analogous to using one GCM and one emissions scenario.

Approximately 25 per cent of runs show a rise in the summer Q95 up to the 2030s, and thereafter all runs show a decreasing mean summer Q95. The width of the plume of values for each year also increases through time, representing increasing uncertainty as the GCM attempts to predict further into the future.

This ecological target flow was set at a conservative level (Exley, 2006) and such that the breaching of this threshold was not expected. However, according to the ensemble, 25 per cent of the runs will have a long-term summer Q95 at a level where the invertebrate community will be changing by the late 2070s.

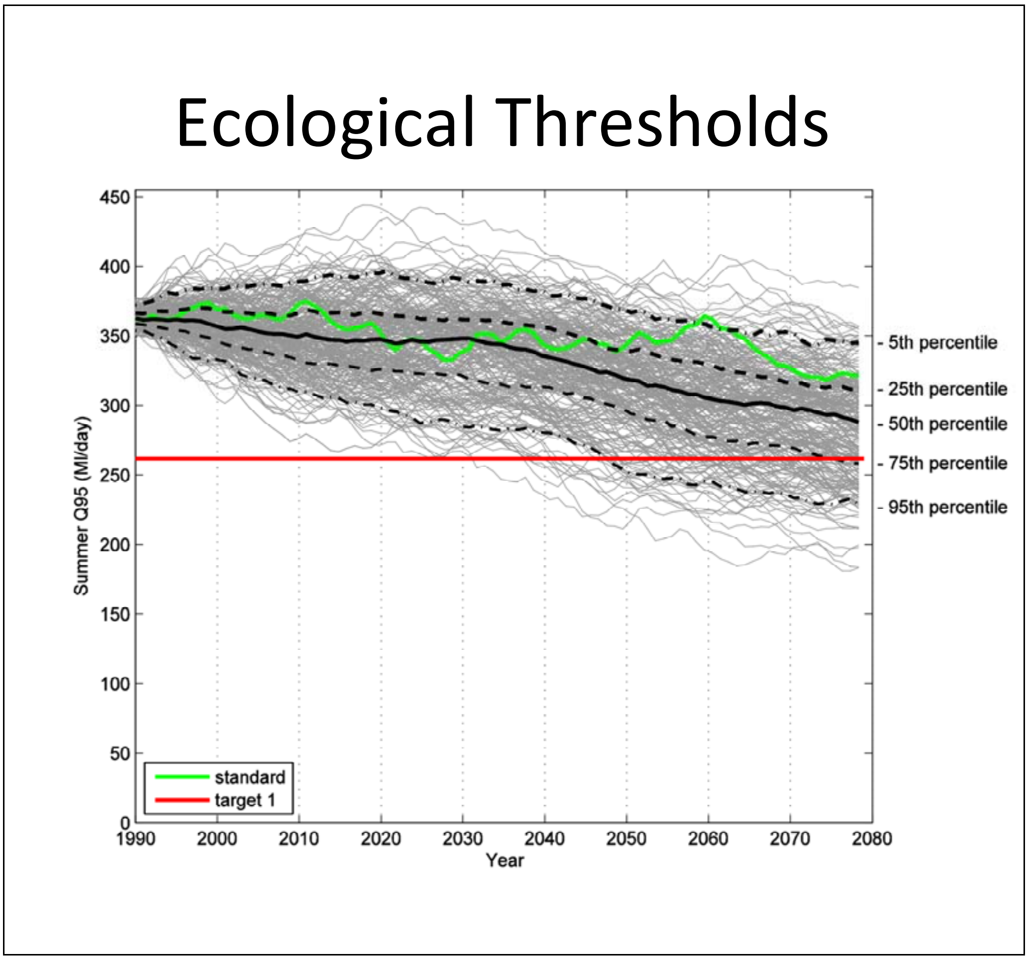


Figure 0.1 Mean summer Q95 with moving 30-year window for naturalised flows.

5.3 Ecological matrix

To provide a richer story, a matrix is proposed for analysing the effects of the river on biodiversity which combines both the thresholds described in detail in Appendix I and expert opinion on how the ecology of the River Itchen will react to climate change. On one axis of the matrix is the duration of the low flow (or the number of consecutive years of low flow). On the other axis is the extent (or the value of the annual Q98). In each of the matrix cells is a qualitative description of the ecological status of the river (see Table 1).

The matrix has been used to analyse the percentage of ensemble members that experience each of the river ecology impacts at selected time horizons, colour coded into five categories representing the percentage of runs that fall into each part of the matrix.

The figure shows that in the 2020s, in more than 50 per cent of runs, there is a high risk of the invertebrate community being harmed, followed by a chance that recovery may not occur once higher flows return. By the 2070s, over 25 per cent of runs show high risk of damage to the invertebrate community with an equal percentage of runs showing that there will be either recovery or a permanent change in the community. As the twenty-first century progresses, the colours towards the top left of the matrix become bluer, and the middle to bottom right change towards orange, representing a growing risk of the invertebrates being harmed. However, in this set of simulations, the risk of a highly modified community remains less than five per cent.

Ecological Impacts Matrix

	1 year only	2-4 consecutive years	> 5 consecutive years
Upper flow warning band (198 - 262Ml/day)	No adverse impacts on invertebrates and overall ecology of river remains healthy	Some risk of invertebrate community being harmed but recovery possible	High risk of community changing with some chance of recovery
Lower flow warning band (157 - 198Ml/day)	Some risk of invertebrate community being harmed but recovery possible	High risk of invertebrate community changing but with high chance of recovery	High risk of community changing with some species remaining
Below flow warning band and RAM threshold (< 157Ml/day)	Invertebrate community harmed and some risk that recovery is not possible	High risk of invertebrate community changing permanently to slow flow-type communities	Highly modified community more typical of arid environments could develop, including species with adaptive strategies enabling survival over extended periods of drought. Iconic species such as salmon, lamprey, otter no longer present

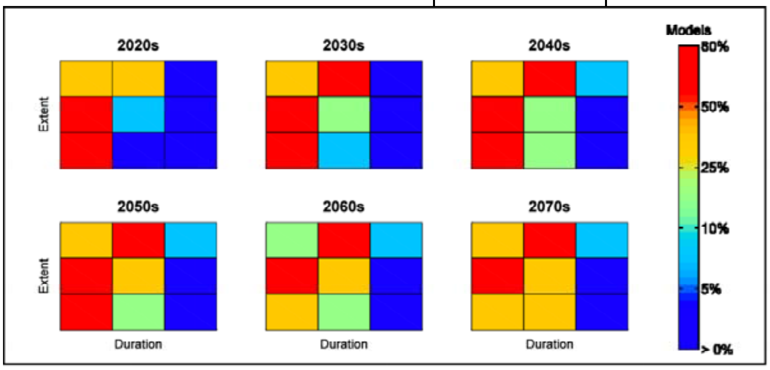


Figure 0.2 Matrices of climate change impacts on ecology of River Itchen through the twenty-first century.

5.4 Adaptation through river support

The annual augmented flow required each year to sustain daily flow such that it does not reach the flow threshold of a value of 262 Ml/day is plotted in Figure 0.3. Each grey dot represents the total augmented flow for each year for each CATCHMOD run. For years where there is no augmentation, a dot is not plotted, hence the broken lines for the percentile plots, for example the 25th percentile shows one value for 2026 and 2030 but no values in between, meaning that no augmentation was required for at least 25 per cent of the runs during this period.

The results show that up to the mid-2020s, only 5 per cent of the runs require augmentation. However by the 2060s, 50 per cent of the runs need additional flow and as time progresses, the amount of flow increases. For example in the mid-2040s the flow required by 50 per cent of runs is of the order of 10Ml/year, however by the 2070s this increases by one order of magnitude to over 100Ml/year.

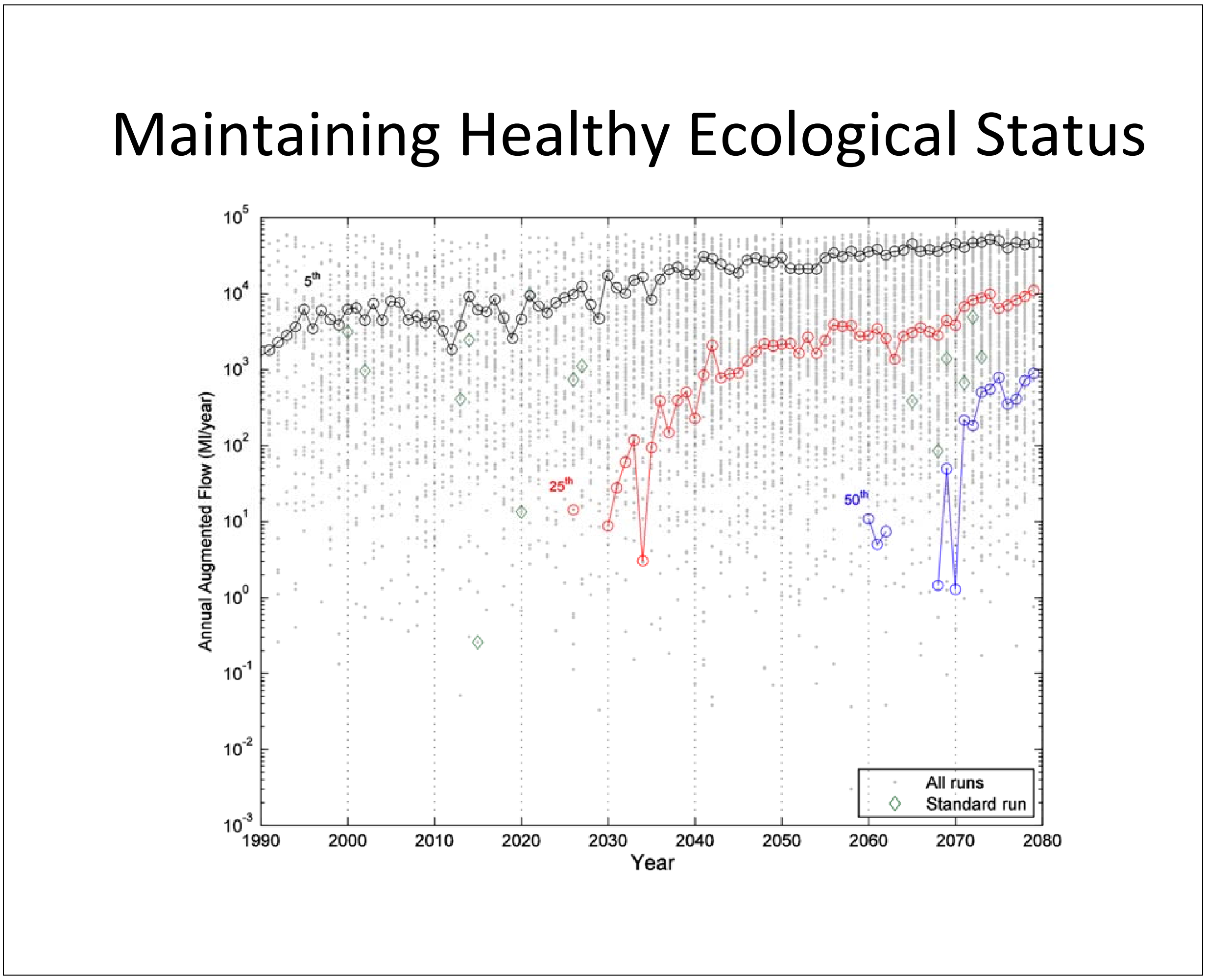


Figure 0.3 Time series of volume of annual augmented flows required to maintain healthy ecological status. Individual grey dots represent total augmented flow in one year for one CATCHMOD run. Green diamonds mark the results for the standard run. The black, red and blue lines represent the total annual augmented flow that 5%, 25% and 50% of the ensemble exceeds respectively.

6. Discussion

In this section, a number of the problems that were encountered in the study are identified and suggestions for improvements to the whole process are proposed.

6.1 Case studies and UKCIP

In anticipation of new probabilistic scenarios for the UK from UKCIP in the spring of 2009, there is great interest in how probabilistic information can be used in decision-making; indeed, this is one of the motives for this study. Any direct comparisons between these projections and the information used in the case studies in this report should be made with caution, as the methodologies in producing the climate change projections are very different. The UKCIP methodology provides the projections as probability density functions (PDF) whereas the frequency distributions arising from the ClimatePrediction.net ensembles for the case studies presented in this report are not PDFs.

A key feature of the UK Climate Projections (UKCP) is that the future climates are presented as probabilities. Instead of a single best estimate of the change for each emission scenario, users are provided with a range of possible climates, each variant of which has a measure of the relative strength of evidence that supports it (interpreted as probabilities). These probabilities are not predictions of the real climate probabilities, but rather statements of the extent to which various possible future climates are consistent with the evidence considered.

The way the probabilistic projections have been established is described in the UKCP science reports. The approach combined outputs from the Met Office Hadley Centre (MOHC) climate models (HadCM3 and HadRM3) and outputs from climate models produced by other modelling centres. This involved running alternative simulations of the MOHC climate model in which a number of the parameters that represent physical processes within the model are varied within physically plausible limits (the perturbed physics ensemble described previously). The introduction of the outputs from climate models produced by other modelling centres (multi-model ensemble) brought into the projections consideration of uncertainties as a result of different model structures.

In addition to the probabilistic enhancement of the projections, UKCP will also have a number of other changes from UKCIP02 (UKCP, 2009) . The spatial resolution of the projections is 25km (whereas UKCIP02 is 50km) and in terms of the temporal resolution, although the projections are still presented as 30-year monthly, seasonal and annual averages, there are seven 30-year time periods covering the period from 2010 to 2100. Additionally, projections are presented for three emission scenarios. The emission scenarios labelled ‘high’ and ‘low’ in UKCP09 are the same as those used in UKCIP02. The ‘medium-low’ and ‘medium-high’ emission scenarios used in UKCIP02 have been replaced by a single ‘medium’ emission scenario (SRES A1B). A further enhancement is the availability of a user interface through which users will be able to interactively access and download the available projections and produce graphics.

An additional functionality included as part of UKCP09 is a weather generator that can be used to produce daily and hourly time series consistent with the probabilistic climate projections. Access to this weather generator and its accompanying threshold detector, as well as downloading the resulting time series, is achieved through the previously mentioned user interface.

In order to obtain the multi-year time series of daily of precipitation and potential evaporation necessary to run the hydrological and water resource models described in our case studies, the weather generator in UKCIP09 will have to be used to generate daily data. It is clear from our work that it is very important to understand long-term variability correctly for water resource management and ecological impacts, since both systems would be sensitive to, for instance, a run of two or three consecutive drier than average seasons.

However, the weather generator is programmed to randomly generate daily (or sub-daily) series conditional on the statistics of each individual month, and cannot produce information regarding changes in variability on time scales larger than a few weeks (Kilsby *et al.*, 2007). Therefore any time series generated by the weather generator will not have information about the long-term inter-annual variability of the climate variables, seriously limiting the applicability of this approach to the study of climate change impacts on water resource systems.

6.2 Links with other Environment Agency projects

A number of studies commissioned by the Environment Agency are particularly relevant to this project, including:

- **Climate change and river flows in the 2050s (conducted by the Centre for Ecology and Hydrology)**. Using UKCIP02 climate scenarios the impacts of climate change on UK rivers was investigated. These used high, medium and low scenario results from regional climate models. The river flows predicted by the Environment Agency using CATCHMOD and Hydrosolutions appear to be very different and are currently being considered by the Environment Agency. Note that the procedure concentrated on ungauged sites.
- **DRIED-UP 1 and 2**. As mentioned throughout the ecology case study, the recent work carried out by Dunbar *et al.* (2006) and Dunbar and Mould (2008) show that the sensitivity and uncertainty in the statistical models built to relate river flow and LIFE score is highly relevant and could change the sensitivity of the study. However, the conclusions in terms of the usability of probabilistic scenarios remain unchanged.
- **Probabilistic information to inform Environment Agency decision-making on climate change impacts**. The UKCIP will be released later in 2009 and the Environment Agency has commissioned a project related to how UKCIP can be used to look at the impacts of climate change on its activities. The case studies presented in this report will inform the Environment Agency's UKCIP project.
- **Water temperature archive (SC070035)**. The archive of water temperature data across England and Wales may be used to develop better ecological response models that can be used in future climate change impact studies.
- **Ecoforesight (SC080009)**. This ongoing project looks at Environment Agency biological data across England and Wales to see whether there has been any response to recent climate changes. The datasets and methods used may also help us develop better ecological models and support future impact studies.

6.3 Lessons learned and future challenges

Overall comments

This study has required a multi-disciplinary approach, involving climate, hydrological and ecological scientists. At the project start-up meeting, many members of the ecological and water resources community in the Environment Agency were consulted. This was an extremely useful process which helped raise relevant issues and allowed stakeholders to become familiar with probabilistic approaches. However, with a major topic such as climate change, this case study can only address a small number of issues, not just because of resource constraints but also the type of work possible given the type of information that is available from climate scenarios. It appears that a key message needs to be conveyed about the limits of climate change impacts assessments: impacts can only be assessed if models exist that can be related to climate variables. Moreover, for large climate model ensembles, these impacts models must be able to run several hundreds, if not thousands, of times.

However, this work has shown that where a suitable impacts model exists and sufficient understanding is available on ecological responses to changing local flow conditions, then taking an ensemble approach to assessing future conditions does provide a richer picture of potential future impacts than single GCM applications. In particular, this approach provides a better indication of potential future risk.

It should be noted that the river ecology study was focused on future climate impacts on flows and low flows in particular. However, there could also be high flow impacts arising from climate change, for example washout of invertebrates with increase in spate flows or increased mobilisation of sediments related to intense rainfall events. Such events may become more frequent and could be particularly problematic in the summer, when mobilised sediments may “stick” in the river if flood events are followed by normal or reduced summer discharge patterns. Although suitable models of temperature changes would be particularly useful in helping assess the combined effects of changing temperatures and water quality impacts, these models are yet to be developed

Ecological data and modelling

In the UK, there is a lack of good long-term coupled flow and ecology datasets and most modelling efforts so far have used statistical methods. A problem encountered in this study was the projection of scenarios which have no precedence in the observed dataset, which brought difficulties when trying to interpret the implications on taxa. There appears to be some efforts in the DRIED-UP 2 project to couple long-term ecological datasets with model output from continuous estimation of river flows (CERF), which will hopefully fill in some of the knowledge gaps, for example for multi-year droughts. There is also the potential to look at ecological impacts from historic power station outflows to understand the effects of much higher temperatures.

Although uncertainty was explored in this study, the focus was mainly on the range of possible climate futures, and although confidence limits were used to establish the flow warning band to provide a range of possible flows that indicate community change, no formal assessment of the uncertainty in the relationships developed in the statistical modelling was performed. Future work should attempt to address these matters too.

Ecological impacts

Unfortunately, the lack of data on ecological response to climate shifts or extreme events also presents difficulties in the assessment of adaptation options as little quantitative data is available in determining the effects of different measures on river ecology. However, the DRIED-UP projects commissioned by the Environment Agency suggest that looking at the response and sensitivity of LIFE scores with river modification may provide some new quantitative tools to assess the impact of various adaptation pathways.

River flow modelling

Although CATCHMOD was used in this study, the Environment Agency has provided considerable resources to set up a model, MODFLOW, which captures groundwater processes in a more sophisticated manner. The model contains 50,000 cells and is computationally intensive, requiring several hours to complete a run (CATCHMOD takes several seconds). The climate data available is sourced from one GCM box and downscaling procedures to convert this information to finer resolutions in both time and space is still a very new science. With the limited climate information and the computer resources available, CATCHMOD was deemed more appropriate for the task. However, the available parameterised CATCHMOD model for the Itchen was not set up with abstraction information. Although this was not essential in this study, it is envisaged that when a more predictive tool is required by the Environment Agency abstractions may become important. But whether a more sophisticated model, like MODFLOW, will be a more suitable tool for this type of analysis is unclear.

References

DEFRA (Department for Environment, Food and Rural Affairs), 2008. Future Water: The Government's water strategy for England. (ed. Affairs, D. f. E. a. R.).

DUNBAR, M. and MOULD, D.,2008. Distinguishing the Relative Importance of Environmental Data Underpinning flow Pressure assessment (DRIED-UP) 2. *Environment Agency Report*.

DUNBAR, M., YOUNG, A. and KELLER, V., 2006. Distinguishing the Relative Importance of Environmental Data Underpinning flow Pressure assessment (DRIED-UP). *Environment Agency Report***,** 67.

EXLEY, K., 2006. River Itchen Macro-Invertebrate Community Relationship to River Flow Changes. *Environment Agency Report*.

EXTENCE, C. A., BALBI, D. M. and CHADD, R. P., 1999. River flow indexing using British benthic macroinvertebrates: A framework for setting hydroecological objectives. In *Regul River*, Vol. 15 pp. 543-574.

FUNG, C.F., LOPEZ, A., NEW, M., WATTS, G., EXTENCE, C. AND ORR, H., 2009. The implications of using large ensembles of climate scenarios for the management of river ecology in a chalk stream in the South of England. *River Research and Applications*, In preparation.

GIORGI, F. and FRANCISCO, R., 2000. Evaluating uncertainties in the prediction of regional climate change. *Geophysical Research Letters,* **27,** 1295-1298.

INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE (IPCC), 2000. *Emissions Scenarios. A Special Report of IPCC Working Group III.,* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

KILSBY, C. G., JONES, P. D., BURTON, A., FORD, A. C., FOWLER, H. J., HARPHAM, C., JAMES, P., SMITH, A. and WILBY, R. L., 2007. A daily weather generator for use in climate change studies. *Environmental Modelling & Software,* **22,** 1705-1719.

LOPEZ, A., FUNG, C.F., AND NEW, M., 2009. From climate model ensembles to climate change impacts: A case study of water resource management in the South West of England. *Water Resources Research,* **Submitted**.

MURPHY, J. M., SEXTON, D. M. H., BARNETT, D. N., JONES, G. S., WEBB, M. J. and COLLINS, M., 2004. Quantification of modelling uncertainties in a large ensemble of climate change simulations. In *Nature*, Vol. 430 pp. 768-772.

NEW, M., LOPEZ, A., DESSAI, S. and WILBY, R., 2007. Challenges in using probabilistic climate change information for impact assessments: an example from the water sector. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* **365,** 2117-2131.

SOLOMON, S., QIN, D., MANNING, M., CHEN, Z., MARQIS, M. and AVERY, K., 2007. *IPCC 2007: Climate Change 2007: The Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change,* Cambridge University Press, Cambridge, United Kingdom and New York,USA.

STAINFORTH, D. A., AINA, T., CHRISTENSEN, C., COLLINS, M., FAULL, N., FRAME, D. J., KETTLEBOROUGH, J. A., KNIGHT, S., MARTIN, A., MURPHY, J. M., PIANI, C., SEXTON, D., SMITH, L. A., SPICER, R. A., THORPE, A. J. and ALLEN, M. R., 2005. Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature,* **433,** 403-406.

UK CLIMATE IMPACTS PROGRAMME (UKCIP), 2009. UK Climate Projections 2009

WILBY, R. L., 2005. Uncertainty in water resource model parameters used for climate change impact assessment. *Hydrological Processes,* **19,** 3201-3219.

Glossary

A1B	One of the scenarios described in the IPCC's Special Report on Emissions Scenarios (IPCC, 2000). It represents a world in the twenty-first century with very rapid economic growth, rapid introduction of new and more efficient technologies and a world that does not rely too heavily on one particular energy source.
CPDN	ClimatePrediction.net.
Emissions scenarios	Future levels of global greenhouse gas (GHG) emissions, and by association future climate, are a product of very complex, ill-understood dynamic systems, driven by forces such as population growth, socio-economic development and technological progress. Scenarios are images of the future, or alternative futures. They are neither predictions nor forecasts. Rather, each scenario is one alternative image of how the future might unfold.
Equilibrium experiment	In the $1xCO_2$ control simulation the model is run with pre-industrial concentrations of carbon dioxide. In the $2xCO_2$ phase, the carbon dioxide atmospheric concentration is instantaneously doubled and after a transient or time dependent phase where all the climate variables change in time as a response to the instantaneous change in atmospheric carbon dioxide concentration, the model moves towards reaching a stationary or time independent phase. In other words, the climate variables reach equilibrium. This experiment is designed to investigate the characteristics of the equilibrium state reached by the atmosphere after a sudden doubling of carbon dioxide concentrations.
GCM	Global climate models
HadCM3L	A version of the UK Met Office Unified Model comprising a standard resolution atmospheric model coupled to a lower resolution ocean model. A lower resolution ocean has the same resolution as the atmospheric model, while in the standard HadCM3 model the ocean runs at a higher resolution than the atmospheric model, particularly near the equator.
HadSM3	This version of the model always uses a global domain, and usually includes a sea ice submodel as part of the slab ocean. It is primarily used for short climate sensitivity experiments, and for examination of equilibrium climate change responses in comparison to transient responses from the full model.
IC Ensemble	Initial conditions ensemble.
IPCC	Intergovernmental Panel on Climate Change.

PPE	Perturbed physics ensemble.
SRES scenarios	Scenarios from the “Special Report on Emissions Scenarios” (IPCC, 2000).
Transient experiment	An experiment where a comprehensive atmosphere–ocean model such as those contributing to the last IPCC report is forced by greenhouse gas concentrations that vary in time.
UKCIP	UK Climate Impacts Programme.
UKCP	UK Climate Projections.

Appendix I: Water resources case study

From climate model ensembles to climate change impacts: A case study of water resource management in the South West of England.

Ana Lopez*, Fai Fung, Mark New
Climate Systems and Policy Group, School of Geography and Environment
Oxford University Centre for the Environment,
South Parks Rd, Oxford, OX1 3QY, U.K.

Glenn Watts
Environment Agency, Science Department, Government Buildings,
Westbury-on-Trym, BS10 6BF, UK

Alan Weston
Environment Agency, Manley House, Kestrel Way, Exeter EX2 7LQ, UK

Rob Wilby
Lancaster Environment Centre, Farrer Avenue, Lancaster, LA1 4YQ, UK

• Email:ana.lopez@ouce.ox.ac.uk

Abstract:

The majority of climate change impacts and adaptation studies so far have been based on at most a few deterministic realisations of future climate, usually representing different emissions scenarios. Large ensembles of climate models are currently available either as ensembles of opportunity, or perturbed physics ensembles, providing a wealth of additional data that is potentially useful for improving adaptation strategies to climate change. With the release of the UK 21st Century Climate Scenarios (2008), UKCIP08, users from different sectors will have access to probabilistic projections of climate change for the UK. Due to the novelty of this ensemble-like climate change information, there is little previous experience of practical applications or of the added value of this information for impacts and adaptation decision-making. Here we describe a methodology to perform a top-down approach to impacts assessment using large ensembles of climate change information. We use as a case study a water resource system in the South West of England. The climate data are obtained from the largest perturbed physics ensemble publicly available to date, climateprediction.net. River flows are simulated using a rainfall runoff model and feed into the water resource system model. This model is designed to analyse the interactions between water supply and demand for the water supply zone of interest, allowing for the exploration of various adaptation paths given the climate change information available. We analyse the response of the water resource system when driven by the climate model ensemble data, and operating under different scenarios of demand and supply management. Our research shows that the additional information contained in the climate model ensemble provides a better understanding of the possible ranges of future conditions, compared to the use of single model scenarios. Furthermore, with careful presentation, decision-makers will find the results from large ensembles of models more accessible and be able to more easily compare the merits of different management options and the timing of different adaptation. The overhead in additional time and expertise for carrying out the impacts analysis will be justified by the increased quality of the decision making process. We remark that even though we have focused our study in a water resource system in the UK, our conclusions about the added-value of climate model ensembles in guiding adaptation decisions can be generalized to other sectors and geographical regions.

1 Introduction

Global climate models (GCMs) forced by scenarios of greenhouse gases predict significant changes in Earth's climate in this century (Solomon et al. 2007). However, the range in the projections is in some cases very large, in particular at the regional and local scales relevant for the analysis of impacts and adaptation options in the face of climate change. To deal with this problem we need to be able to quantify the uncertainty in GCM projections. Several sources of uncertainty are present in GCM's simulations, including forcing, initial conditions, model formulation and model inadequacy (Stainforth et al. 2007). Recently, perturbed physics ensembles (PPEs) have been developed in an attempt to quantify initial condition and model formulation uncertainty (Murphy et al. 2007; Murphy et al. 2004; Stainforth et al. 2005) . These ensembles comprise a large number of runs of a state of the art climate model. Each individual run uses a model with parameters representing various physical processes set to different values within their acceptable range, as defined by the experts in each particular area of physics parameterisation. For each combination of parameter values an initial condition ensemble is used. PPEs provide a new approach for exploring a wide range of future climates and use this information to assess potential impacts of climate change. In this work we concentrate on climate model uncertainty, discussing the use of a large PPE to provide information for the study of impacts and adaptation to climate change in a water resource system.

The PPE is part of the climateprediction.net (CPDN) project, the largest PPE experiment to date, here comprising a set of model runs obtained by perturbing twenty-six parameters in a version of the Hadley Centre GCM, HADCM3L. We apply the CPDN projections to the Wimbleball water resource zone in the South West of England. This zone has a variety of sources of water, which allows some flexibility in the choice of adaptation measures, but at the same time is simple enough to make the analysis transparent. We make use of CATCHMOD and LANCMOD, generic rainfall-runoff and water resource system models used by the Environment Agency of England and Wales for behavioural analysis of water resources supply systems.

In the process of translating the climate model outputs into the appropriate inputs for the hydrological and water resource models, we make some simplifying assumptions. Firstly, we consider a PPE based on only one "parent" GCM, ignoring any model formulation uncertainty (commonly termed model structure uncertainty). Secondly, we use the individual model runs in the PPE without any prior evaluation of skill or adequacy of each run in representing the climate system (i.e., an un-weighted assessment). We also use a relatively simple procedure to downscale GCM-resolution data over the South West of England to the spatial and temporal scales appropriate for the hydrological system, ignoring possible additional sources of uncertainty in the downscaling process.

Our choice of these simple methodologies is justified because our goal is to explore in what sense, if any, information from a PPE is useful and represents an improvement compared to the use of a single/few model scenarios. Our exploratory analysis does not therefore represent a robust prediction of climate change or impacts, but illustrates the potential for using large PPEs in adaptation decision-making.

We will see that there are basically two advantages in using large ensembles like climateprediction.net data over other sources that provide just change factors at different time slices in the future, or single model scenarios. In the first case, CPDN stores time series of climate variables from each ensemble member, providing time dependent information extremely valuable for water resources management. As this time dependent information has been generated by a fully dynamical climate model, we can assume that it provides a range of future possible evolutions of the climate system consistent with the current state of the art climate science. This means that we can look at relative changes in time in the frequency of occurrence of different events of interest. This is an important issue given that we are trying to quantify the impacts on water supply infrastructure and management of changes in a non-stationary system.

In the second case, we will see that the use of just one realization of future climate can give a false sense of security and does not provide the rich picture that the ensemble does. Moreover, our results strongly indicate that the practice of using a single model run, or for that matter ensemble means instead of the individual model runs, can be misleading when analysing impacts of climate change.

The paper is organised as follows. In section 2 we introduce the PPE climate model data and describe how we use it to simulate the catchment river flows using the hydrological model CATCHMOD. We also describe the basic features of the water resource management model LANCMOD. In section 3 we discuss the results obtained when LANCMOD is run into the future with climate change projections under a "business as usual" demand and supply-infrastructure scenario. In section 4 we analyse how these results change under different scenarios of demand and supply infrastructure that could be implemented to adapt or manage the effects of climate change in the future. In section 5 we summarize our results and discuss their implications for impacts studies beyond this particular case study.

2 Data and methods

The water resources system LANCMOD requires daily time series of river flows at different water abstraction points. In this section we firstly describe the CPDN experiment and the downscaling and bias correction techniques that we utilize to adjust GCM monthly time series to the appropriate daily input for the CATCHMOD rainfall-runoff model. We then describe CATCHMOD and the main characteristics of the simulated river flows. Finally, we describe the main features of LANCMOD when set up to simulate Wimbleball water resource zone.

2.1 CPDN and climate data:

The climate data used in our analysis has been generated by CPDN second experiment launched in February 2006. The GCM used is the HADCM3L, a version of the UK Met Office Unified Model comprising a standard resolution atmospheric model coupled to a lower resolution ocean model. The experiment explores the effects of perturbing twenty-six parameters that are relevant to the way radiation, large scale clouds formation, ocean circulation, sulphate cycle, sea ice formation, the land surface and convection are simulated by the GCM[1].

Each simulation involves a 160-year control run with constant forcing at pre-industrial concentrations and a 160-year transient run. The transient simulations include two phases. In the first phase from 1920 until 2000 the experiment is forced with historical

[1] For information on the experimental set up including a description of perturbed parameterisations, forcing scenarios and data available see http://www.climateprediction.net and http://results.cpdn.org.

records of CO_2, volcanic and anthropogenic emission, and solar forcing. In the second phase, a range of possible future scenarios are used to force the model response between 2000 and 2080.

Climateprediction.net is an ongoing experiment in which individual model simulations are carried out using idle processing capacity on personal computers volunteered by members of the general public. In our study, we concentrate on the first 246 transient simulations that were completed, and which are now part of the much larger ensemble of completed simulations. Within this subset, all model runs were subjected to the A1B SRES forcing scenario. One member of the ensemble has the standard (un-perturbed) values of the model parameters used in earlier single model scenario simulations by the UK Met Office. In the rest of the paper this particular model run is termed the *"standard version"* of HADCM3L.

The CPDN experiment archives a variety of climate variables at different temporal (monthly to decadal means), and spatial scales (grid points to continental averages). Monthly time series are available, for several variables, as the global mean, the area average over 22 continental to sub continental regions similar to those defined by Giorgi and Francisco [2] (Giorgi; Francisco 2000), for six ocean "basins" and for eight individual grid boxes over the United Kingdom. We use monthly time series of temperature, precipitation, and relative humidity for the grid box corresponding to the South West of England (48.75N ,5.625W – 51.25N 1.875W).

We also make use of observed data, which comprises daily time series of precipitation, potential evaporation (PET) and naturalised river flows. These data were provided by the Environment Agency of England and Wales and are used in the operation of existing operational hydrological and water resources models. Precipitation data are the area average over the Thorverton catchment derived using three groups of rain gauges for the period 1930-1984. Potential evaporation is an area average over the catchment, estimated based on a regression with Central England temperature record for 1930-1960, and MOSES v2 data for 1961-1984. River Exe flows at Thorverton are naturalized flow sequences from 1957-2005.

The hydrological model that we use to simulate daily discharge in the River Exe at Thorverton is CATCHMOD which requires daily time series of precipitation and potential evaporation to simulate runoff. Thus we describe in detail these time series before concentrating on the simulation of river flows.

Precipitation:

Area-average monthly precipitation for the GCM grid box over SW England is available directly from the CPDN model runs. The simulated precipitation shows a seasonally varying bias when compared to the observed rainfall (Figure 1), underestimating the mean monthly values for all model runs, especially during the summer months. This is not a surprising result, as strong biases are often found in climate model simulations, particularly when looking at individual grid boxes rather than larger regions or continents. As the hydrological model is parameterised to simulate river flows when driven by observed rainfall, any large biases in simulated precipitation will force the model to work

[2] These regions are defined as rectangles covering the same land area as the Giorgi regions but including the adjacent oceans, and follow the naming convention of the IPCC 4AR, http://www.ipcc.ch/ipccreports/ar4-wg1.htm

outside the range for which it has been calibrated producing meaningless results (Ebi et al. 2007; Wilby et al. 2000; Wood et al. 2004; Wood et al. 2002).

To correct the biases in simulated precipitation and simultaneously downscale in time to generate daily precipitation, we adapt a standard methodology based on a gamma transform (or quantile-quantile mapping) that preserves the monthly precipitation distribution (Hay et al. 2002; Panofsky; Brier 1968; Wood et al. 2004). For the period in which observed precipitation is available (1930-1984), a gamma distribution is fitted (using maximum likelihood estimation) to the observed monthly precipitation and to each monthly precipitation from the model run. To correct for GCM bias in the *period with observations* the quantile for any GCM monthly precipitation value is determined, after which that model monthly value is replaced with the amount corresponding to the closest quantile in the observed distribution. At the same time, the corresponding daily data for that particular month in the observations are used, which produces a daily series that is both bias corrected and has a realistic day-to-day structure. For the rest of the analysis period (1985-2079), the model 1934-1984 distribution is used to compute the quartiles associated to each monthly value from the model in that period (1985-2079), and each model value is then replaced with the observation value closest to the mapped quantile, including the corresponding daily structure.

The effect of this approach on model bias is shown in Figure 1. After correction, the long-term mean monthly precipitation of each model is very similar to the observed mean, and represents a reasonable bias-corrected estimate of precipitation over the catchment.

Since the Gamma transform method is based on mapping observed and simulated quantiles of their corresponding Gamma distributions, the methodology preserves the model intra-annual variability in the sense that the sequence of wet and dry months in the raw model data is replicated in the bias corrected data, by sampling the wettest or driest quantiles in the observed distribution. However, since the model monthly values are effectively replaced by observed monthly values, the methodology is conservative in the sense that it is impossible to obtain daily or monthly precipitation totals that are larger or smaller that those in the observations. This will affect particularly the distribution of the extreme monthly precipitation within the ensemble, since they are all mapped onto the extreme values that appear in the climatology.

Previous work using ensembles of opportunity (including combinations of global and regional climate models) to analyse impacts of climate change on hydrological systems, indicates that the results depend in part on the downscaling methodology (Fowler et al. 2008; Manning et al. 2008; Salathe et al. 2007). However, the downscaling uncertainty is typically a smaller component of the total uncertainty compared with that associated with parent climate models. Therefore, while acknowledging that alternative downscaling techniques will produce results that differ from our approach, we concentrate here on the influence of a large PPE on impacts and adaptation, and will address the issue of alternative downscaling approaches in forthcoming work.

<u>Potential evaporation (PET):</u>
The procedure to obtain potential evaporation is more involved since this variable is not available directly from CPDN. We use temperature, and relative humidity from CPDN model runs, and observed wind speed and percentage of sunshine to estimate monthly time series of PET using Penman formulation (Penman 1948). To simplify the calculations we assume that wind speed and percentage of sunshine do not change in

the future. Furthermore, since large scale PET correlates fairly well with local PET we assume that the potential evaporation calculated with the SW England grid box data is a good representation of the catchment PET, and that monthly mean values approximate reasonably well daily values.

When compared with the historical PET monthly means over 1930-1984 (Figure 2), CPDN model runs overestimate PET throughout the year, primarily due to the GCMs temperature being overestimated (not shown). In order to correct for these biases, the simulated PET monthly means were scaled by a factor that makes the simulated long term monthly mean equal to the observed long term monthly mean over 1930-1984 (Durman et al. 2001). Thus, after bias correction, model monthly means end up superimposed with the observed ones (Figure 2). Note that this methodology only adjusts the long term mean, and does not incorporate additional corrections to the variability as in the precipitation bias correction methodology. Since PET is overestimated through the year, the simulated monthly values will be multiplied by monthly scales that are smaller than one, therefore reducing the range of simulated PET distributions compared with the raw model data.

2.2 CATCHMOD and river flows:

CATCHMOD is a rainfall-runoff model used by the EA for water resource planning and abstraction licence allocation. The model is described in detail by Wilby et al. (1994). It uses daily time series of precipitation and potential evaporation for the river catchment to simulate daily time series of runoff.

For our case study CATCHMOD is set up to simulate river runoff for the Exe River at Thorverton. The effective catchment area consists of approximately 600 km^2 underlain by sandstone. Five hydrological model parameters are determined through calibration against observed discharge. Since in this work we only explore climate model uncertainty, we run CATCHMOD as calibrated for operational use by the Environment Agency.

We run the 246 downscaled and bias-corrected precipitation and PET time series through CATCHMOD and obtain an ensemble of flows for the Exe at Thorverton. Figure 3 illustrates the percentage change of mean monthly flow between 2020-2039 and 1961-1990. A large proportion of model runs show substantial reductions in the mean flows during the summer months, 82%, 93% and 91% in June, July and August respectively. This produces large reductions in low flows, illustrated in Figure 4, where flow duration curves for daily flows over the period 1961-1990 and over 2020-2039 are illustrated. The fact that the simulated low flows using observed data are larger than the observed flows is a consequence of the inability of CATCHMOD to simulate low flows precisely when it is calibrated to reduce errors in the whole range of flows. Consistently, low flows across the model ensemble are larger than observed. Moreover, the fact that the observed highest flows are about twice as large as the simulated highest flows (Figure 4a) indicates that CATCHMOD is not specifically designed to simulate peak flows (Wilby et al. 1994).

The spread in the range of simulated flows increases with time as members of the PPE diverge in their response to the A1B forcing scenario. For instance the ensemble range in the simulated flow exceeded 90% of the time (Q90) increases by about 50% between the baseline period (Fig 4a) and 2020-2039 (Fig 4b). However, some changes are common to most of the PPE: for instance, driven by a general decrease in summer precipitation, low flows decrease relative to the baseline period as can be seen by the change in the relative position of CPDN low flows with respect to the observed low flows. Analogously, driven by a general increase in winter precipitation, high flows increase relative to the baseline period except for the highest flows (Q02 and beyond). In this case simulated peak flows are always smaller than baseline peak observed flows, perhaps due to the fact that CATCHMOD was not calibrated for high flows. Further work is required to confirm whether this is a real result or a consequence of the hydrological model or downscaling errors.

In what follows we assume that the simulated flows described in this section provide information on the spread of plausible future natural flows of the river Exe at Thorverton, and consequently a range of future water availability in that catchment. In order to assess the implications of this spread of future flows for water resources, we use these simulated river flows to run the water resources model which is described next.

To end this section we comment briefly on the hydrological model uncertainty. As with any hydrological model, when CATCHMOD is parameterized, there is a range of values of the parameters for which the simulated flows are close enough to the observed one according to an objective function such as the Nash-Sutcliffe measure (Wilby; Harris 2006). This range of parameters translates into a range of flows all consistent with the observed flow according to a set of tolerances for this measure. Even though this uncertainty is not negligible, previous work has shown that in CATCHMOD it is small compared to the climate model uncertainty (New et al. 2007; Wilby; Harris 2006). As we wish to focus on uncertainty associated with the climate model PPE, we do not explore this aspect of uncertainty in this work.

2.3 Water resource management system.

The Wimbleball water resource zone is situated in SW England and supplies water to the counties of Devon and Somerset. In our simplified version of the zone simulated using LANCMOD (Figure 5), water is supplied by two reservoirs (Wimbleball and Clatworthy), the river Exe (at two abstraction points, Exebridge and Thorverton,) and from a sandstone groundwater source. The largest demands are East Devon, which includes the city of Exeter, Somerset and “Peak”. The latter two represent transfers out of the catchment to a neighbouring water utility, Wessex Water. There is also a “pumped storage”, which is water that is available to be transferred from the river Exe at Exebridge to Wimbleball to refill the reservoir during the winter months.

The main reservoir within the catchment is Wimbleball. It was built in 1979 on Exmoor, and impounds water from the river Haddeo, a tributary of the Exe, with net storage of 21320Ml and a surface area of 150 hectares. It supplies Exeter and parts of East Devon by releasing water into the river Exe to support abstraction at Tiverton and Exeter.

LANCMOD requires as inputs daily time series of river Exe flows at Thorverton and Exebridge, and daily inflows into Wimbleball and Clatworthy. Thorverton flow is simulated by CATCHMOD as described in the previous section. The other three flow time series are calculate by scaling the Thorverton flows by a factor that ensures that the long term mean flows coincide with those calculated using the flow estimation software, Low Flows 2000 (Young et al. 2003). This simplification has been demonstrated by the Environment Agency to be effective in modelling current operation of the Wimbleball system. It is important to note that we assume that the scaling factors will remain the same under climate change. Thus the effects of changes in the reservoir inflows due to climate change are taken into account by representing them as scaled versions of flows of Exe at Thoverton.

LANCMOD is set up to simulate the functioning of the system when different demand profiles, and control rules for river abstractions and functioning of the reservoirs are stipulated. The current figures used by LANCMOD as demand profiles (Table 1) are based on present values of water consumption within the catchment. These are mean monthly demands that do not include inter-annual and intra-month variability, concealing the fact that, for instance during summer hot spells peak demands can be much higher. Indeed, our simplified water resource model is not suitable for assessing the impact of peak demands since more information about the structure of the demand and much more detail about the system's constraints would be required. Solutions to guarantee peak demands usually include improving local storage (service reservoirs), larger pumps, pressure reduction, etc., which Lancmod, in common with other simplified models, can not simulate. However models such as LANCMOD are widely used because they represent an efficient way to explore how climate change will affect water supply. They constitute one step in a tiered approach to supply system design where detailed design and day-to-day operational modelling would require complex models that could not easily simulate the impacts of a hundred years of climate data.

The pumped storage is modelled as a demand, and represents the water pumped from the Exe at Exebridge that is available to be transferred to Wimbleball reservoir to ensure the refilling of the reservoir during the winter. It is set up to transfer 150Ml/d from November to March when required by the control rules governing the reservoir, up to an annual maximum of 13633Ml. The fisheries bank only takes up 150Ml/d on August 2 to 4 and September 2 to 4.

In the following section we will concentrate on East Devon and the two demands representing the water transferred to Wessex Water (Peak demand and Somerset), since these are the most significant ones. Notice that here Peak demand is just the name of a demand and does not represent a peak demand in the operational sense.

To illustrate how the functioning of Wimbleball reservoir is simulated, Figure 6 shows reservoir storage levels for each month of the year over the period 1930-2005, simulated using CATCHMOD river flows between 1930 and 1957, and observed naturalized flows between 1957 and 2005. We also show selected percentiles from the distribution of monthly historical reservoir levels, along with the only time dependent operating control rule for the reservoir. The other control rules (not shown) are constants at 21320 Ml, 1100Ml and 0Ml (100%, 5% and 0% of capacity). The operation of the reservoir by LANCMOD is as follows:

- When the storage level is between the maximum capacity (21320Ml) and the time varying control rule, water is released into the system at a rate of 350Ml/d and there is no transfer from the pumped storage.
- When the reservoir storage falls under the time varying control level, the transfer of water from the pumped storage is triggered at a rate of 150Ml/d up to a maximum of 13633 Ml per annum, but only between November and March.
- The same rule applies if the storage level falls under 1100Ml.
- For any storage level there is a compensation flow released back into the river of 9.1Ml/d.

Clearly this system is demand driven, as its priority is to satisfy the different demands. One consequence of these rules is that water from the reservoir is always released into the system at a maximum rate of 350Ml/d, limited only by the volume of water left in the reservoir, even when its level is so low that it would in practice be inappropriate to operate in this way. In other words, in our simulation the only role of the control rules is to determine when water is pumped into Wimbleball. The volume supplied by the pumped storage is limited by what can be extracted at Exbridge, where the flow has to exceed 400 Ml/day (4.62 m^3/sec) to be able to supply 150 Ml/day (1.73 m^3/sec) to the pumped storage. When the flows fall under 340 Ml/day, 280 Ml/day, 220 Ml/day, 160 Ml/day, 130 Ml/day, and 120 Ml/day, water is supplied to the pumped storage at a rate of 120 Ml/day, 90 Ml/day, 60 Ml/day, 30 Ml/day, 15 Ml/day, and 10 Ml/day respectively.

3 Water resources model under business as usual demand scenario

In this section we describe the response of the water resource system when run into the future with current reservoir capacities and demand profiles, and under the same operational rules; this is termed the "business as usual "(BAU) scenario.

We will present our results as monthly averages for the different variables of interest, as the daily structure of precipitation that we used to generate the river flows was borrowed from the observations. In doing the bias correction and simultaneously the temporal downscaling, we have assigned to each model month a daily structure taken from the observed month with the closest quantile in its Gamma distribution. Therefore any property that depends closely on daily structure will be partly reflecting characteristics of the observed climate and not necessarily of model data. On the other hand, we expect monthly averages to be more faithful indicators of model behaviour.

3.1 Wimbleball reservoir:

A natural question to ask is whether the management of the reservoir would need changing under future climatic conditions. To this end, we assume that our ensemble of climate model runs provides a sample of what might happen at any chosen time slice in the future. Figure 7 is similar to Figure 6 except we now show the distribution of Wimbleball reservoir levels for a single year in the future, as simulated using the 246 members of the PPE. A similar diagram could be constructed for any year in the future. The different percentiles in Figure 7 represent the storage level exceeded by a given fraction of models in each month in 2040. This figure suggest that if one uses the climate model ensemble as practitioners usually look at historical records, the existing operating control rule designed following historical records might need some adjustment in the future. To illustrate this we look at the driest period of the year, August to October. In the case of reservoir capacity simulated with the historical records, in half of the years reservoir levels are above 55% capacity, and in three quarters of the years are above 40% capacity. In the case of the ensemble simulations in the 2040s, the reservoir level exceeded by half the models is lower, at 40% while that exceeded by three quarters of the models drops to 25% of capacity. Assuming that the percentiles in the climate change simulations can be interpreted in a similar way to the percentiles in Figure 6, this comparison suggests that changes in the control rules must be introduced in order to guarantee that the reservoir operates at safe levels.

More interestingly, we can explore how the reservoir storage level across the ensemble changes over time. Figure 8 represents the storage level for a single month as a function of time between 1960 and 2079 - we show September as one crucial month towards the end of the summer, when the reservoir level becomes particularly low. This figure shows that the storage levels associated with each percentile decrease slowly from the present to about the 2020s, and more rapidly later on. For instance the 50th percentile goes from nearly 60% of full capacity to about 50% by the 2020s, and ends up at nearly 30%by the end of the simulation period. Thus, the evolving risk of the reservoir reaching critically low levels under current operating rules and for this particular climate model ensemble can be quantified.

3.2 East Devon and Somerset demands:

LANCMOD is designed so that different priorities can be assigned for the order in which demands are supplied from different sources. For instance Peak demand is only supplied from Wimbleball reservoir, while Somerset demand is satisfied first by Wimbleball and, if not enough water is available from this reservoir, the rest will be taken from Clatworthy. In the case of East Devon, the demand is supplied firstly from the ground water source, then from river Exe at Thorverton, and finally from Wimbleball. This priority order is important when analysing how demands are satisfied under different scenarios. For instance East Devon has priority over the other demands on the groundwater source. Since in the present configuration groundwater supply is fixed to be 50Ml/d, nearly half of East Devon annual mean (120Ml/d) is guaranteed by this source, imposing a lower bound on the possible deficit even under climate change.

When LANCMOD is run using historical flows between 1930 and 2005, the only time that East Devon demand cannot be satisfied is September 1976, representing a ~1% risk of failure. On the other hand, when run using the CPDN ensemble, between zero and 3 models fail for any given year during the baseline period, 1960-1989 (Figure 9), representing a risk of failure not larger than 1.2% across the ensemble. This is consistent with reservoir levels shown in Figure 8, where fewer than 2.5% of the models have storage levels below the control rule line in September. Of course, the fact that the storage is less than the control rule value does not imply automatically that a demand will not be satisfied, since LANCMOD is set up to try to satisfy all the demands as its first priority. Therefore, before failing, LANCMOD will try to exhaust all possibilities including depleting the reservoirs and looking for alternative sources of water within the system. In particular, in the case of East Devon, it will be supplied first by the ground water source and Exe at Thorverton, and ultimately by Wimbleball. Recall that in our simplified version of the system, the ground water source guarantees a constant supply of 50Ml/d unaffected by climate change. This correlates with the fact that even though about 2.5% of the models have very low reservoir level in September 1960-1990, only a small fraction of them actually fails to satisfy East Devon demand.

Looking to the future, the ensemble shows that the fraction of simulations failing to supply East Devon demand in September for any decade beyond 2030 is at least three times that in the baseline period (~0.6%), and reaches about 5% of the models in the 2070s (Figure 9). The bottom panel in Figure 9 shows analogous information for October. A higher fraction of models fail in this month at any time compared to September, suggesting that the critical period for satisfying demand will shift towards the autumn, according to our climate model ensemble. The pattern of failures in November (not shown) is similar to the one in September, and there are even fewer failures from December through the rest of the winter.

At Somerset BAU demand is roughly half East Devon and can also be satisfied by Clatworthy. Therefore, even though the fraction of models failing in the baseline period is similar to East Devon (about 0.2% on average), the increase in the future is lower, with only about 2% of simulations failing by the 2070s (Figure 10). For Somerset, there is also an increment in the fraction of models failing in October (bottom panel) and similarly in November (not shown) compared to September.

To finish this section we discuss briefly what happens if instead of having the climate model ensemble that we have used, there was a single model simulation, such as the standard version of HADCM3 model. This is analogous to the information that would have been available with the 2002 UK climate change scenarios (Hulme et al. 2002), or a single one of the GCMs used in the IPCC 4AR (Solomon et al. 2007; Wiley; Palmer 2008). In this case, we have to use this simulation in the same way that we use historical records, for instance by looking at how many times in a specific time period demand was not satisfied in a particular month of the year. The only time the standard model simulation fails to satisfy East Devon demand between 1960 and 2079 is in October and November of 2078, and it never fails to satisfy Somerset demand. This information is clearly very limited compared with the climate model ensemble information: it tells us about just one possible future path consistent with the current climate knowledge; it will depend on the period of time we look at within the time series; and it does not tell us anything about how the risk of failure will change in time as the climate models are forced into the future. Clearly, this one realization of future climate gives a false sense of security and does not provide the rich picture that the ensemble does. If a single simulation had produced an extreme drying in the future, an equally false sense of alarm might have been created.

Arguably the use of a single model run (or several from an ensemble of opportunity) to analyse impacts of climate change would not be appropriate from the dynamical point of view. Due to the non-linearity of the system, a more reasonable approach, ignoring model uncertainty, would be to analyse an initial-condition ensemble, where an ensemble is generated by running the same climate model starting from slightly different initial conditions. Studies carried out with a slab version of the Hadley centre model where larger initial conditions ensembles for each model run were available (Stainforth et al. 2007), have shown that initial conditions uncertainty can be comparable to the model parameter uncertainty. Unfortunately our ensemble does not contain initial condition ensembles large enough to confirm this finding in the case of the fully coupled climate model used to generate the PPE used for our case study.

Our results strongly indicate that the practice of using a single model run, or for that matter ensemble means instead of the individual model runs, can be misleading when analysing impacts of climate change. In the case of the use of the ensemble mean, it will clearly suppress the ensemble variability and all the information contained in it, particularly that related to extremes.

4 Adaptation and management options under climate change.

Up to this point we have described the simulated changes in water availability under a business as usual scenario, assuming that demand patterns and reservoir maximum storage will not change in the future. We will discuss next how the system responds under different scenarios for supply and demand management options.

Various changes can be made to the water resource model set up to explore how different adaptation strategies can decrease the risk of supply failure in the future, making the system more resilient to climate change. Options include reducing demands to comply with water saving policies, increasing the volume of water available in the reservoirs, reducing the transfer of water outside the catchment, increasing the pumping rate to the reservoir, and changing the control rules that govern the river abstractions reducing the flows maintained for the environment. The above is simply a list of the changes that could be simulated given our water resource model.

In a real situation the path chosen to adapt to possible impacts of climate change will depend on many factors that include, but are not limited to, the climate information. In particular issues such as the cost of the different options, their impacts on the environment, public response, technical feasibility, as well as demographic and water use changes, will play important roles in the decision.

In this case study we will concentrate on four different scenarios that can be simulated by making minor changes to LANCMOD set up. Two scenarios are based on consumption reduction, one on increasing supply and one on combined increased supply and reduced demand. Our goal here is to analyse how the climate model information can be used to help inform these management options. An integrated assessment of possible adaptation strategies, taking into account the full range of socio-economic factors and their uncertainties, will be the focus of future work.

4.1 Demand reduction options:

For the purposes of this study, we have assumed that the baseline household demand in the area is 150 l/h/d, the current average for England and Wales. The recent UK government water strategy (DEFRA 2008) aims for this to reduce to 130l/h/d, suggesting that a reasonable scenario for demand reduction would be about 15% less than the current figures. In this scenario, we are implicitly assuming that non-household and other demands also fall by the same proportion.

Since the two most significant demands through the year are East Devon and Somerset combined with Peak demand, we devise two different scenarios involving them. The other demands are either very small (less than 2% of East Devon or Somerset), or operate only a few days during the year (Fisheries bank), having relatively little impact on the whole system, therefore we leave these unaltered.

In the first demand management scenario, labelled ED_{red}, we assume that only the annual East Devon profile is reduced by 15%. East Devon is the largest demand in the system with a yearly figure of 120 Ml/d, and ED_{red} results in a reduction of 18 Ml/d. This illustrative scenario could be seen as representing, for example, a demand management programme targeted on part of the resource zone, and addressing long-term water consumption as opposed to peak demands.
In the second scenario, labelled ALL_{red}, we reduce by 15% all main demands: East Devon, Peak and Somerset, amounting to an annual average reduction of about 28 Ml/d. Both scenarios assume that a water saving strategy is put in place, and other factors, such as population changes, remain constant.

4.1.1 Somerset and East Devon demand response:

Since one of our goals is to understand how different management options affect the response of the water resource model in the future compared with the current operation of the system, we compute changes in the proportion of models failing to supply any given demand relative to the proportions in both the baseline period and under the BAU scenario. Results for Somerset and East Devon are listed in Table 2.

If the BAU management scenario is maintained through the future, the fraction of models that fail to supply both Somerset and East Devon increases markedly in the future. For example single month failures occur 1-4 times as frequently by the 2030s, and 9-10 times more often in the 2070s. The ED_{red} scenario significantly reduces the number of models failing to supply demand in the future, by up to two thirds compared to the BAU in 2070s. Compared to the present day BAU, ED_{red} still produces more failures but the increase is much lower than under BAU. The ALL_{red} scenario does not affect East Devon significantly, but is more effective at Somerset, as this scenario involves a reduction in Somerset demand on top of the East Devon reduction.

From the water resource management point of view, it is important not only to know whether there will be a failure, but also the frequency of occurrence of any number of consecutive monthly or annual failures. For instance, we might be interested in knowing how the occurrence of one monthly failure will change in the 2030s compared with the baseline across the climate model ensemble. Or the analogous change for failures that occur in two or more consecutives months, and how these changes depend on the demand scenario proposed. An important advantage of working with the CPDN ensemble is that climate time series of inputs for any given model run are available. Therefore we can compute how frequencies of occurrence of consecutive events change in time as the climate models are run into the future.

In Table 2 we show the results for the number of models that fail to satisfy Somerset and East Devon demand during a single month, and from two to six consecutive months, over seven decades in the future. We show both the total number of models that fail to satisfy the demand, and the total number of failures. For more than six consecutive monthly failures (not shown) there are no failures, except for one single model failing in the last decade.

As would be expected, the fraction of models failing in the historical baseline period for ED_{red} scenario is equal or smaller than for the BAU scenario. If all demands are reduced (ALL_{red}) the situation is further improved specially for Somerset, with zero consecutive failures in the baseline period in this case. In the future, under any scenario, the number of models failing increases, consistent with the reduction in summer river flows simulated by the ensemble; even though winter flows increase in some ensemble members, they are clearly not enough to refill the reservoirs (see next section). Compared to the BAU scenario, both ED_{red} and ALL_{red} result in far fewer consecutive monthly failures, especially after the 2040s. ALL_{red} scenario is again particularly effective for Somerset, completely eliminating isolated monthly failures and working very well until the 2060s for 2 or 3 consecutive monthly failures.

A comparison of ED_{red} and ALL_{red} scenarios for East Devon suggests that the management of different demands interacts non-linearly within this system, since even though reducing all demands does not affect particularly the number of isolated monthly failures in East Devon, it does have an effect for 2 consecutive monthly failures.

We also evaluate the changes in multi-year system failure. Table 3 shows the number of ensemble members failing to meet demand in single and multiple consecutive years, over thirty year periods. Failures for more than six consecutive years are very rare and appear mostly in the last three decades of the simulation period. Here we define an annual failure whenever the annual volume of water supplied does not coincide with the annual volume required, independently of whether that occurs in just one or more months within the year. Therefore, these tables do not provide information about when and how the demand was not satisfied within any particular year. Nevertheless, they do provide information about how demand management options can remediate the fact that under simulated future climate and BAU demand and supply, the fraction of models failing two or more consecutive years increases in time.

Under the BAU scenario only one ensemble member fails to meet Somerset demand in any two consecutive years in 1960-1989, but this increases to 10 and 27 members for 2020-2049 and 2050-2079 respectively; the increase in consecutive year failures is even greater at East Devon. However, after East Devon demand is reduced by 15% (ED_{red}), the number of models failing reduces by three times at Somerset and at least six times at East Devon for 2020-2049. Implementing the additional 15% reduction in Somerset and Peak demand (ALL_{red}) completely eliminates two annual consecutive failures in the future, apart from final period for East Devon. Thus, for this system, relatively small year-round demand reductions could eliminate the need for more drastic measures in critical dry consecutive years.

If the single model realisation using the standard version of HADCM3 is used, it never fails to supply East Devon or Somerset under these two demand reduction scenarios. This suggests that, potentially, a single-scenario based approach could produce an over-optimistic view of the future water supply situation.

4.2 Supply management options:

An alternative to reducing demand is to add another source of water. One way to do this in LANCMOD is to increase the size of the reservoir. Although this may not be feasible in practice for Wimbleball, increasing reservoir size is often an option, as it is relatively uncontroversial and often cost-effective. It is also an easy way to represent an additional source of water within the current model set up. Increasing the depth of the reservoir by 1m augments the storage from 21320 Ml to 25075Ml, an increase of 18% in the volume of water stored. Since we do not change any other parameter in the model, such as link capacities or control rules, the limitations in the amount of water that can be released into the system will still be controlled by these factors. However, the fact that the reservoir can store more water during the periods of high flows changes the behaviour of the reservoir in relation to other scenarios. This is illustrated in Figure 11 which shows Wimbleball reservoir storage in September as a function of time for the ALL_{red} demand reduction scenario, the increased reservoir level scenario (L_{res}), and these two scenarios implemented in combination (L+ ALL_{red}).

If only demand reduction is implemented, much of the effect of drier summers can be alleviated: many more models exceed any given threshold compared to the BAU scenario. For example, the storage level exceeded by half the models in the 2070s shifts from 30% under BAU to 40% under ALL_{red}. Furthermore, the risk of occurrence of very low reservoir levels across the ensemble, as indicated by the 2.5 percentile, is delayed from the 2030s under BAU until the 2070s under ALL_{red}.

When the reservoir capacity is increased without reducing demand, we see that the behaviour of the 50th percentile is similar to the ALL_{red} case, improving the chances of having the reservoir half full as compared with the BAU scenario. However, the risk of very low reservoir levels as indicated by the 2.5th percentile does not change significantly compared to the BAU scenario, suggesting that even though there is more storage capacity within the system, the change in river flows across the ensemble are not enough to make use of this greater capacity in the driest years. If capacity is increased and demand reduced (L+ALL_{red}) there is little improvement over ALL_{red} when looking at the behaviour of the percentiles as a function of time. Obviously in absolute values, the fractions of storage level represent a larger storage capacity for L_{res} and L+ALL_{red} (fractions of 25075Ml) than ALL_{red} (fractions of 21320Ml).

How the supply to different demands is affected by these two last scenarios can be assessed in Tables 2 and 3. In the case of Somerset demand we observe that scenarios ALL_{red} and L+ ALL_{red} are equally effective in reducing the number of consecutive monthly and annual failures, and much more effective than ED_{red} and L_{res} in isolation. ED_{red} and L_{res} are roughly equally effective until the 2040s, but the former becomes more effective thereafter, when it is clear that increasing the size of the reservoir does not improve Somerset situation significantly as compared to the BAU scenario. This is consistent with the previous observation that increasing the size of the reservoir does not change significantly the risk of very low reservoir level across the ensemble after the 2030s.

For East Devon the situation is different. Once again increasing the size of the reservoir only is not as effective in reducing failures as ALL_{red}. However, if this is combined with a reduction in all demands (L+ ALL_{red}), the number of single month failures reduces after the 2040s, compared with the demand reduction only scenarios. Similarly, for two or more consecutive monthly failures L+ ALL_{red} performs equally or better than ED_{red} and ALL_{red} at any time. This suggests that increasing the reservoir capacity combined with demand reduction measures can work effectively at reducing the number of consecutive monthly failures.

A similar response emerges for failures in consecutive years. Increasing the reservoir size only is not very effective, suggesting than even though a large proportion of the ensemble projects wetter winters, these do not completely compensate for the drier summers. However when a larger reservoir size is combined with demand reductions, the number of isolated annual failures goes from 49 at the baseline for BAU, to 27 in the period 2020-2049. For 2 or more consecutive failures the demand reduction scenarios and L+ ALL_{red} are equally effective up to the middle of the 21st century, suggesting that the main limitation to reduce the number of consecutive annual failures is water availability and not storage capacity, at least until the early 2050s.

5 Discussion

In this work we have described an approach to use a large perturbed-physics GCM ensemble to provide potentially useful information for the study of impacts and adaptation to climate change in a water resources system. We base our analysis on the only publicly-available perturbed physics ensemble (climateprediction.net), an hydrological model (CATCHMOD), and a water resource system model (LANCMOD); the latter two are operational decision-support tools used by the Environment Agency of England and Wales. In this way, we ensure that our case study is a working example of direct relevance for current environmental planning in UK.

In the process of translating the climate model outputs into the appropriate inputs for the hydrological and water resource models, we have made some simplifying assumptions.

Firstly, we use all ensemble members "as is", without any previous evaluation of their relative skill in simulating the climate system. Various methodologies have been proposed to weight different model runs within a perturbed physics ensemble (Murphy et al. 2007) and different GCMs within an ensemble of opportunity (Lopez et al. 2006; Tebaldi; Knutti 2007; Tebaldi et al. 2005), or to constraint climate predictions using observations of past climate change (Stott; Forest 2007). These approaches assume that models can be weighted according to a number of possible metrics in order to obtain a meaningful probabilistic projection for the climate variables of interest. The metrics can be either global, regional/local or a combination of both. Global metrics assume that models should perform adequately at the global scale. These include for instance the climate prediction index (Murphy et al. 2004). Regional/local metrics quantify how different variables perform at the scale relevant for the climate change impact being analysed and weight the models accordingly; an example of this being the impacts relevant climate prediction index of Wilby and Harris (2006). At the other end of the spectrum, some authors (Stainforth et al. 2007) argue that using current observations to calibrate or weight models to produce forecast probabilities of climate change is incorrect, and misleading to the users of climate science. The underlying reason is that climate models are simulating a non-stationary system and past observations can not possibly sample the full state space. In our work we ignore these issues and take the very practical approach of considering all stable model runs as member of our sample.

Secondly, we have assumed that the model data for the grid box over the South West of England is a reliable input for the downscaling method used to derive local daily precipitation and PET inputs to the CATCHMOD model. Further, although using the quantile-quantile transform method to bias correct/downscale precipitation has removed GCM precipitation biases, more work is needed to develop bias correction and downscaling methodologies that ensure the correct time and spatial correlations in the downscaled data (Hay et al. 2002; Venema et al. 2006; Wood et al. 2004).

Our choice of these relatively simple methodologies to process the climate model data is justified by the fact that in this work we are mostly interested in analysing how the climate model ensembles can be used in impacts/adaptation studies as compared to single model information, and not in predicting accurately how any particular climate variable will behave in the future.

Once the river flows simulated by CATCHMOD are fed into the water resource management model we observe that the reservoir operating rules that work properly under historical conditions might need some revision in the future provided that we interpret the information across the ensemble in the same way practitioners use historical information, i.e., fraction of models having a given reservoir level at any time slice in the future as fraction of time that the given reservoir level was observed in the historical record.

Even more valuable perhaps is the fact that the climateprediction.net experiment stores time series of relevant climate variables for each ensemble member. This provides time-dependent information that is internally consistent for each perturbed-physics model, a feature that is extremely important for water resources management. Since this time dependent information has been generated by a fully dynamical climate model, we assume that it provides a range of future possible paths consistent with the state of the art climate science. Therefore we can then look at relative changes in time in the reservoir storage across the model ensemble for instance, or compute changes in the frequency of occurrence of different events of interest simulated using our PPE. This is particularly relevant for multi-month and multi-year dry periods.

Our results show that for this perturbed-physics ensemble, the fraction of ensemble members failing to satisfy demand in the period 1960-1989 is similar to the failure frequency when using observed river flow data for 1930-2005. However, the frequency of failure increases steadily in the future under a business as usual demand and supply management scenario.

To illustrate how different management options can affect this result, we analyse the response of the system under four alternative scenarios, a 15% demand reduction at East Devon, a 15% demand reduction in all major demands, an 18% increase in capacity for Wimbleball reservoir, and a final one combining the last two options. We note in passing that many other strategies could have been explored within the modelling framework, such as, increased groundwater exploitation, or changes to the consented conditions for pumped storage (i.e., volume and season of take) to better utilise the available resource during the wetter winters.

The effectiveness of the different measures depends on the component of the demand that is analysed and the planning horizon of interest. For instance, both demand management options can be quite effective in reducing the number of failures across the ensemble, particularly the ALL_{red} scenario for Somerset. In the case of East Devon, when demand management is supplemented with a larger storage capacity, the frequency of failures is even further reduced towards the end of the 21st century. For that planning horizon this ensemble indicates that larger storage capacity only is not enough to significantly reduce the frequency of failures, largely due to the lack of water available to be stored. However, a larger storage capacity combined with demand reduction (L+ ALL_{red}) seems to be a more appropriate choice to largely reduce the possibilities of failure to supply East Devon demand.

As we have already discussed, the scenarios proposed here are simple options that can be easily implemented with LANCMOD, and allow us to describe how the system responds and whether there are any physical limitations imposed by, for instance, lack of water available to be stored in the system. In a more realistic situation the path chosen to adapt to possible impacts of climate change will depend on many other factors that include the climate information, but are not limited to that. An integrated assessment of possible adaptation strategies, taking into account issues such as the cost of the different options, their impacts on the environment, public response, technical feasibility, population and water use changes, will be the focus of future work.

This study demonstrates the value added by the use of large climate model ensembles as opposed to a small number of scenarios used in impacts studies to date. It is clear that a single HADCM3 model run fails to capture the full range of climate possibilities and might lead to false confidence, suggesting in our case that there is no need for intervention while the full ensemble indicates the need for adaptive management.

Moreover, the ensemble information provides a particularly effective way to consider the benefit of different management options in a way that a few deterministic scenarios would not. We expect that the overhead in additional time and expertise for carrying out the impacts analysis will be justified by the increased quality of the decision making process.

It is clear that adaptation to climate change is often context specific. Different sectors will have different climate information needs and more or less sophisticated approaches to use this information for the impacts' analysis. In this sense, the UK water sector is perhaps one of the better prepared to undertake the challenge of using large ensembles of climate models since it already posses hydrological and water resource management models potentially adaptable to the novel climate data.

However, even though our case study is specific to the water sector, the key conclusions regarding the value added by the use of large climate model ensembles in impacts studies can be generalized to other sectors.

Acknowledgments

We thank Nick Faull, Tolu Aina and Milo Thurston from the climateprediction.net team for their support in obtaining the data. This study was supported by Environment Agency Science Project SC050045 and by the Tyndall Centre for Climate Change. The views expressed in the paper reflect those of the authors and are not necessarily indicative of the position held by the Environment Agency.

6 References

DEFRA, 2008: Future Water: The Government's water strategy for England., D. f. E. a. R. Affairs, Ed.

Durman, C. F., J. M. Gregory, D. C. Hassell, R. G. Jones, and J. M. Murphy, 2001: A comparison of extreme European daily precipitation simulated by a global and a regional climate model for present and future climates. *Q J R Meteor Soc*, **127,** 1005-1015.

Ebi, K. L., R. Woodruff, A. v. Hildebrand, and C. Corvalan, 2007: Climate change-related health impacts in the Hindu Kush-Himalayas. *Ecohealth*, **4,** 264-270.

Fowler, H. J., S. Blenkinsop, and C. Tebaldi, 2008: Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*, **27,** 1547-1578.

Giorgi, F., and R. Francisco, 2000: Evaluating uncertainties in the prediction of regional climate change. *Geophys. Res. Lett.*, **27,** 1295-1298.

Hay, L. E., and Coauthors, 2002: Use of Regional Climate Model Output for Hydrologic Simulations. *Journal of Hydrometeorology*, **3,** 571-590.

Hulme, M., and Coauthors, 2002: Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report, 120pp pp.

Lopez, A., C. Tebaldi, M. New, D. A. Stainforth, M. A. Allen, and J. A. Kettleborough, 2006: Two approaches to quantifying uncertainty in climate change. . *J. Clim.*, **19,** 4785.

Manning, L. J., J. W. Hall, H. J. Fowler, C. G. Kilsby, and C. Tebaldi, 2008: Using probabilistic climate change information from a multi-model ensemble for water resources assessment.

Murphy, J. M., B. B. B. Booth, M. Collins, G. R. Harris, D. M. H. Sexton, and M. J. Webb, 2007: A methodology for probabilistic predictions of regional climate change from perturbed physics ensembles. *Phil.Trans. R.Soc. A* **365,** 1993-2028.

Murphy, J. M., D. M. H. Sexton, D. N. Barnett, G. S. Jones, M. J. Webb, M. Collins , and D. A. Stainforth, 2004: Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, **430,** 768-772.

New, M., A. Lopez, S. Dessai, and R. Wilby, 2007: Challenges in using probabilistic climate change information for impacts assessments: an example from the water sector. *Phil.Trans.R.Soc. A* **365,** 2117-2131.

Panofsky, H. A., and G. W. Brier, 1968: *Some applications of Statistics to Meteorology.* The Pennsylvania State University Press.

Penman, H., 1948: Natural evaporation from open water, bare soil and grass. *Proceedings of the Royal Society, London*, **A193,** 120-146.

Salathe, E. P., P. W. Mote, and M. W. Wiley, 2007: Review of scenario selection and downscaling methods for the assessment of climate change impacts on hydrology on the United States Pacific Northwest. *International Journal of Climatology*, **27,** 1611-1621.

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marqis, and K. Avery, 2007: *IPCC 2007: Climate Change 2007: The Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press.

Stainforth, D. A., M. R. Allen, E. R. Tredger, and L. A. Smith, 2007: Confidence, uncertainty and decision-support relevance in climate predations. *Phil. Trans. R. Soc. A*, **365,** 2145-2161.
Stainforth, D. A., and Coauthors, 2005: Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature*, **433,** 403-406.
Stott, P. A., and C. E. Forest, 2007: Ensemble climate predictions using climate models and observational constraints. *Phil. Trans. R. Soc. A*
365, 2029-2052.
Tebaldi, C., and R. Knutti, 2007: The use of multi-model ensemble in probabilistic climate projections. *Phil. Trans. R. Soc. A*, **365,** 2053-2075.
Tebaldi, C., R. L. Smith, D. Nychka, and L. O. Mearns, 2005: Quantifying uncertainty in projections of regional climate change: a Bayesian approach to the analysis of multi-model ensembles. *J. Clim.*, **18,** 1524-1540.
Venema, V., S. Bachner, H. W. Rust, and C. Simmer, 2006: Statistical characteristics of surrogate data based on geophysical measurements. *Nonlin. Processes Geophys.*, **13,** 449-466.
Wilby, R., B. Greenfield, and C. Glenny, 1994: A coupled synoptic hydrological model for Climate Change Impact Assessment. *Journal of Hydrology*, **153,** 265-290.
Wilby, R. L., and I. Harris, 2006: A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the river Thames, UK. *Water Resources Research*, **42**.
Wilby, R. L., and Coauthors, 2000: Hydrological responses to dynamically and statistically downscaled climate model output. *Geophyscial Research Letters*, **27,** 1199-1202.
Wiley, M. W., and R. N. Palmer, 2008: Estimating the Impacts and Uncertainty of Climate Change on a Municipal Water Supply System. *Journal of Water Resources Planning and Managment***,** 239-246.
Wood, A. D., L. R. Leung, V. Sridhar, and D. P. Lettenmaier, 2004: Hydrological implications of dynamical and statistical approaches to downscaling climate model outputs. *Clim. Change*, **62,** 189-216.
Wood, A. W., E. P. Maurer, A. Kumar, and D. P. Lettenmaier, 2002: Long-range experimental hydrological forecasting for the eastern United States. *Journal of Geophysical Research*, **107,** 4429.
Young, A. R., R. Grew, and M.G.R.Holmes, 2003: Low flows 2000: a national water resources assessment and decision support tool. *Water Science and Technology*, **48,** 119-126.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
East Devon	114	116	116	115	120	130	138	138	115	111	111	114
Somerset	47.35	48	48.2	49.15	50.3	53.55	56.75	59.55	48.2	46.85	46.1	46
Peak demand	6.3	6.3	6.3	14.7	14.7	14.7	14.7	14.7	14.7	0	6.3	6.3
Pumped Storage	150	150	150	0	0	0	0	0	0	0	150	150
Ktt	0.5	0.5	0.5	0.5	1.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5
Crediton	0	0	0	0	.54	.54	.54	.54	0	0	0	0

Table 1: Annual demand profiles for Wimbleball water resource system. The figures in the table are in Ml/d.

	Consecutive Monthly Failures														
	1					2					3				
Demand Scenario	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{re}	$L+All_{red}$
1960-1989	3(3)	2(2)	0	3(3)	0	3(3)	1(1)	0	2(2)	0	2(2)	2(2)	0	2(2)	0
2020-2029	2(2)	2(2)	0	2(2)	0	5(6)	2(2)	0	4(6)	0	7(7)	1(1)	0	5(5)	0
2030-2039	2(2)	2(2)	0	3(3)	0	21(23)	10(10)	0	17(19)	0	6(6)	3(3)	0	6(6)	0
2040-2049	10(11)	4(4)	0	8(8)	0	24(27)	7(7)	0	22(23)	0	8(8)	7(7)	0	6(6)	0
2050-2059	14(14)	4(4)	0	13(14)	0	28(31)	9(9)	0	18(19)	0	13(14)	5(5)	1(1)	9(9)	1(1)
2060-2069	17(19)	5(5)	0	14(16)	0	35(40)	16(16)	2(2)	32(35)	2(2)	13(15)	5(5)	0	8(10)	0
2070-2079	29(33)	9(10)	0	22(25)	0	51(53)	16(17)	2(2)	31(31)	1(1)	20(24)	12(16)	1(1)	21(22)	1(1)

	Consecutive Monthly Failures														
	4					5					6				
Demand Scenario	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{re}	$L+All_{red}$
1960-1989	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2020-2029	2(2)	2(2)	0	2(2)	0	0	0	0	0	0	0	0	0	0	0
2030-2039	5(5)	6(6)	0	6(6)	0	4(4)	2(2)	0	3(3)	0	0	0	0	0	0
2040-2049	5(5)	4(4)	0	5(5)	0	2(2)	1(1)	0	1(1)	0	0	0	0	0	0
2050-2059	7(8)	5(6)	0	6(7)	0	2(2)	1(1)	0	2(2)	0	0	0	0	0	0
2060-2069	7(7)	6(6)	0	6(6)	0	1(1)	0(0)	0	1(1)	0	0	0	0	0	0
2070-2079	14(19)	9(9)	0	13(16)	0	3(3)	4(4)	1(1)	4(4)	0	1(1)	1(1)	0	1(1)	1(1)

Table 2a: The number of models that fail to satisfy Somerset demand for between 1 and six consecutive months, on a decadal basis. In the baseline period (1960-1989), this is the mean number of models per decade. Different columns within each number of consecutive monthly failures correspond to the five demand/supply scenarios analysed. The numbers in brackets indicate total number of failures.

	Consecutive Monthly Failures														
	1					2					3				
Demand Scenario	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{re}	$L+All_{red}$
1960-1989	10(10)	2(2)	2(2)	5(5)	0	5(5)	1(1)	0	5(5)	0	1(1)	0	0	1(1)	0
2020-2029	19(21)	4(4)	3(3)	14(14)	3(3)	13(13)	3(3)	1(1)	9(9)	0	8(9)	0	0	5(5)	0
2030-2039	31(35)	4(4)	5(5)	22(24)	5(5)	28(31)	12(12)	9(9)	18(22)	5(5)	15(15)	1(1)	0	8(8)	0
2040-2049	41(49)	12(12)	11(11)	29(30)	8(8)	53(63)	13(13)	10(11)	38(44)	3(4)	19(19)	5(5)	2(2)	14(15)	2(2)
2050-2059	63(79)	19(21)	18(19)	41(53)	6(6)	60(78)	14(15)	8(8)	40(48)	5(6)	26(26)	5(5)	4(5)	12(13)	3(4)
2060-2069	82(108)	14(14)	13(14)	45(50)	5(5)	70(99)	23(24)	15(15)	47(55)	14(14)	27(31)	6(6)	5(5)	23(25)	3(3)
2070-2079	93(137)	32(37)	30(33)	57(77)	18(18)	110(168)	28(30)	15(16)	75(100)	10(10)	31(34)	5(6)	5(6)	22(23)	5(6)

	Consecutive Monthly Failures														
	4					5					6				
Demand Scenario	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{re}	$L+All_{red}$
1960-1989	0(0)	0	0	0	0	0(0)	0	0	0	0	0(0)	0	0	0	0
2020-2029	0(0)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2030-2039	1(1)	0	0	1(1)	0	0	0	0	0	0	0	0	0	0	0
2040-2049	3(3)	0	0	1(1)	0	0	0	0	0	0	0	0	0	0	0
2050-2059	5(6)	1(1)	0	3(4)	0	0	0	0	0	0	0	0	0	0	0
2060-2069	4(4)	0	0	4(4)	1(1)	1(1)	1(1)	1(1)	1(1)	0	1(1)	0	0	0	0
2070-2079	9(10)	1(1)	1(1)	5(6)	0	0	0	0	0	0	0	0	0	0	0

Table 2b: The number of models that fail to satisfy East Devon demand for between one and six consecutive months, on a decadal basis. Numbers in the baseline period (1960-1989) are for the mean number of models per decade. Different columns within each number of consecutive monthly failures correspond to the five demand/supply scenarios analysed. The numbers in brackets indicate total number of failures..

	Consecutive Yearly Failures														
	1					2					3				
Demand Scenario	BAU	ED$_{red}$	ALL$_{red}$	L$_{res}$	L+All$_{red}$	BAU	ED$_{red}$	ALL$_{red}$	L$_{res}$	L+All$_{red}$	BAU	ED$_{red}$	ALL$_{red}$	L$_{re}$	L+All$_{red}$
1960-1989	24(25)	15(15)	0	22(22)	0	1(1)	1(1)	0	1(1)	0	0	0	0	0	0
1990-2019	33(34)	17(17)	1(1)	29(30)	0	2(2)	1(1)	0	2(2)	0	0	0	0	0	0
2020-2049	64(84)	36(42)	0	57(69)	0	10(10)	3(3)	0	10(10)	0	1	1(1)	0	1(1)	0
2050-2079	122(208)	71(94)	7(7)	103(161)	6(6)	27(30)	10(11)	0	22(24)	0	5(5)	1(1)	0	4(4)	0

	Consecutive Yearly Failures														
	4					5					6				
Demand Scenario	BAU	ED$_{red}$	ALL$_{red}$	L$_{res}$	L+All$_{red}$	BAU	ED$_{red}$	ALL$_{red}$	L$_{res}$	L+All$_{red}$	BAU	ED$_{red}$	ALL$_{red}$	L$_{re}$	L+All$_{red}$
1960-1989	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1990-2019	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2020-2049	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2050-2079	2(2)	0	0	1(1)	0	0	0	0	0	0	0	0	0	0	0

Table 3a: Somerset demand: number of models that fail to satisfy Somerset demand during 1to 6 consecutive years for the thirty year periods shown in the left column.

	Consecutive Yearly Failures														
	1					2					3				
Demand Scenario	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{re}	$L+All_{red}$
1960-1989	47(49)	9(9)	8(8)	30(30)	2(2)	1(1)	0	0	1(1)	0	0	0	0	0	0
1990-2019	81(97)	19(19)	11(11)	61(73)	9(9)	4(4)	0	0	3(3)	0	0	0	0	0	0
2020-2049	126(206)	49(54)	39(42)	101(144)	26(27)	20(21)	0	0	12(12)	0	1(1)	0	0	1(1)	0
2050-2079	190(500)	89(138)	78(111)	149(315)	53(64)	60(91)	10(10)	5(5)	44(53)	4(4)	16(19)	0	0	7(7)	0

	Consecutive Yearly Failures														
	4					5					6				
Demand Scenario	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{res}	$L+All_{red}$	BAU	ED_{red}	ALL_{red}	L_{re}	$L+All_{red}$
1960-1989	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1990-2019	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2020-2049	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2050-2079	2(2)	0	0	1(1)	0	0	0	0	0	0	0	0	0	0	0

Table 3b: East Devon demand: number of models that fail to satisfy East Devon demand during 1 to 6 consecutive years for the thirty year periods shown in the left column.

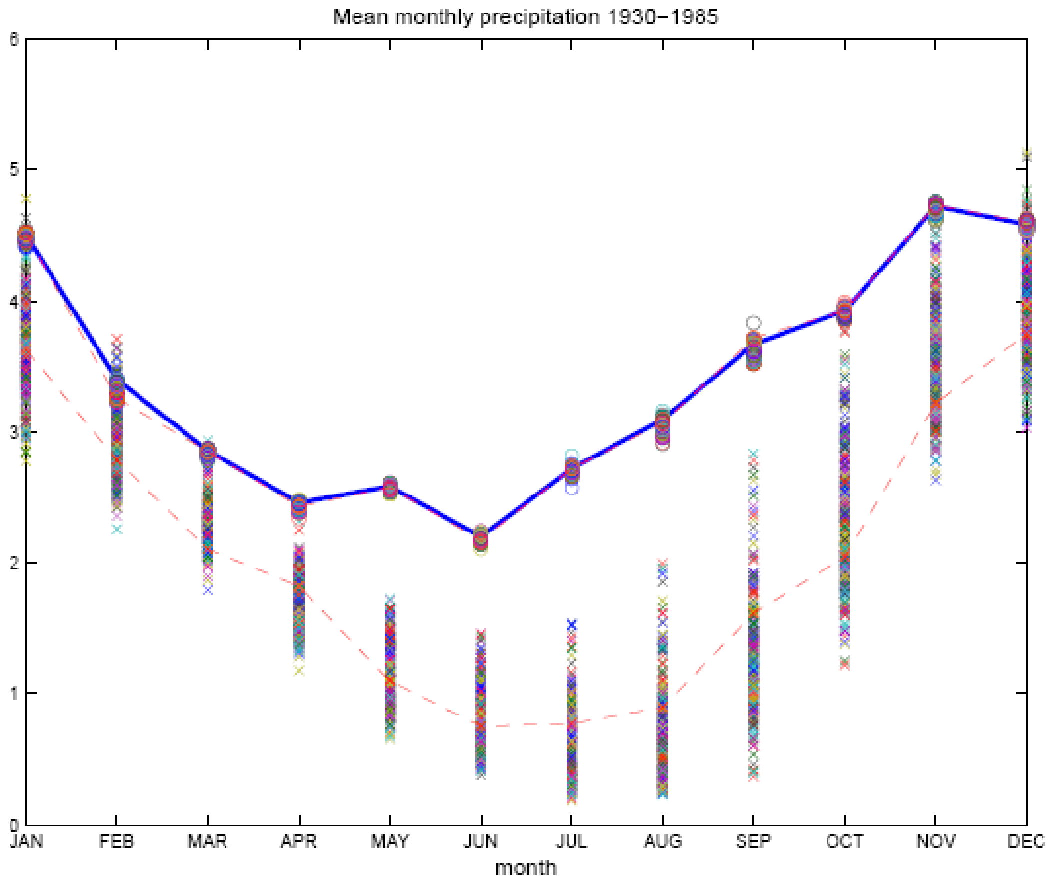


Figure 1: Mean monthly precipitation (mm/day) for the period 1930-1984. The dark blue line corresponds to observed monthly means, colour crosses to CPDN model runs without bias correction and colour circles to CPDN model runs after bias correction. The red dashed line indicates a simulation with the standard version of the HADCM3L model.

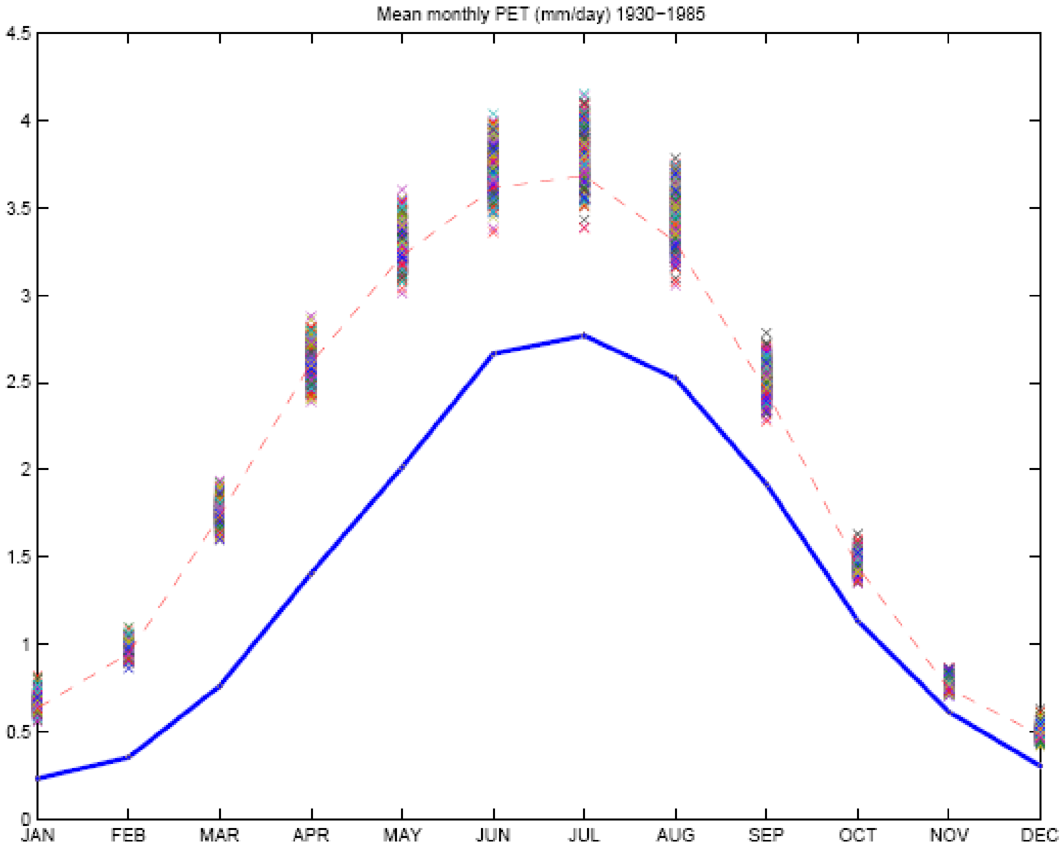


Figure 2: Mean monthly PET (mm/day) for the period 1930-1984. The dark blue line corresponds to observed monthly means, and the colour crosses to CPDN model runs without bias correction. The red dashed line indicates corresponds to the standard version of HADCM3L.

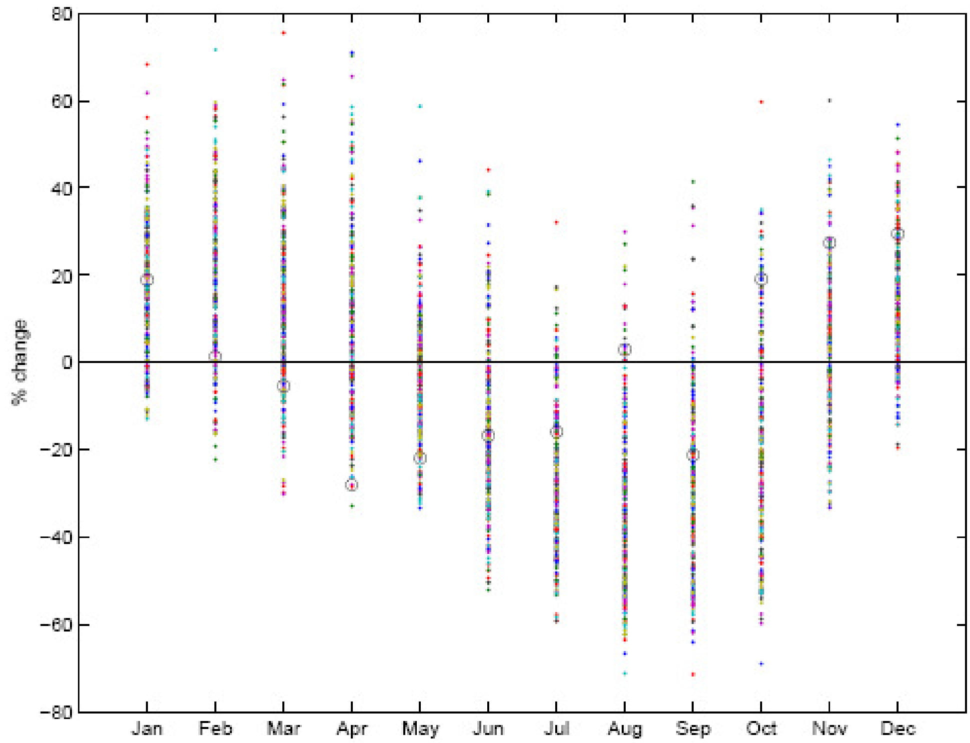
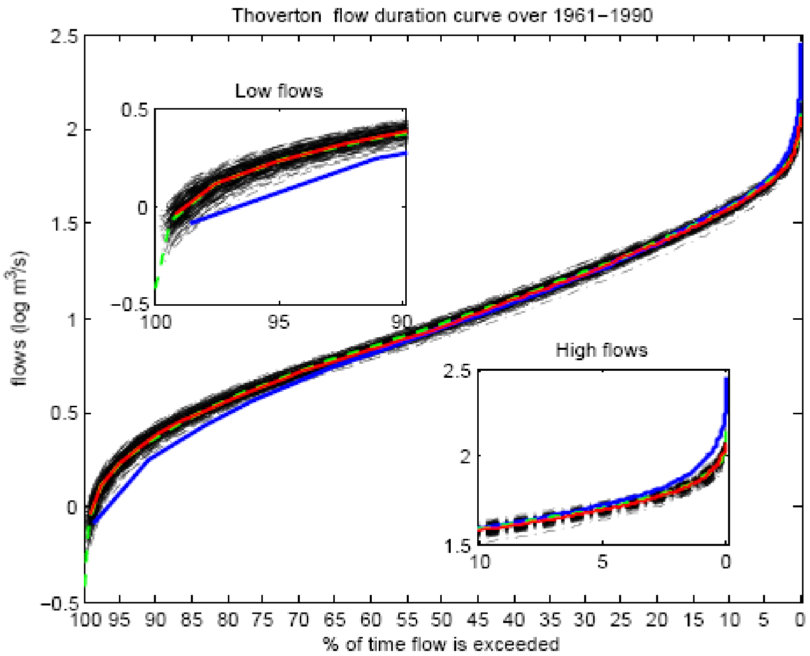
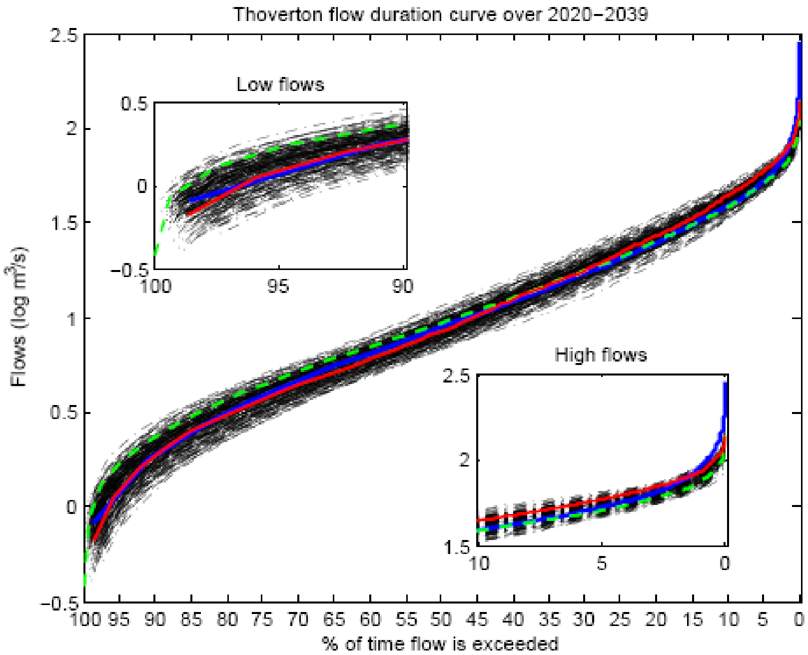


Figure 3: Changes in monthly mean River Exe flow at Thorverton between 2020-2039 and 1961-1990. Black circles indicate the standard version of HADCML3 model run.



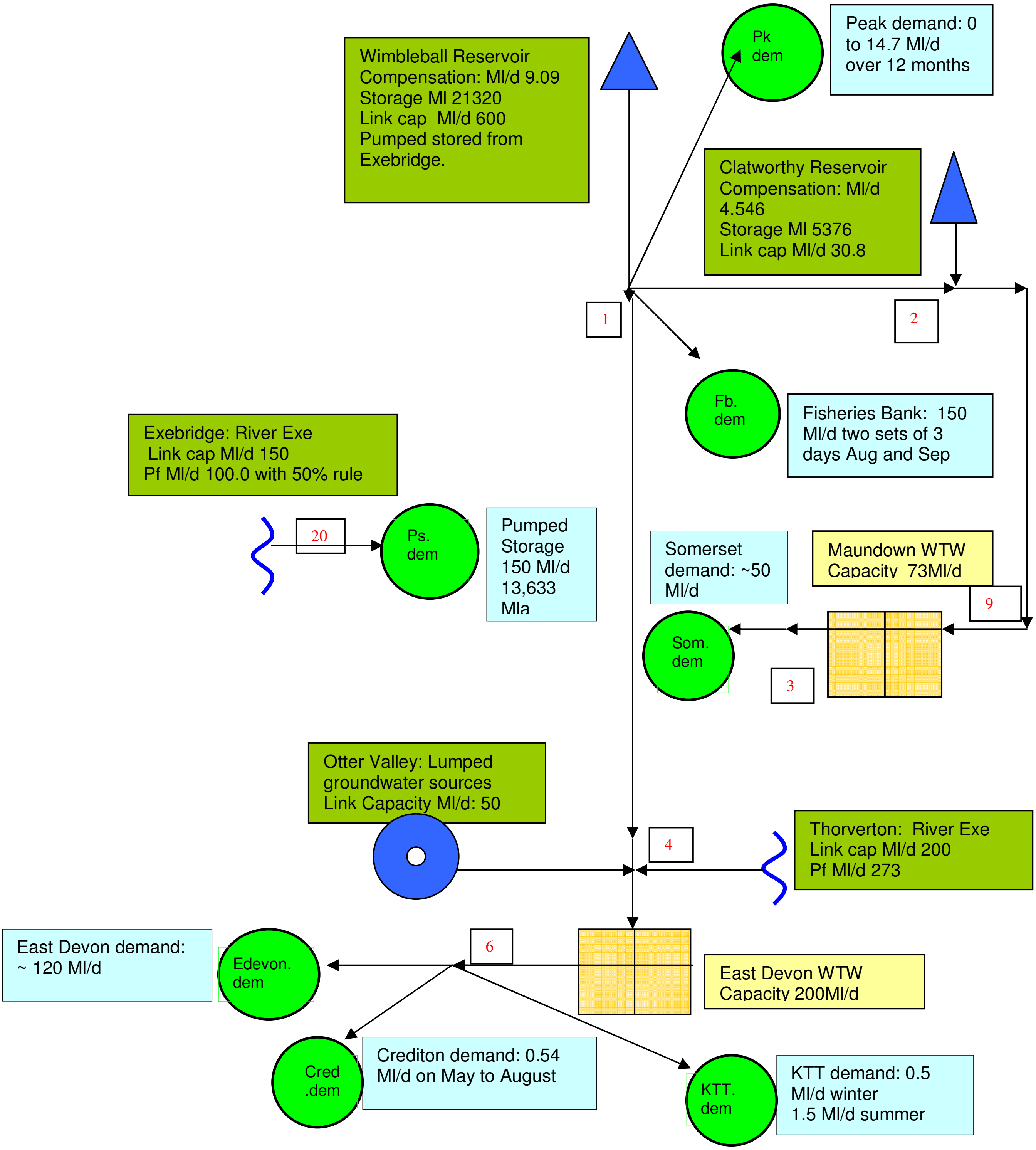
a)



b)

Figure 4: Flow duration curve for daily flows at Thoverton over the period 1961-1990 (a) and 2020-2039 (b). The blue lines correspond to observed flows, green dashed lines to simulated flows using observed precipitation and PET, black dashed to CPDN model runs, and the red lines to the CPDN model run with standard values of the physical parameters. The blue and green lines are included for reference in panel b).

Figure 5: Wimbleball water resource zone. Reservoirs, river abstraction points and groundwater sources are represented by blue triangles, wiggly lines and circles respectively. Green circles represent different demands. Yellow squares are water treatment plants and black arrows indicate direction of flow between different sources and demands.



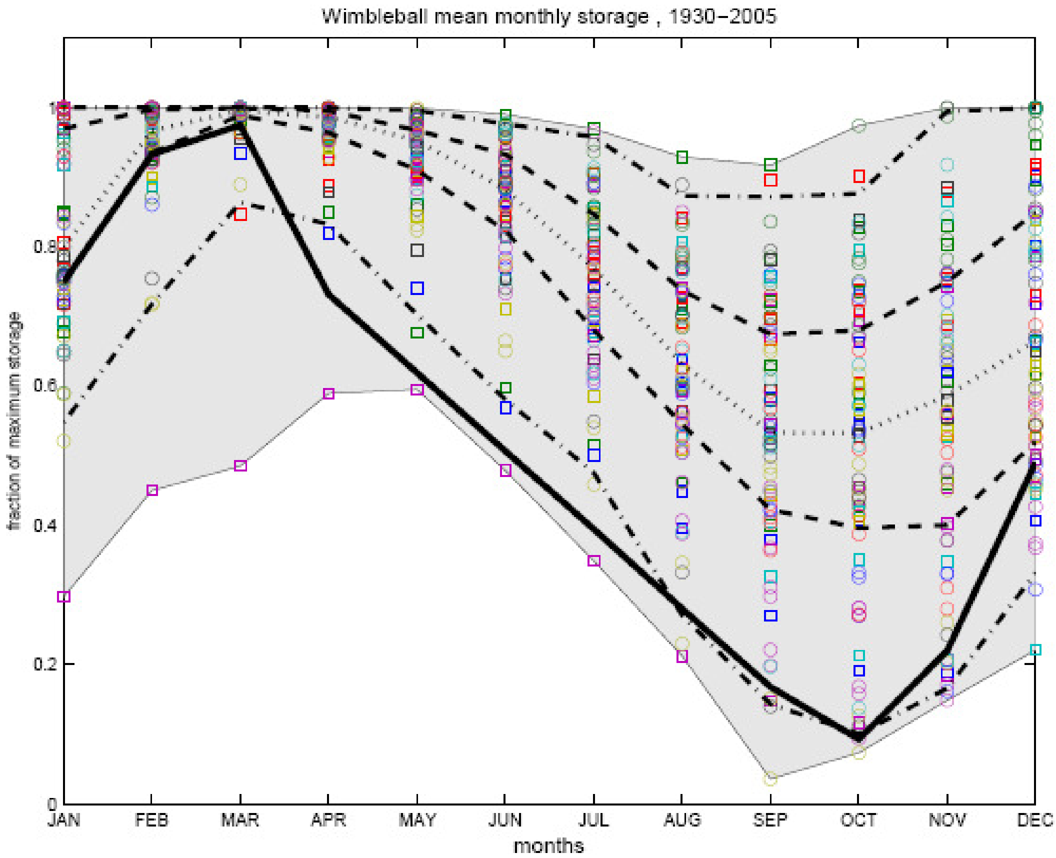


Figure 6: Wimbleball mean monthly storage for historical data represented as fraction of maximum storage. Colour squares are storage levels simulated with simulated flows between 1930 and 1957. Colour circles are simulated levels with observed river flows between 1957 and 2005. The black solid line indicates the control rule described in the text. Dashed lines represent from bottom to top, the reservoir level found 2.5, 25, 50, 75, and 97.5% of the time respectively.

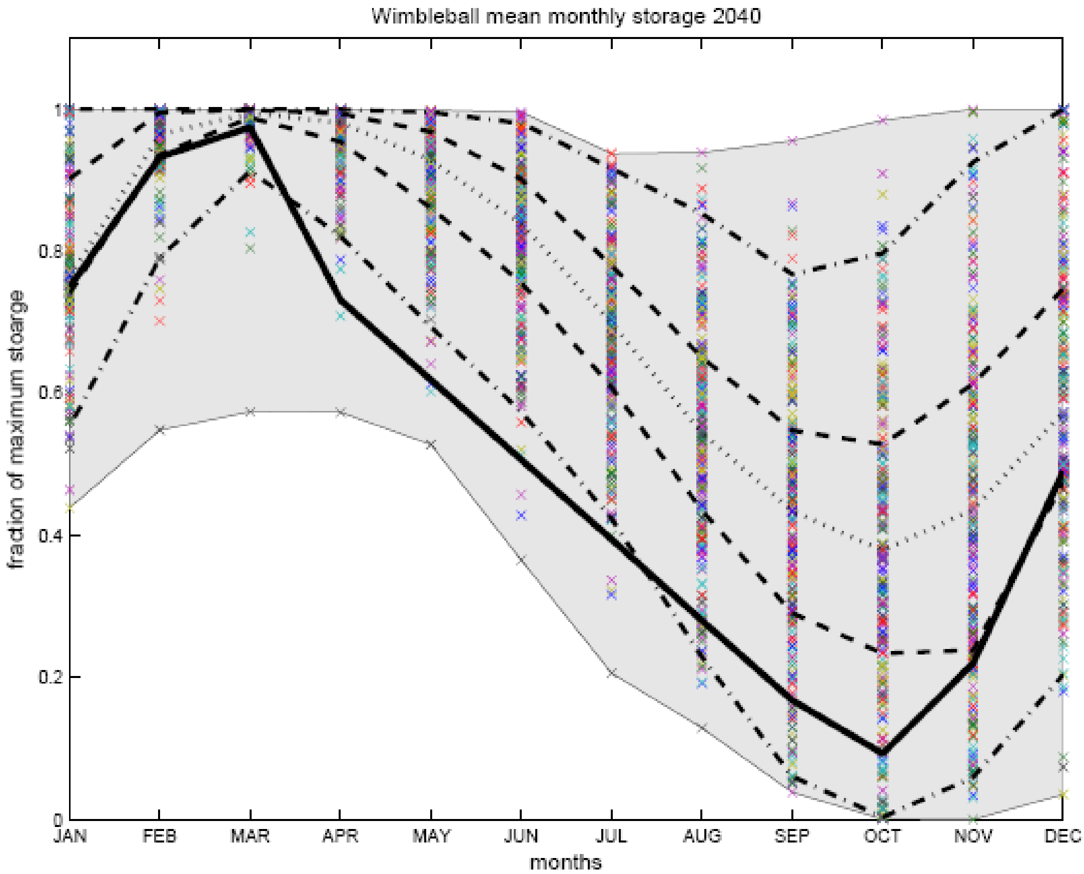


Figure 7: Wimbleball fraction of maximum storage level for 2040 using CPDN ensemble (colour crosses). The black solid line indicates a control rule described in the text. Dashed lines represent from bottom to top the reservoir level simulated by 2.5, 25, 50, 75, and 97.5% of the model runs respectively.

.

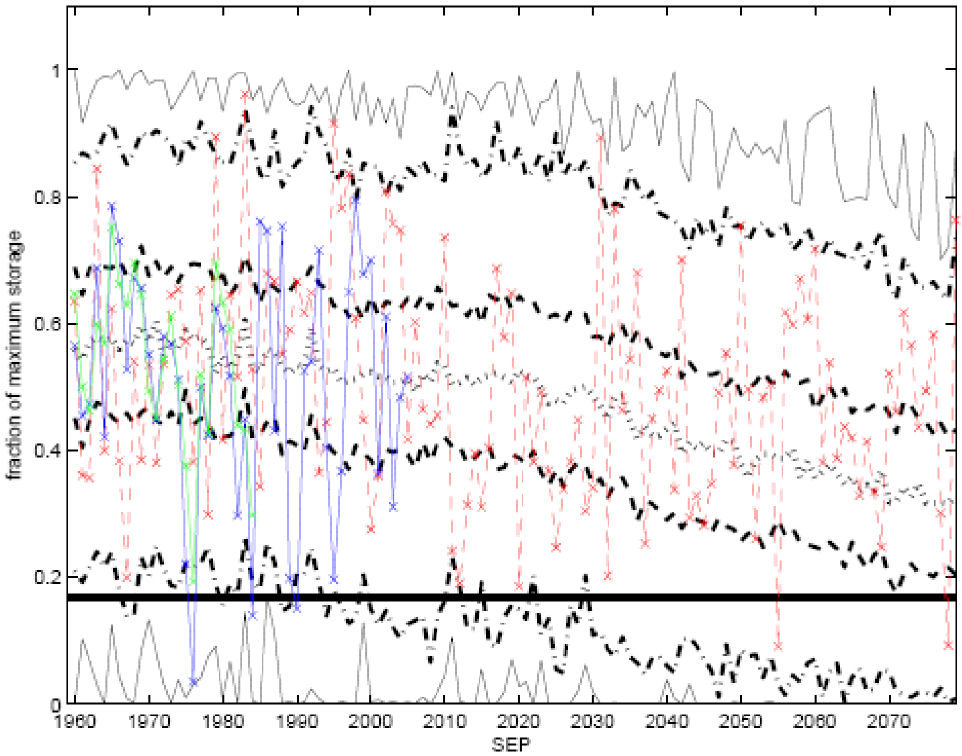


Figure 8: Mean monthly fraction of maximum storage level for September between 1960 and 2079. The black lines represent from top to bottom: maximum values (solid), 97.5% (dotted-dashed), 75% (dashed), 50% (dotted), 25% (dashed), 2.5% (dotted-dashed), minimum values (solid), across the climate model ensemble. The thick solid line corresponds to the control rule described in the text. Blue and green crosses indicate storage levels simulated by LANCMOD using observed flows and simulated historical flows respectively. Red crosses correspond to storage levels for the CPDN model run with standard values of the physical parameters.

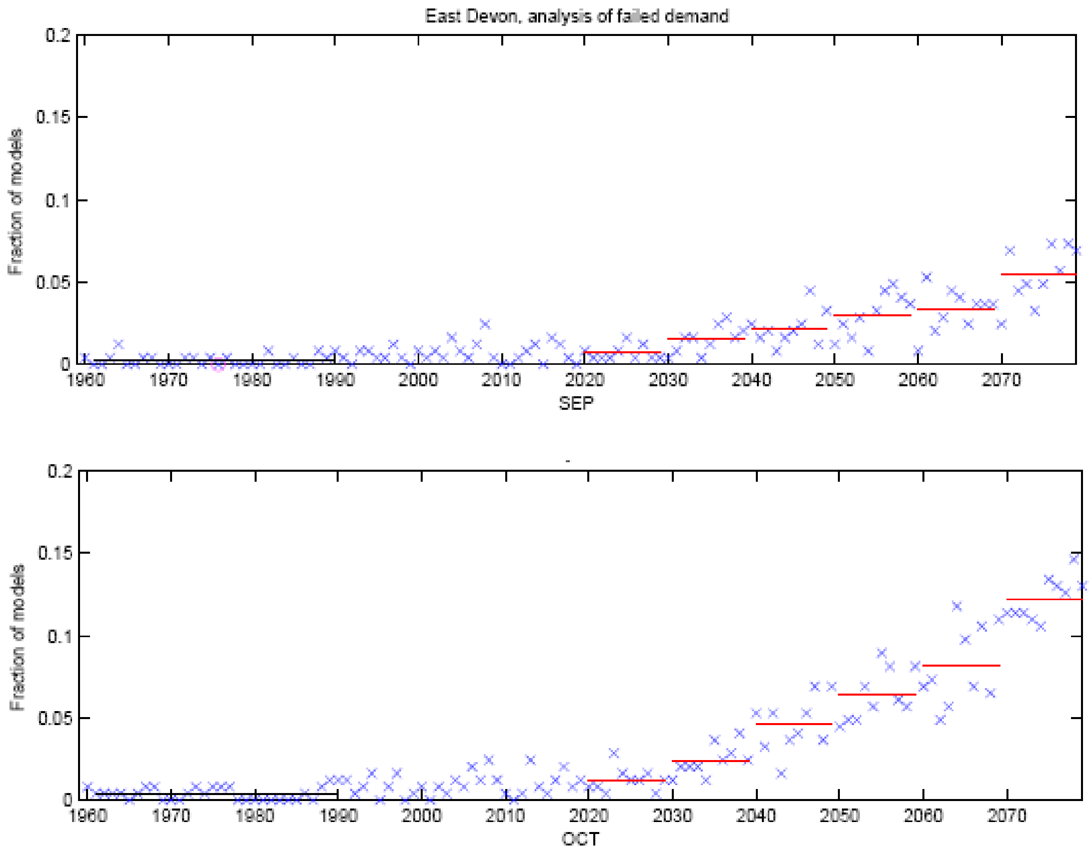


Figure 9: East Devon demand. The top panel (bottom panel) indicates the fraction of models that fail to supply September (October) average monthly demand each year. The black horizontal line is mean over 1960-1989, and the red lines are averages over the corresponding decades. The magenta circle indicates the only time demand failed within the historical record (September 1976).

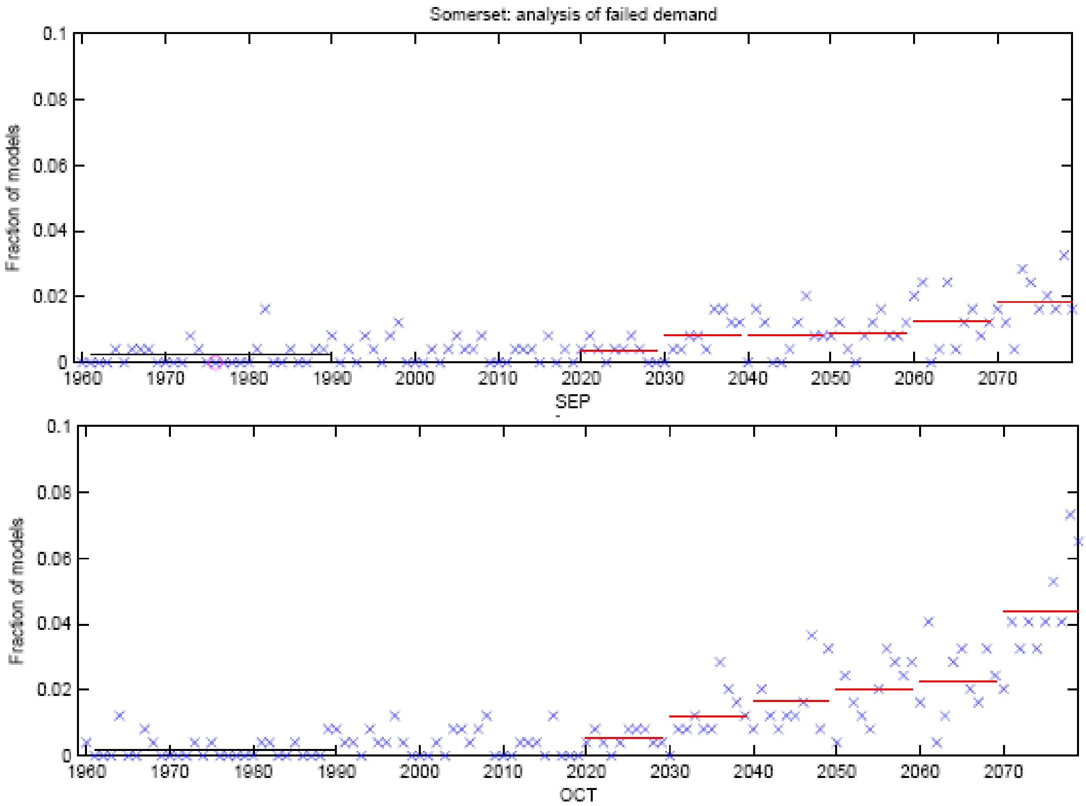


Figure10: Same as figure 9 for Somerset demand.

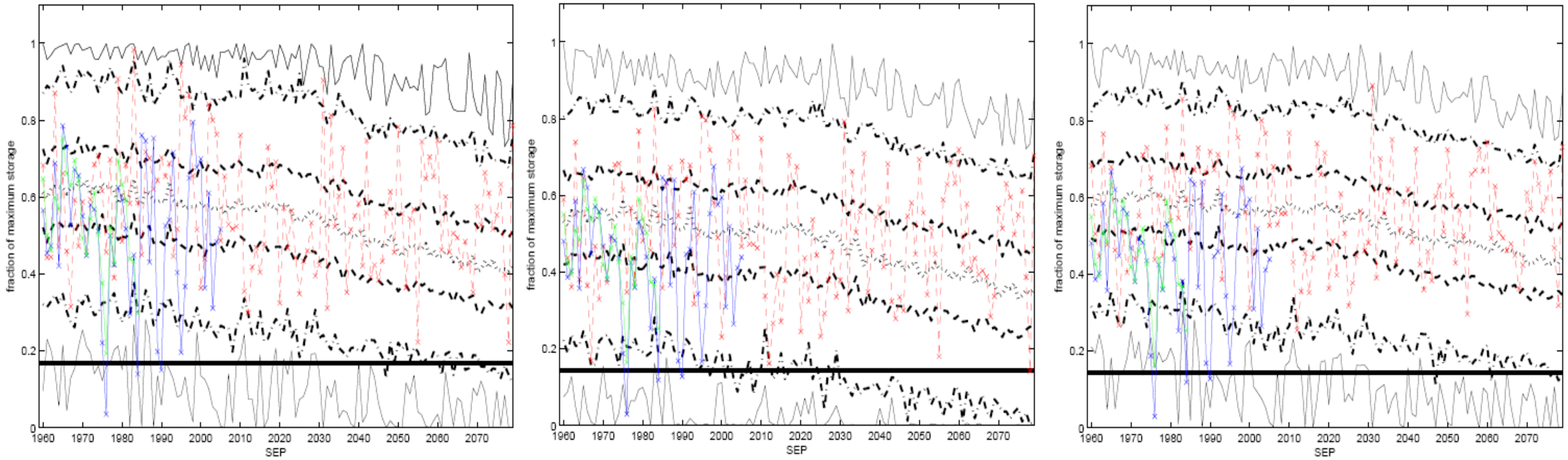


Figure 11: Wimbleball storage levels as a function of time (September) for ALL_{red} (a), L_{res} (b) and L+ ALL_{red} (c) demand and supply management scenarios. The black lines represent from top to bottom: maximum values (solid), 97.5% (dotted-dashed), 75% (dashed), 50% (dotted), 25% (dashed), 2.5% (dotted-dashed), minimum values (solid), across the climate model ensemble. The thick solid line corresponds to the control rule. Blue and green crosses indicate storage levels simulated by LANCMOD using observed flows and simulated historical flows respectively, and are included here for reference. Red crosses correspond to storage levels for the CPDN model run with standard values of the physical parameters.

Appendix II: Water supply case study

PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY A

Phil. Trans. R. Soc. A (2007) **365**, 2117–2131
doi:10.1098/rsta.2007.2080
Published online 14 June 2007

Challenges in using probabilistic climate change information for impact assessments: an example from the water sector

By Mark New[1,*], Ana Lopez[1], Suraje Dessai[2] and Rob Wilby[3]

[1] *Centre for the Environment and Tyndall Centre, Oxford University, Oxford OX1 3QY, UK*
[2] *Tyndall Centre, University of East Anglia, Norwich NR4 7TJ, UK*
[3] *Environment Agency of England and Wales, Cardiff CF24 0TP, UK*

Climate change impacts and adaptation assessments have traditionally adopted a scenario-based approach, which precludes an assessment of the relative risks of particular adaptation options. Probabilistic impact assessments, especially if based on a thorough analysis of the uncertainty in an impact forecast system, enable adoption of a risk-based assessment framework. However, probabilistic impacts information is conditional and will change over time. We explore the implications of a probabilistic end-to-end risk-based framework for climate impacts assessment, using the example of water resources in the Thames River, UK. We show that a probabilistic approach provides more informative results that enable the potential risk of impacts to be quantified, but that details of the risks are dependent on the approach used in the analysis.

Keywords: climate change; impacts; uncertainties; probabilities; water resources; ensembles

1. Introduction

Climate change impact assessments have to date relied predominantly on the scenario-based approach (Carter *et al.* 2001; Mearns *et al.* 2001). It has long been recognized that any one scenario represents a single trajectory through the cascade of uncertainty: emissions → concentrations → regional climate response → local climate response → impact (with or without feedbacks between each component of the cascade, e.g. New & Hulme 2000; IPCC 2001). The use of one or more scenarios, while useful for exploring potential climate change impacts, presents difficulties when adaptation decisions have to be made. Scenarios typically have no associated likelihood, so decision-makers faced with alternative scenarios cannot assess the relative risk of particular adaptations; the tendency may then be to choose a response to a middle of the road scenario or more conservatively, a strategy that is robust in the face of all available scenario-based information. Even a robust strategy may be difficult to implement if the decision-maker is concerned about impacts that fall outside the range suggested by the scenarios at hand.

* Author for correspondence (mark.new@ouce.ox.ac.uk).

One contribution of 13 to a Theme Issue 'Ensembles and probabilities: a new era in the prediction of climate change'.

Probability distributions of climate change impacts allow us to move to a risk-based impact and adaptation decision-making framework (Pittock *et al.* 2001). However, even for global-scale metrics such as climate sensitivity or the likelihood of exceeding a given 'dangerous' global temperature threshold, a unique probability distribution is impossible to derive due to the imprecise information available, scientific and modelling uncertainties, and different statistical estimation approaches (Hall 2007; Hall *et al.* 2007; Rougier 2007).

Although there have been previous attempts to assess local impacts within a probabilistic framework, these studies have typically scaled one or a few GCM responses by probabilities derived from a simple climate model (e.g. Jones 2000; New & Hulme 2000; Prudhomme *et al.* 2003), or have involved an assessment of the relative size of climate model and impacts model uncertainties (e.g. Aggarwal & Mall 2002; Wilby & Harris 2006; Graham *et al.* 2007), rather than a full end-to-end uncertainty analysis. Methods for addressing uncertainty in simulation models are well developed in many natural science fields, most notably hydrology (Freer *et al.* 1996; Beven 2000; Beven & Freer 2001), but relatively few climate change impact studies have drawn on these approaches (Araújo & New 2007). There have also been a number of assessments of regional scale uncertainty in climate change scenarios arising from both GCMs and regional climate models (RCMs) and/or statistical downscaling techniques (e.g. Tebaldi *et al.* 2005; Feng & Fu 2006; Frei *et al.* 2006; Haylock *et al.* 2006; Goodess *et al.* in press) and some attempts to link multiple GCM-downscaling combinations (Benestad 2004; Jasper *et al.* 2004; Pryor *et al.* 2005, 2006; Salathe 2005; Chen *et al.* 2006; Graham *et al.* 2007). But linking all these aspects of uncertainty together to address combined climate model and impacts model uncertainty in an end-to-end probabilistic framework has been fundamentally limited by a lack of sufficiently comprehensive uncertainty analyses of GCMs, which ultimately drive the impacts assessment process (Fowler *et al.* in press).

The large-ensemble GCM-modelling efforts described in this issue (Murphy *et al.* 2007) and elsewhere (Murphy *et al.* 2004; Stainforth *et al.* 2005) offer the opportunity for a 'probabilistic' approach to assess regional and local climate change impacts. Large ensemble GCM simulations, using hundreds to many tens of thousands of GCMs, potentially provide richer regional detail than multiple sampling of a few GCM patterns, as different climate forcings and initial conditions (IC) are propagated through alternative physics to a larger number of model-specific regional responses (e.g. Harris *et al.* 2006); the range in both global and regional responses from large perturbed-physics ensembles have been wider than those produced through analysis of model runs available from the global climate modelling community, the so-called 'ensembles of opportunity'. However, probabilistic climate prediction is a double-edged sword. While undoubtedly providing more information, the regional information arising from large ensemble GCM modelling remains conditional and will suffer from the same lack of uniqueness as distributions for global metrics.

In this paper, we explore the implications of this new generation of probabilistic climate information for end-to-end uncertainty analysis in impacts modelling and assessment. Our focus is at the regional to local scale, where local authorities, environmental agencies, business and other players may need to make decisions on climate change adaptation. We present the first example of how climate data from the climate*prediction*.net project can be used to generate probabilistic information that incorporates *both* climate model and impact model uncertainty, focusing on the Thames River in the UK. We first describe the experimental set-up, including the climateprediction.net data, the hydrological model (CATCHMOD) that we use and the approach to downscale the climate model outputs to the spatial scale required by CATCHMOD. We then describe the resultant probabilistic projections of future flow statistics in the Thames. We conclude the paper with a discussion of the main points arising from this research.

2. Methods and data

We use the initial results from the climateprediction.net experiment described in detail by Stainforth *et al.* (2005). The data from the experiment represent 2700 individual simulations with the HadSM3 climate model; each simulation comprises three 15-year periods: a calibration phase, followed by a 15 year $1\times CO_2$ 'control' simulation, and a $2\times CO_2$ simulation, in which the model moves towards an equilibrium response to $2\times CO_2$. Within this subset of the full first experiment, seven physics parameter values are perturbed and there are 449 unique combinations of perturbations. For most perturbations, there is more than one simulation, with each simulation differing only in IC. The total number of simulations in the 449 IC ensembles adds up to 2700 simulations in the 'grand ensemble'. The ensemble is therefore large, but limited in a number of ways: it comprises a sampling of only some of the uncertain physics parameters in the Hadley Centre climate model; it only samples from a single 'parent' model structure, ignoring uncertainties arising from alternative GCM model structures; it is a $2\times CO_2$ sensitivity experiment, without a full ocean model, rather than a transient experiment with a comprehensive atmosphere–ocean model such as those contributing to the last IPCC report.

Seasonal means from the last 8 years of the control and $2\times CO_2$ runs, and only for a limited number of variables, have been returned by client machines for archival in climateprediction.net data servers; we use precipitation, temperature and cloud fraction data to calculate future daily precipitation and potential evaporation to input into our hydrological model.

Many ensemble members have not reached equilibrium at the end of the $2\times CO_2$ phase. We therefore scale the $2\times CO_2$ 8-year mean responses for each variable by the ratio of global mean temperature for this period to the global mean equilibrium temperature change, estimated using the approach of Stainforth *et al.* (2005).

We use CATCHMOD to simulate daily discharge in the Thames at Teddington, London. CATCHMOD is a rainfall-runoff model used by the Environment Agency (EA) of England and Wales for water resource planning and abstraction licence allocation, and is described in detail by Wilby *et al.* (1994). It uses daily rainfall (PPT) and potential evapotranspiration (PET) data for input at sub-catchments represented in the model. This requires downscaling of the coarser resolution seasonal mean GCM data. As the archived GCM data do not support either dynamical or statistical downscaling, we use a simple *change factor* (CF) downscaling approach to produce input for CATCHMOD. For both PPT and PET, we compute a factor by which the variable will change in the future ($2\times CO_2$) compared to the present day ($1\times CO_2$) for each model run; these CFs are then used to perturb the observed daily climate data used to run CATCHMOD for present day simulations. For precipitation, the CF is the per cent change in seasonal precipitation between $1\times CO_2$ and $2\times CO_2$ periods for the GCM grid box that covers the Thames catchment. The seasonal CFs are linearly interpolated to monthly CFs and applied to the daily observed precipitation data.

The procedure for PET is more complicated as this variable is not available as direct climateprediction.net output; available model outputs of relevance to PET are temperature and cloud cover. We first estimate mean monthly PET for the present day using observed data (temperature, vapour pressure, net radiation and wind speed) with the Penman (1948) formulation. We next calculate CFs for temperature and cloud from the GCM data, which are then used to perturb the observed temperature, vapour pressure and radiation inputs to the PET calculation; the ratio of present day to perturbed Penman PET is then used as a CF to perturb the observed PET daily time series.

We note that our use of CFs forces the future time series to have the same temporal structure as the present day, and that any changes in variance simply reflect a scaling of the observed series (Diaz-Nieto & Wilby 2005). In addition, use of an 8-year average to characterize both $1\times CO_2$ and $2\times CO_2$ mean climate implies that natural variability will contribute more to the resulting CFs than in many previous impacts assessments, where usually differences of 30-year averages are considered. The influence of natural variability is reduced somewhat by averaging across IC-members, but the number of members in each IC ensemble varies from one to eight, and thus natural variability is a varying unknown for each CF.

CATCHMOD was set up with three ‘subcatchments’, each representing the area of the catchment with a similar hydrological runoff response: urban areas, clay geology and chalk geology (Wilby & Harris 2006). For each subcatchment, five parameters for CATCHMOD are determined through calibration against observed discharge. For our research, we explore the effects of uncertainty in these parameters by running CATCHMOD with 100 different combinations of parameter values, all of which produce calibration results within predefined goodness of fit limits (Wilby & Harris 2006). The underlying rationale to exploration of parameter uncertainty is similar to the climateprediction.net project; however, unlike climateprediction.net, the set of parameters values used for CATCHMOD is preselected by evaluation against observed discharge.

3. Results

(a) *Climate change information*

The simulated $1\times CO_2$ and $2\times CO_2$ precipitation and temperature at the GCM grid box covering the Thames basin are shown in figure 1. Temperature shows a similar range and distribution to the global equilibrium temperature results (Stainforth *et al.* 2005), as might be expected from a mid-latitude location. Rainfall changes in winter are almost all positive, and range up to a 50% increase compared to the control simulations. For autumn and spring, both increases and decreases in precipitation are simulated, while in summer nearly all models simulate reduced precipitation; in some instances, the reduction is as much as 80%. Cloud cover changes correlate closely to changes in precipitation (not shown).

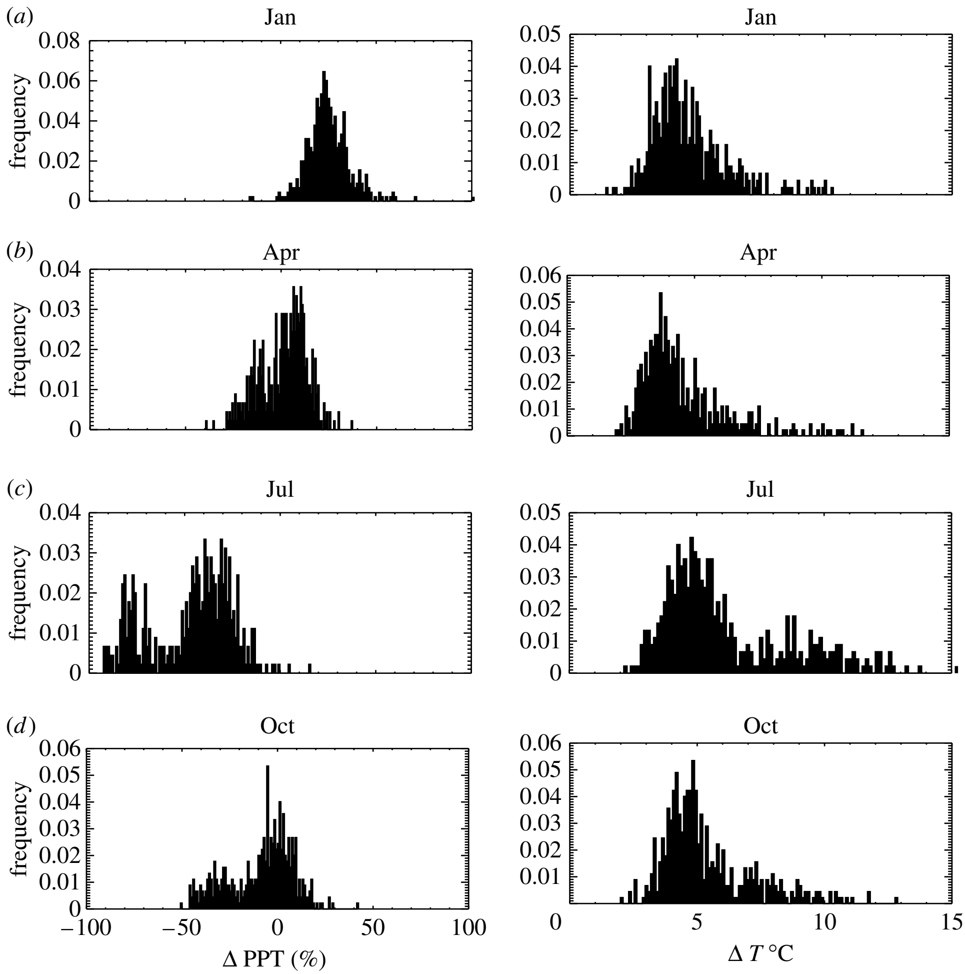


Figure 1. Simulated $1\times CO_2$ and $2\times CO_2$ climate data (precipitation change on the left and temperature change on the right) over the Thames from the climateprediction.net experiment.

In addition to the wide ranges of predicted mean changes in climate, precipitation change shows a bimodal distribution in spring, summer and autumn; this bimodality occurs over all UK and Ireland and adjacent ocean grid boxes, so appears to be a regional characteristic. The bimodality is particularly strong in summer and is not related to any individual parameter perturbation. A clearer understanding of reasons for this is difficult to come by, due to the limited set of model diagnostics that are archived. There is evidence that HadSM3 can become locked into different climate regimes over SW France, due to soil-moisture feedbacks (Clark *et al.* 2006); in some simulations, soil moisture reduces sufficiently to produce persistent surface heating. This would then affect regional circulation patterns, which may in turn affect precipitation. There also appears to be a relationship with the mean pressure gradient over the North Atlantic, since models with a high gradient under $2\times CO_2$ have lower autumn rainfall. This is consistent with an observed link between UK summer rainfall and the

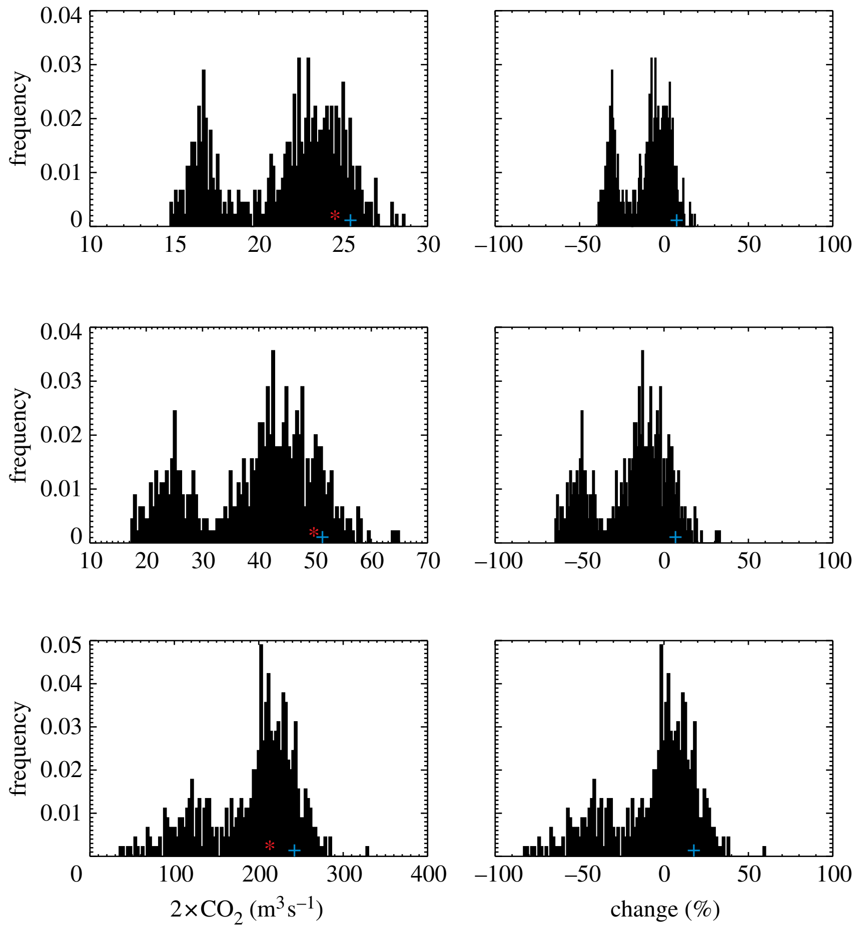


Figure 2. Changes in CATCHMOD simulated low (Q95), average (Q50) and high (Q05) flow statistics due to changes in precipitation and PET downscaled from the climateprediction.net ensemble. Q95 is the daily flow exceeded 95% of the time (low flows); Q50 is the median daily flow; Q05 is the daily flow exceeded 5% of the time (high flows). The red star shows the results when CATCHMOD is run with unperturbed present day climate data (1961–1990); blue symbol shows results for the standard version of HadSM3 climate model used in climateprediction.net.

North Atlantic Oscillation in the preceding winter (Wilby 2001). The available model diagnostics do not allow us to ascertain whether the pressure gradient-rainfall relationship is linked in any way to soil-moisture feedbacks.

(*b*) *Simulated flow*

We first describe how the downscaled climateprediction.net data described above propagate through the 'standard' CATCHMOD version (i.e. the version with a single set of parameter values, as used by the EA). For each of the 449 simulations with CATCHMOD, we calculate $1\times CO_2$ and $2\times CO_2$ flow percentiles as follows:

— Q05, the daily flow exceeded 5% of the time, which represents high flows,
— Q50, the median daily flow, and

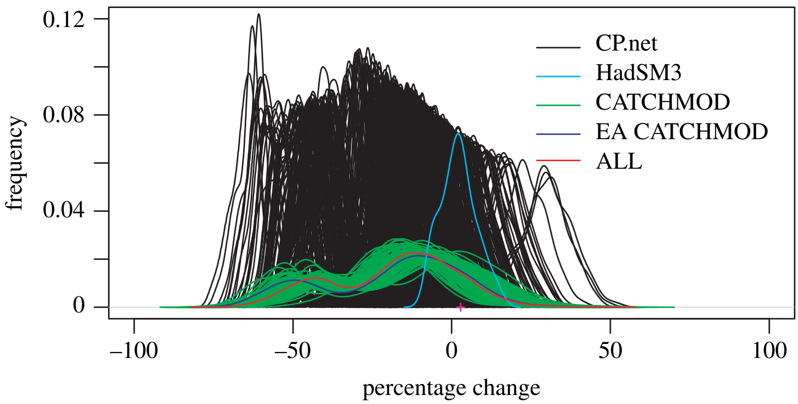


Figure 3. Changes in CATCHMOD simulated Q50 when uncertainties in CATCHMOD parameters are combined with the climateprediction.net ensemble. Each black curve is a smoothed frequency histogram obtained by combining one climateprediction.net IC ensemble with 100 CATCHMOD model versions. Green curves show the response of each CATCHMOD version combined with all climateprediction.net results. The red curve is the frequency distribution from all possible climateprediction.net–CATCHMOD combinations. For reference, the results from (i) the standard HadSM3 model with all CATCHMOD versions (light blue) and (ii) EA CATCHMOD with all climateprediction.net ICs (dark blue) are also shown. The red cross shows the result of the singular combination of the standard HadSM3 and EA CATCHMOD.

— Q95, a low-flow index corresponding to the daily flow exceeded on 95% of days, commonly used for resources assessment in catchment abstraction management plans by the EA.

The distribution of these percentiles across the 449 climateprediction.net ICs are shown in figure 2. For low and median flows, most realizations produce a decrease in the future. Of particular note is that most simulations result in reduced flows when compared with the standard atmospheric model (blue cross in figure 2), which was used, albeit coupled to a full ocean model, to generate the current set of UK climate change scenarios (Hulme *et al.* 2002). This illustrates a potential limitation of a scenario-based approach to impacts assessment; in this case, a single projection using the standard model provides a rather high estimate of future water resource availability when compared with other parameter combinations.

The bimodal distribution in precipitation produces either a second mode (Q95 and Q50) or negative skew (Q05) in the flow statistics. For high flows, while the proportion of simulations showing increases and decreases are roughly equal, the skewed distribution means that there are a relatively large number of cases where high flows are reduced by more than 40%, but all increases (bar one) are less than +40%.

We next consider the changes in simulated flow arising from both climateprediction.net and CATCHMOD parameter uncertainty. Here, we calculate flow statistics for 44 900 simulations with CATCHMOD, each simulation a unique combination of one of the 449 climateprediction.net IC outputs and one of the 100 CATCHMOD parameterizations (figure 3). If the standard HadSM3 model projections are run through all versions of CATCHMOD (light blue curve in figure 3), the range of responses in Q50 is −15 to +20%; similar ranges, with a

Table 1. Frequency of future monthly flows in climateprediction.net–CATCHMOD ensemble *below* low-flow thresholds identified in the present-day (1961–1990) simulations: (i) the lowest flows between 1961–1990 (LMMF 61–90) and (ii) the 10th percentile of monthly mean flow (MMF10).

month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
LMMF 61–90	0.039	0.067	0.033	0.034	0.039	0.056	0.071	0.075	0.311	0.195	0.039	0.065
MMF10 61–90	0.231	0.153	0.130	0.139	0.151	0.217	0.310	0.330	0.380	0.283	0.203	0.306

different central value, arise from combining any one climateprediction.net IC with the 100 CATCHMOD versions (black curves in figure 3). A similar result arises for Q05 and Q95 (not shown). Thus, the wide spread of climateprediction.net outputs dominate the spread in simulated changes, with different versions of CATCHMOD modulating the climateprediction.net signal. Nonetheless, if one compares the range of changes in Q05, Q50 and Q95 when using only the standard CATCHMOD to those using the full ensemble, CATCHMOD parameter uncertainty adds an additional 23% to the range for Q50, 16% for Q05 and 35% for Q95; thus low flows are most sensitive to hydrological model uncertainty.

(*c*) *Implications for water resource planning*

The simulated flows described above provide important information on the spread of plausible future natural flow levels in the Thames, and therefore an indication of possible future change in raw water availability. To illustrate this, we identify the lowest mean monthly flow (LMMF) and the 10th percentile for mean monthly flow (MMF10) in the 1961–1990 period; we then calculate the frequency with which monthly flow in the $2\times CO_2$ in the full climateprediction.net–CATCHMOD ensemble does not reach these levels (table 1). For reference, flows lower than LMMF would have a present-day frequency no higher than 0.033 (return period of 30 years); flows lower than MMF10 have a present-day frequency of 0.10 (10-year return period).

The lowest monthly flows in 1961–1990 occur in 1976 (January–August) and 1974 (September–December); 1976 is well known as a year with the most extensive drought conditions over southern England in recent years, and severe water shortages over most areas of the UK (Jones *et al.* 2006). It is used by some water utilities as a worst-case scenario for future resource planning, especially in southern England. In the Thames, summer 1976 flows are thought to be the lowest since 1865, at just 20% of the 1961–1990 average discharge (Jones *et al.* 2006). In the $2\times CO_2$ ensemble, the frequency of flows lower than LLMF ranges between 3% (similar to today) and 30%, depending on the month, with the highest frequencies occurring in late summer and autumn (a reflection of the reduced summer rainfall across most of the climateprediction.net ensemble). For MMF10, the frequency ranges from 13% in March (similar to present day) to over 30% for late summer and autumn, more than a threefold increase.

While these results provide information about the change in frequency of stressful water resource situations, the use of probabilistic climate data in a planning context requires more than consideration of GCM and hydrological model uncertainties addressed here. Future demand is also subject to considerable ambiguity, mainly because of uncertainty about changes in regional population, housing stock and industrial demands, but also due to changed (probably increased) *per capita* water use in a warmer climate. For example, current projections indicate that about 200 000 new households will form each year out to 2026, of which 60% will be in the south of England (EA 2007). This implies a 10–15% increase in reservoir capacity to meet rising water demand, at a cost of £3 billion. It is also envisaged that measures will be taken to improve water efficiency of new homes as well as the current housing stock. From April 2007, all publicly funded housing will have to be built to the Level 3 standard of the Code for Sustainable Homes, which means no more than 105 l per person per day, compared with the current UK average of 150 l (EA 2007). Making existing homes more water efficient could help meet approximately 40% of the future demand arising from new communities in the region, but considerable uncertainty exists as to the extent to which this can be achieved.

A thorough assessment of the implications of the probabilistic climate data for the Thames would therefore require simulations with a model representing the full water-resource system for the river, with the flexibility to include uncertainty in future demand and possible new abstraction and storage schemes.

We illustrate the type of information that can potentially be provided in such a water resource assessment using the trigger storage levels for reservoirs and flows set by the Environment Agency for the discharge in the River Thames at Teddington. These operating rules set out the demand management measurements that follow from progressively lower reservoir storage levels and river flows in the lower Thames. Under critical water storage conditions that vary through the year, the four trigger levels in the Thames are 800, 600, 400 and 300 Ml d^{-1}. Thus in January, when there remains a good chance of further rainfall to replenish reservoirs before demand peaks in late summer, reservoir storage must drop below 63 000 Ml for the Level 4 threshold of 300 Ml to be reached; in August, when there is little likelihood of replenishment, Level 4 is reached at a much higher storage level of 125 000 Ml. These thresholds invoke water saving publicity campaigns (Level 1), sprinkler bans and voluntary restrictions of inessential water use (Level 2), banning inessential water use and reduced pressure in the distribution system (Level 3) and finally major cuts of supply on a rota basis and use of standpipes (Level 4), respectively.

We first consider the changes in frequency of these thresholds being reached when the outputs from the simulations are used in their 'unprocessed' frequency distribution (i.e. without any post-processing to account, for example, for the uneven sampling of climateprediction.net parameter space). For July, the flow thresholds were not met in the 1961–1990 simulations some 1.5% of the time for the Level 4 trigger and 3.8% of the time for the more lenient Level 1 threshold (table 2; figure 4). When the frequency output from the $2\times CO_2$ ensemble is analysed the Level 1 and Level 4 targets are not met 6 and 16% of the time, respectively; this represents a quadrupling of the likelihood of triggering demand management measures relative to 1961–1990. The highest frequency of future failure is in August, at the end of the summer dry period, where the Level 1 target is not met 22% of the time, or an average of once every 4 years, and the Level 4 target is not met 8.5% of the time, once every 12 years. In January, the frequency of any of the thresholds being met is very low in both 1961–1990 and $2\times CO_2$ simulations owing to the generally higher flows in winter. Note that these will not correspond directly to the frequency of *implementation* of demand management

Table 2. Frequency with which EA water-demand management flow thresholds at Teddington are reached under present-day and $2\times CO_2$ climates (figure 4). ((i) 1961–1990, present-day simulated flows; (ii) unprocessed: using the $2\times CO_2$ climateprediction.net–CATCHMOD outputs directly; (iii) uniform, equal likelihood across the range of the $2\times CO_2$ climateprediction.net–CATCHMOD outputs; (iv) normal, assuming a Gaussian distribution across the range of the $2\times CO_2$ climateprediction.net–CATCHMOD outputs.)

		flow target (Ml d^{-1})			
		300 (Level 4)	400 (Level 3)	600 (Level 2)	800 (Level 1)
January	1961–1990	0.0002	0.0002	0.0005	0.0005
	unprocessed	0.0003	0.0008	0.0034	0.0100
	uniform	0.0090	0.0120	0.0170	0.0230
	Gaussian	0.0016	0.0017	0.0019	0.0021
July	1961–1990	0.0153	0.0278	0.0346	0.0381
	unprocessed	0.0612	0.0821	0.1198	0.1613
	uniform	0.0310	0.0420	0.0640	0.0850
	Gaussian	0.0025	0.0030	0.0045	0.0064
August	1961–1990	0.0274	0.0371	0.0533	0.0688
	unprocessed	0.0850	0.1102	0.1607	0.2237
	uniform	0.0310	0.0420	0.0630	0.0850
	Gaussian	0.0025	0.0030	0.0044	0.0064

measures, which are only triggered if the flow reaches a given threshold *and* the reservoir storage also below a critical threshold; our hydrological model does not simulate reservoir storage, so these joint probabilities cannot be calculated.

(*d*) *Alternative sampling strategies*

The examples presented above represent an illustrative sensitivity study, where the outcomes are conditional on a number of factors arising from the experimental strategy, including: the choice of climate model, hydrological model, climate and hydrological model parameters to be perturbed, sampling across these parameters, climate variables available, and downscaling methodology. A different experimental set-up would produce different results (Rougier 2007), though we cannot say how different they would be. For example, the bimodal distribution in rainfall change may contain real information about the behaviour of the climate system or it may be an artefact of the GCM structure, the limited number of GCM parameters assessed or of GCM parameter combinations that, with more extensive evaluation, are considered to produce unrealistic climate system behaviour. Various post-processing methods to account for some of the artefacts of the experimental set-up are possible. An emulator can be used to estimate the full response surface across the parameter space, as will be done for the 2008 UK climate change scenarios (Murphy *et al.* 2007); similarly, evaluation of the climateprediction.net ensemble against observations may down weight or exclude particular areas of parameter space (Murphy *et al.* 2004).

Given that the distribution of climate impacts will depend on experimental set-up and post-processing, we explore the effect of two simple alternatives to the direct use of climateprediction.net–CATCHMOD data to estimate frequency of low-flow

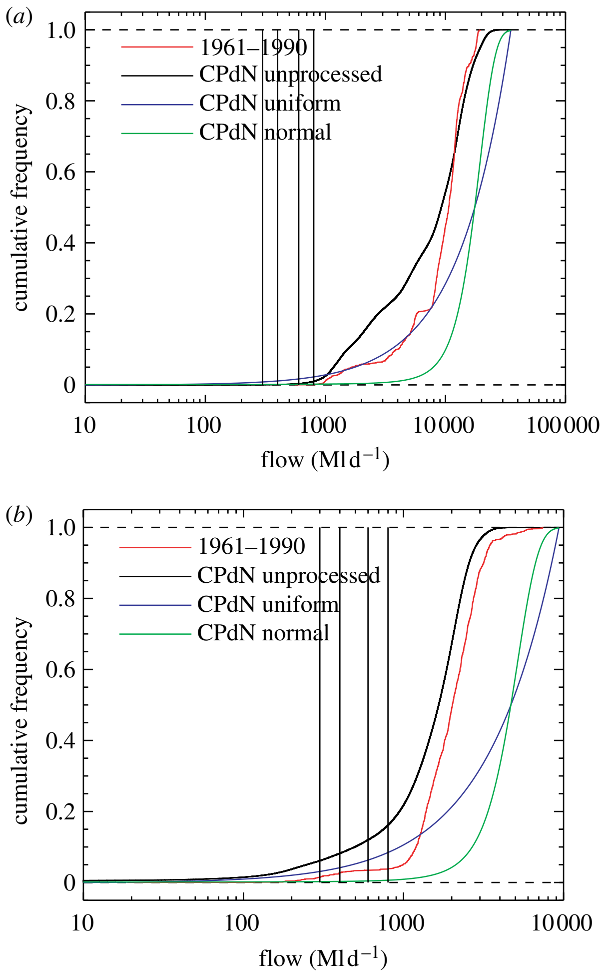


Figure 4. Cumulative frequencies of (*a*) January and (*b*) July monthly discharge for the Thames at Teddington, in the context of environmental flow targets (300, 400, 600 and 800 Ml d^{-1}) set by the Environment Agency for different reservoir capacities. Red shows the frequency for the present day flows (1961–1990). The remaining curves show the frequency from the climateprediction.net–CATCHMOD under different sampling strategies: black, sampling of unprocessed output; blue, assuming a uniform distribution over the range of outputs; green, assuming a Gaussian distribution centred on the middle of the range.

thresholds. These illustrate the point that different likelihoods of impacts will arise dependent on the methodology chosen. The first approach uses uniform sampling across the range of the ensemble, making no assumptions about the distribution within the range; all outcomes within the range of predicted flow statistics are equally probable. The second analysis assumes that the distribution is Gaussian across the range of the unprocessed data; here we set the middle of the range to the mean, and the range is assumed to correspond to 6 standard deviations of the Gaussian.

Results (table 2; figure 4) show that with uniform sampling the likelihood of any demand management threshold being reached is lower in the key summer months of July and August when compared with using unprocessed output. This is because the distribution of the unprocessed $2\times CO_2$ ensemble flows is strongly skewed towards reduced flows (figure 2); uniform sampling reduces the likelihood in this more-populated negative part of the range. For the same reason, Gaussian sampling also reduces the likelihoods of the thresholds in summer. These likelihoods are similar or smaller than the present day (1961–1990) ones, whereas the unprocessed data yield up to a quadrupled likelihood; for example, unprocessed data suggest a Level 3 likelihood in August of 0.11, while the Gaussian or uniform sampling data suggest a likelihood not much greater than today. A water utility may make quite different infrastructure decisions when faced with a Level 3 situation occurring more than once in every 10 years compared to only once every 25 years.

Clearly, if the flow thresholds of interest were nearer the middle of the range (or closer to the end of the range) of simulated flows, the relative frequencies would change; however, they would remain different, in some cases markedly different, in a way that is dependent on the post-processing strategy. For the January flow targets, uniform sampling does, in fact, produce a higher frequency of failure than the unprocessed distribution (albeit a low 0.9 and 2% for 300 and 800 Ml d^{-1}). The few very low flows in January produce a long tail to the distribution of the $2\times CO_2$ ensemble flows; in such a situation, uniform sampling results in a cumulative frequency in the tails of the distribution that is greater than the raw data.

4. Discussion

Our analysis has *illustrated* the potentially rich information that can be obtained by using large perturbed-physics ensemble outputs in a climate change impact assessment. The approach can clearly provide more information than a scenario-based impact assessment. This is illustrated in figure 2, where a scenario approach might produce one or several points on the horizontal axis, whereas with probabilistic information, a frequency distribution or probability distribution can be estimated, and the risks of an adverse impact can be calculated and used to make a risk-based judgement. But figure 4 also shows that different approaches to analysing probabilistic information may lead to a different risk-based decision.

Moving from such an illustrative example to a more complete analysis would require a number of additional elements in the methodology we have used. These include, but are not limited to: (i) use of the transient climateprediction.net ensemble which assesses a wider range of physics perturbations and simulates the transient response to past and future GHG forcing with a coupled ocean–atmosphere model, (ii) incorporation of more sophisticated downscaling methodologies, (iii) consideration of GCM, downscaling and hydrological model structural uncertainties, (iv) estimation of the true response surface(s) for impacts across the parameter ranges in the hierarchy of models used in the end-to-end impacts forecast system, (v) a more sophisticated approach to assessing (and weighting) the skill of individual model combinations in the forecast system, (vi) use of a water resource systems model that enables the assessment of the interplay of demand and supply under different socioeconomic and water infrastructure scenarios, and finally (vii) the development of a methodology that links all these components.

The development of an approach that comprehensively addresses these issues in an end-to-end probabilistic assessment is non-trivial and may be beyond the resources of many organizations. The next set of UK Climate Change Scenarios will provide an 'off-the-shelf' set of probabilistic climate information for many users, but with the proviso the information is dependent on a specific methodology. Further, a full probabilistic impact assessment will require considerable work to estimate probabilities across the entire 'uncertainty cascade'. Organizations without sufficient resources to undertake a full assessment may still be interested in information arising from perturbed-parameter modelling. For example, simply looking at the ranges of predicted outputs, even though their reliability may be questioned, enables an analysis of exposure to them and the risk of not taking the right decisions (Stainforth *et al.* 2007). If potential exposure is deemed serious—and this raises socio-political considerations as individual judgements will need to be made in relation to the accepted level of risk—then a more comprehensive probabilistic assessment might be justified.

However, even with a more comprehensive methodology, the resulting outputs remain conditional: they are the research team's current impacts likelihoods, given the available data and resources (Dessai & Hulme 2004; Rougier 2007). With more data, more resources or an alternative experimental design, the likelihoods will not be the same, though they may or may not be similar.

The challenge therefore is to make use of the richer information that large-ensemble impacts forecasts provide, but to avoid the temptation to consider the results to be fixed, that is, to be 'the probability' of a particular impact. The impacts assessment and, if required, assessment of adaptation options need to be robust in the face of wide uncertainties and the inevitability of estimates of the uncertainty changing over time (Popper *et al.* 2005; Lempert *et al.* 2006). Blind use of a single generation of probabilistic impact information raises the possibility of maladaptation.

The design of methodologies for using large-ensemble climate modelling data in impacts assessment is a developing field, in terms of (i) post-processing of global climate model data and downscaling (Murphy *et al.* 2007; Fowler *et al.* in press), (ii) linking the climate data through impacts to create an end-to-end 'probabilistic forecast system', and (iii) development of approaches for making decisions with probabilistic impacts information. We have shown what an end-to-end impacts assessment might look like, but considerable further work is required to ensure that uncertainty at all steps of the assessment are quantified (such as in the downscaling). Future work is aimed at improving the end-to-end methodology, exploring the relative advantages of simple and sophisticated approaches to probabilistic impacts modelling, and, through the use of real-water resource planning models, developing methodologies for assessing adaptation options and making adaptation decisions.

This study was supported by Environment Agency Science Project SC050045 and by the Tyndall Centre. The views expressed in the paper reflect those of the authors and are not necessarily indicative of the position held by the Environment Agency.

References

Aggarwal, P. K. & Mall, R. K. 2002 Climate change and rice yields in diverse agro-environments of India. II. Effect of uncertainties in scenarios and crop models on impact assessment. *Clim. Change* **52**, 331–343. (doi:10.1023/A:1013714506779)

Araújo, M. B. 2007 Ensemble forecasting of species distributions. *Trends Ecol. Evol.* **22**, 42–47. (doi:10.1016/j.tree.2006.09.010)

Benestad, R. E. 2004 Tentative probabilistic temperature scenarios for northern Europe. *Tellus Series A-Dyn. Meteorol. Oceanogr.* **56**, 89–101.

Beven, K. 2000 On model uncertainty, risk and decision making. *Hydrol. Process.* **14**, 2605–2606. (doi:10.1002/1099-1085(20001015)14:14<2605::AID-HYP400>3.0.CO;2-W)

Beven, K. & Freer, J. 2001 Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *J. Hydrol.* **249**, 11–29. (doi:10.1016/S0022-1694(01)00421-8)

Carter, T. R. *et al.* 2001 Developing and applying scenarios. In *Climate change 2001: impacts, adaptation, and vulnerability* (ed. IPCC), pp. 145–190. Cambridge, UK: Cambridge University Press.

Chen, D. L. *et al.* 2006 Using statistical downscaling to quantify the GCM-related uncertainty in regional climate change scenarios: a case study of Swedish precipitation. *Adv. Atmos. Sci.* **23**, 54–60. (doi:10.1007/s00376-006-0006-5)

Clark, R. T., Brown, S. J. & Murphy, J. M. 2006 Modeling northern hemisphere summer heat extreme changes and their uncertainties using a physics ensemble of climate sensitivity experiments. *J. Clim.* **19**, 4418–4435. (doi:10.1175/JCLI3877.1)

Dessai, S. & Hulme, M. 2004 Does climate adaptation policy need probabilities? *Clim. Policy* **4**, 107–128.

Diaz-Nieto, J. & Wilby, R. L. 2005 A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. *Clim. Change* **69**, 245–268. (doi:10.1007/s10584-005-1157-6)

EA 2007 Climate change and water management: a UK perspective. In *Time to Adapt—Climate Change and the European Water Dimension, Berlin, 12–14 February 2007.*

Feng, J. M. & Fu, C. B. 2006 Inter-comparison of 10-year precipitation simulated by several RCMs for Asia. *Adv. Atmos. Sci.* **23**, 531–542. (doi:10.1007/s00376-006-0531-2)

Fowler, H. J. *et al.* In press. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *Int. J. Climatol.*

Freer, J., Beven, K. & Ambroise, B. 1996 Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach. *Water Resour. Res.* **32**, 2161–2174. (doi:10.1029/96WR03723)

Frei, C., Schöll, R., Fukutome, S., Schmidli, J. & Vidale, P. L. 2006 Future change of precipitation extremes in Europe: intercomparison of scenarios from regional climate models. *J. Geophys. Res. Atmos.* **111**, D06 105. (doi:10.1029/2005JD005965)

Goodess, C. M. *et al.* In press. An intercomparison of statistical downscaling methods for Europe and European regions—assessing their performance with respect to extreme weather events and the implications for climate change applications. *Clim. Change.*

Graham, L., Andréasson, J. & Carlsson, B. 2007 Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods: a case study on the Lule River basin. *Clim. Change* **81**, 293–307.

Hall, J. 2007 Probabilistic climate scenarios may misrepresent uncertainty and lead to bad adaptation decisions. *Hydrol. Process.* **21**, 1127–1129. (doi:10.1002/hyp.6573)

Hall, J., Fu, G. & Lawry, J. 2007 Imprecise probabilities of climate change: aggregation of fuzzy scenarios and model uncertainties. *Clim. Change* **81**, 265–281. (doi:10.1007/s10584-006-9175-6)

Harris, G. R., Sexton, D. M. H., Booth, B. B. B., Collins, M., Murphy, J. M. & Webb, M. J. 2006 Frequency distributions of transient regional climate change from perturbed physics ensembles of general circulation model simulations. *Clim. Dyn.* **27**, 357–375. (doi:10.1007/s00382-006-0142-8)

Haylock, M. R., Cawley, G. C., Harpham, C., Wilby, R. L. & Goodess, C. M. 2006 Downscaling heavy precipitation over the United Kingdom: a comparison of dynamical and statistical methods and their future scenarios. *Int. J. Climatol.* **26**, 1397–1415. (doi:10.1002/joc.1318)

Hulme, M. *et al.* 2002 Climate change scenarios for the United Kingdom: the UKCIP02 scientific report. Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK.

IPCC 2001 Climate change 2001: synthesis report—summary for policymakers.

Jasper, K. *et al.* 2004 Differential impacts of climate change on the hydrology of two alpine river basins. *Clim. Res.* **26**, 113–129.

Jones, R. N. 2000 Analysing the risk of climate change using an irrigation demand model. *Clim. Res.* **14**, 89–100.

Jones, P. D., Calanca, P., Gyalistras, D. & Fuhrer, J. 2006 Extended riverflow reconstructions for England and Wales, 1865–2002. *Int. J. Climatol.* **26**, 219–231. (doi:10.1002/joc.1252)

Lempert, R. J., David, G. G., Steven, W. P. & Steve, C. B. 2006 A general, analytic method for generating robust strategies and narrative scenarios. *Manage. Sci.* **52**, 514–528. (doi:10.1287/mnsc.1050.0472)

Mearns, L. O. *et al.* 2001 Climate scenario development. In *Climate change 2001: the scientific basis* (eds J. T. Houghton, Y. Ding, D. J. Griggs, M. Noguer, P. J. van der Linden, X. Dai, K. Maskell & C. A. Johnson), pp. 739–768. Cambridge, UK: Cambridge University Press.

Murphy, J. M., Sexton, D. M., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M. & Stainforth, D. A. 2004 Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature* **430**, 768–772. (doi:10.1038/nature02771)

Murphy, J. M., Booth, B. B. B., Collins, M., Harris, G. R., Sexton, D. M. H. & Webb, M. J. 2007 A methodology for probabilistic predictions of regional climate change from perturbed physics ensembles. *Phil. Trans. R. Soc. A* **365**, 1993–2028. (doi:10.1098/rsta.2007.2077)

New, M. & Hulme, M. 2000 Representing uncertainty in climate change scenarios: a Monte–Carlo approach. *Integr. Assess.* **1**, 203–213. (doi:10.1023/A:1019144202120)

Penman, H. L. 1948 Natural evaporation from open water, bare soil and grass. *Proc. R. Soc. A* **193**, 120–145. (doi:10.1098/rspa.1948.0037)

Pittock, A. B., Jones, R. N. & Mitchell, C. 2001 Probabilities will help us plan for climate change—without estimates, engineers and planners will have to delay decisions or take a gamble. *Nature* **413**, 249–249. (doi:10.1038/35095194)

Popper, S. W., Lempert, R. J. & Bankes, S. C. 2005 Shaping the future. *Sci. Am.* **292**, 66–71.

Prudhomme, C., Jakob, D. & Svensson, C. 2003 Uncertainty and climate change impact on the flood regime of small UK catchments. *J. Hydrol.* **277**, 1–23. (doi:10.1016/S0022-1694(03)00065-9)

Pryor, S. C., Schoof, J. T. & Barthelmie, R. J. 2005 Climate change impacts on wind speeds and wind energy density in northern Europe: empirical downscaling of multiple AOGCMs. *Clim. Res.* **29**, 183–198.

Pryor, S. C., Schoof, J. T. & Barthelmie, R. J. 2006 Winds of change?: projections of near-surface winds under climate change scenarios. *Geophys. Res. Lett.* **33**, L11 702. (doi:10.1029/2006GL026000)

Rougier, J. 2007 Probabilistic inference for future climate using an ensemble of climate model evaluations. *Clim. Change* **81**, 247–264. (doi:10.1007/s10584-006-9156-9)

Salathe, E. P. 2005 Downscaling simulations of future global climate with application to hydrologic modelling. *Int. J. Climatol.* **25**, 419–436.

Stainforth, D. A. *et al.* 2005 Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature* **433**, 403–406. (doi:10.1038/nature03301)

Stainforth, D. A., Downing, T. E., Washington, R., Lopez, A. & New, M. 2007 Issues in the interpretation of climate model ensembles to inform decisions. *Phil. Trans. R. Soc. A* **365**, 2163–2177. (doi:10.1098/rsta.2007.2073)

Tebaldi, C., Smith, R. L., Nychka, D. & Mearns, L. O. 2005 Quantifying uncertainty in projections of regional climate change: a Bayesian approach to the analysis of multimodel ensembles. *J. Clim.* **18**, 1524–1540. (doi:10.1175/JCLI3363.1)

Wilby, R. L. 2001 Seasonal forecasting of UK river flows using preceding North Atlantic pressure patterns. *J. Chart. Inst. Water Environ. Manage.* **15**, 56–63.

Wilby, R. L. & Harris, I. 2006 A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the River Thames, UK. *Water Resour. Res.* **42**, W02 419. (doi:10.1029/2005WR004065)

Wilby, R., Greenfield, B. & Glenny, C. 1994 A coupled synoptic hydrological model for climate-change impact assessment. *J. Hydrol.* **153**, 265–290. (doi:10.1016/0022-1694(94)90195-3)

Appendix III: River ecology case study

Introduction

The following provides a summary of the results from the ecological impacts case study which was aimed at stimulating discussion between the ecologists, water resources planners and climate modellers who were involved in the project. Only the key results are presented; further details of the work will be published in Fung *et al*. (2009). It is important to note here that the study is purely an illustrative one, demonstrating how information from new developments in climate modelling can be used and does not in any way aim to provide accurate predictions of the future in the study region.

Case study region

The River Itchen was chosen as the case study catchment on the strength of having a relatively long-term ecological and flow dataset (from 1978 to 2002) and having been an area of intensive study in the past. It is a chalk stream located in the south of England (see Figure I.1) and a candidate Special Area of Conservation (SAC). It has also been designated a Site of Special Scientific Interest (SSSI), achieved due to the number of rare species and the richness of the macro-invertebrate community in the river catchment. The river also supports a large range of protected species from the otter to the tiny brook lamprey.

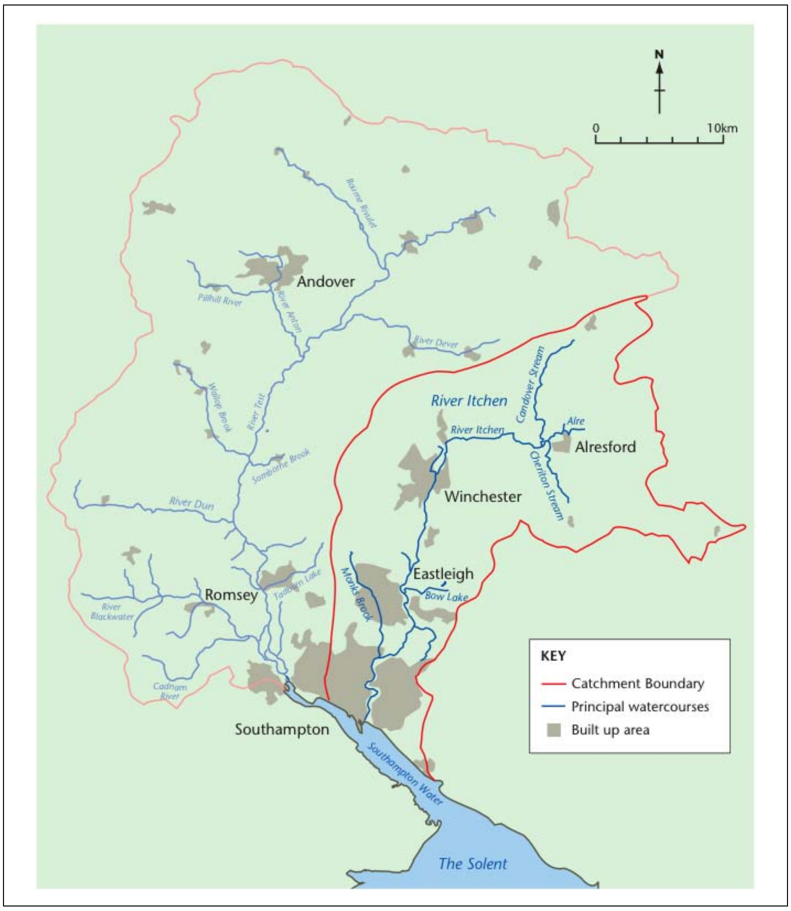


Figure I.1 Itchen catchment (Crosswaite, 2008)

From climate change to impacts on river ecology

In this section, the characteristics of newly available climate change data will be described along with the steps employed to link it to river flow modelling and then to an assessment of river ecology.

Previous studies

Recent climate change impact studies on river flows in the Itchen include Byrne (2006) and Halcrow (2004); both studies used UKCIP02 climate scenarios developed by the UK Climate Impacts Programme (UKCIP), to drive their hydro-/hydrogeological impacts models. The UKCIP02 climate change scenarios provide four alternative descriptions of how the climate of the UK might evolve over the course of this century (Hulme et al, 2002). Therefore for each of the impact studies, only four different pathways were used to span the uncertainty of future trends and behaviour, such as population growth, socio-economic development and technological progress, and how these might influence future global emissions of greenhouse gases (UKCIP, 2002).

Using climate model data

The CPDN data is a gridded dataset with seven squares representing the whole of the UK (see Figure I.2), each typically 300km by 200km. The grid square containing the River Itchen catchment and representing Kent, Sussex and Hampshire was chosen for this study. The climate is then downscaled to the catchment level, details of which are provided in Appendix II.

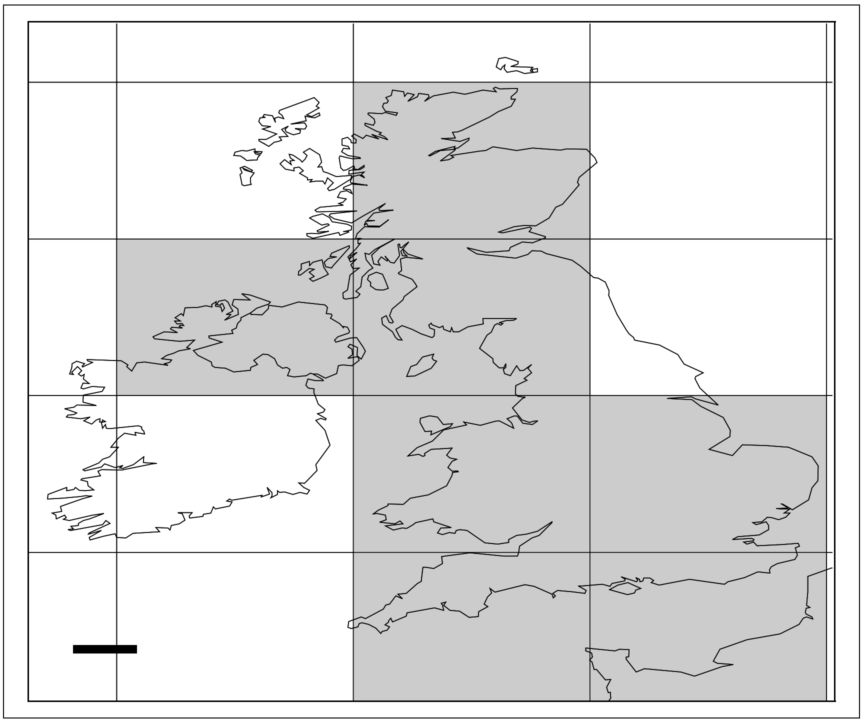


Figure I.2 GCM grid resolution with UK cells highlighted in grey.

Modelling river flows

The ecological status of rivers can be affected by a whole host of factors including channel modification, local land use and water temperature to name a few. However, the assessment of climate change impacts is restricted to variables that can be derived from climate models. Although river flow can be modelled directly using precipitation, and potential evaporation can be modelled indirectly through other climate variables, models for water temperature are still relatively new.

An ensemble of 246 transient simulations for future climate was obtained from CPDN which was then used to drive the rainfall runoff model, CATCHMOD. The model has been used previously for a climate change study in the Itchen by Byrne (2006) and has been calibrated at Allbrook and Highbridge in the lower Itchen catchment (see Figure I.1).

Abstractions have not been included in CATCHMOD as it was the intention of this study to use tools that already exist in the Environment Agency, rather than recalibrating and setting up a new CATCHMOD model for the Itchen. Moreover, this is an illustrative study investigating the methodology required to tease information out of probabilistic climate change scenarios. The study has therefore concentrated on the effects of climate change on the naturalised flows of the River Itchen without abstractions. Recalibration of CATCHMOD for this site would enable the dual effects of climate and abstracted flows to be assessed. The approach could also be readily applied to other sites where a parameterised flow model exists.

Linking river flow to ecology

In order to link the modelled river flow to ecology, the Lotic Invertebrate Flow Evaluation (LIFE) score has been used whereby the invertebrate community is linked to flow largely through sensitivity to water velocity and siltation, driven by flow variability at sites with fixed channel dimensions (Extence *et al.*, 1999). The index is widely recognised as a good indicator of the “health” (or “integrity”) of the river in a reach (Exley, 2006). A study was recently undertaken by Exley (2006) in the River Itchen during a Catchment Abstraction Management Strategy (CAMS), exploring the relationship between flow and LIFE score. It was found that there was a statistically significant relationship between the LIFE score in spring and the previous year’s summer Q95, where the summer Q95 is the value that 95 per cent of flows exceed between April and September. By using the LIFE score, expert opinion and other statistical tools, a number of flow thresholds were determined, marking flows at which clear changes in the macro-invertebrate community can be observed.

Management of rivers and ecological flow targets

Three flow targets were developed for the whole of the River Itchen during the CAMS process and the targets at Allbrook and Highbridge in particular are detailed in Figure I.3. Note the difference between targets and flow thresholds, in particular for Target 3, which comprises a flow threshold as well as a threshold for its frequency of occurrence. On the right-hand side of the figure, the flow thresholds are plotted as levels marking out a “flow warning band” where the invertebrate community is changing. It is described in Atkins (2007) as follows:

> “Above the flow warning band, the invertebrate communities essentially remain in good condition (i.e. healthy), although still experiencing flow related changes; within it, the risk of more significant flow induced changes in community structure, such as a reduction in abundance scores for certain family groups, starts to increase. Below the band, there is a high risk that macroinvertebrate communities may suffer longer term damage characterised by large changes in the abundance scores of many families and the loss of some family groups.
>
> Small reductions in abundance with no reduction in richness are seen only as changes, as they are relatively easily rectified once flow conditions return to normal (i.e. the risk of an adverse impact is low or negligible).

Large losses in abundance and/or reduction in richness, however, are much more likely to have an adverse effect on the population, since heavily reduced abundances and lost groups can only be replenished by active repopulation and recolonisation; the latter either by larvae drifting in from upstream, up or downstream migration of adults or migration of adults from other catchments (the latter two depending on the family lost)."

Target 1 The long-term average summer Q95 flow should be above 262Ml/day

Target 2 River flow should not fall below 198Ml/day

Target 3 The annual summer Q95 should not fall below 237Ml/day more frequently than recorded in the gauged flow record, i.e. one in six years

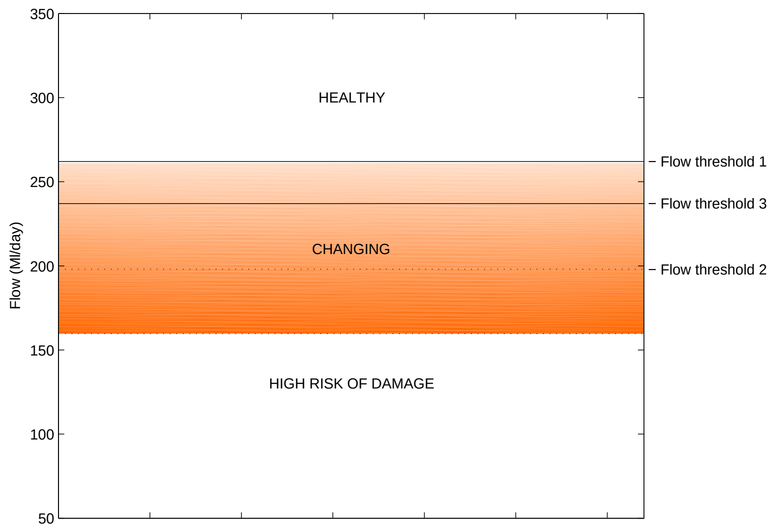


Figure I.3 Targets set during CAMS at Allbrook and Highbridge.

Exley (2006) also conducted a multivariate ordination analysis where it was found that for flows at Allbrook and Highbridge between 232Ml/day and 237Ml/day, the invertebrate community exhibit a clear shift away from the typical chalk stream community. It was found that taxa preferring fast flowing water were being lost during critical low flow periods and the same was observed for the species abundance. At flows lower than 232Ml/day there was a lower abundance of Baetidae (olive mayfly), Caenidae (anglers curse mayfly), Ephemerellidae (blue-winged olive mayfly) and Gammaridae (freshwater shrimp). Gammaridae, Ephemerellidae and Batidae are important food sources for the SAC fish species, salmon and bullhead. Notably there was no increase in the abundance in low flow communities at low flows. Above the flow of 270Ml/day, no ecologically significant changes to invertebrate community were observed (Exley, 2006).

Impacts of climate change

In the following sections, each of the targets will be examined with the large ensemble of future flows in order to assess how probabilistic information can be used in an analysis of climate change impacts on river ecology.

It is important to note here that CATCHMOD has been calibrated to a dataset that does not capture low flows well, and any real interpretation must be made in this light. This is because of the way CATCHMOD was parameterised at this site by a previous study (see Fung *et al*., 2009), but this could be overcome and would not preclude the use of this approach at other sites. The role of the following results is to attempt to tease out the useful information that can be gained from using large ensemble datasets.

Target 1

Graph explained

This target is based on the observed long-term averaged summer Q95, that is, the summer Q95 averaged over the period of 1970 to 2002. In Figure I.4, the grey lines represent the mean summer Q95 averaged over the previous 30 years and each line is calculated from the flow generated by a single CATCHMOD run using climate data from one member of the CPDN climate ensemble. The grey plume therefore represents the whole 246-member ensemble of CATCHMOD runs. The black lines summarise the distribution across the ensemble: the bottom line is the 95th percentile, indicating the flow which 95 per cent of all runs exceed. For example, Figure I.4 shows that by the 2050s, 5 per cent of the ensemble fail Target 1 and by the late 2070s, about 25 per cent of the ensemble fail Target 1. To demonstrate the added-value of the information provided by the ensemble, the green line represents the standard run. This is the run that uses climate parameters from the GCM model that has an unperturbed parameter set analogous to using one GCM and one emissions scenario.

Features

Approximately 25 per cent of runs show a rise in the summer Q95 up to the 2030s and then all runs show a decreasing mean summer Q95 thereafter. The range of possible futures values of Q95 for each year also increases through time, representing increasing uncertainty as the GCM attempts to predict further into the future.

Impacts on ecology

Target 1 was set at a conservative level (Exley, 2008) and such that the breaching of this flow threshold was not expected. However, if 25 per cent of the runs have a long-term summer Q95 below Target 1, the invertebrate community will be changing by the late 2070s.

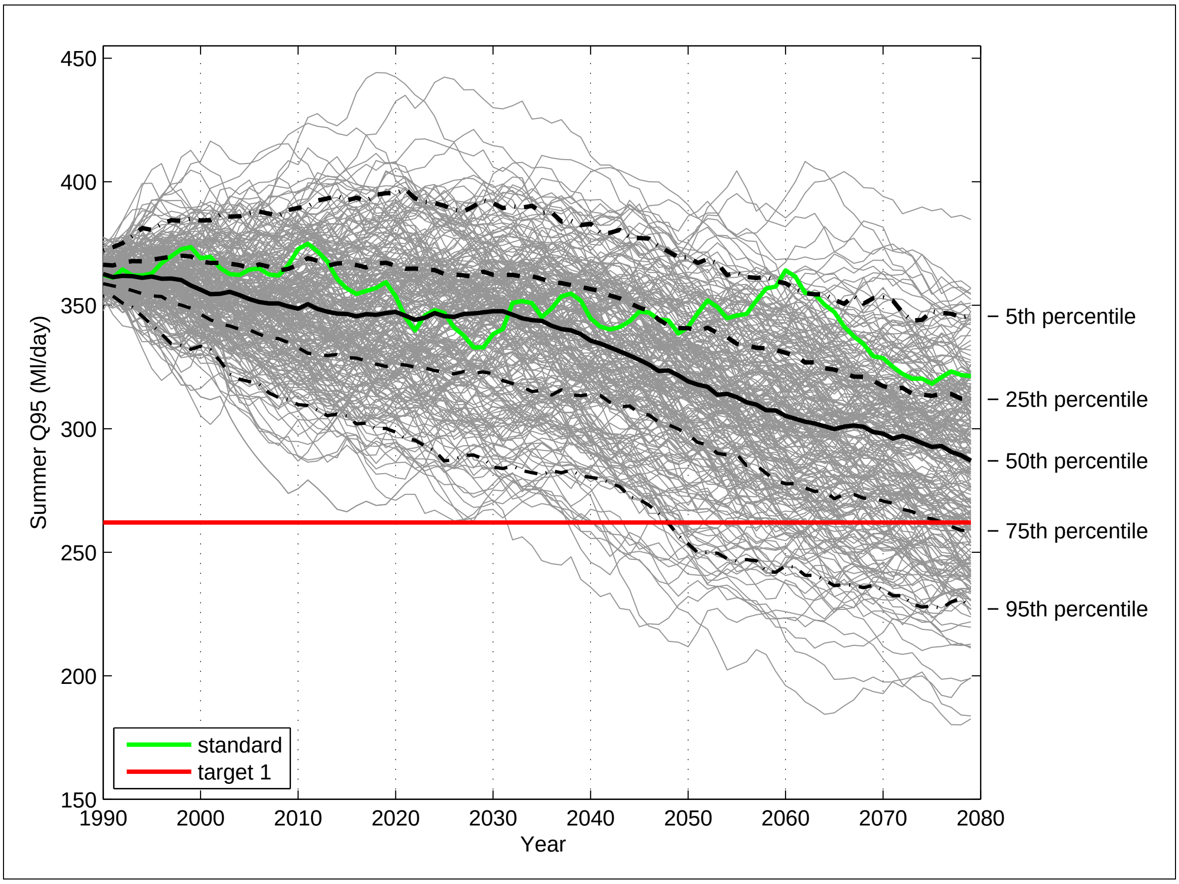


Figure I.4 Target 1: Mean summer Q95 with moving 30-year window for naturalised flows.

Notes

The nature of the long-term mean summer Q95 may mask the variability of the actual summer Q95. It is therefore difficult to interpret how these long-term statistics can be used to determine the impact on the invertebrate community.

Target 2

Graphs explained

The percentage of runs that fail Target 2 is presented in Figure I.5a, showing that during the baseline period (1961-90), fewer than five per cent of runs generate daily flows less than the flow threshold of Target 2 (198Ml/day) . However, there are an increasing number of runs that fail through the century, reaching about 40 per cent by the late 2070s. In order to explore the results further, the percentage of runs that fail Target 2 in each month of the year has been plotted in Figure I.5b. The mean percentages over a decade are shown and as with the previous figure, for the decades between 1961 and 1990, fewer than five per cent of the runs fail in any month. As the twenty-first century progresses, an increasing number of runs start failing, with the greatest number between October and December: by the 2070s, 25-30 per cent of models fail in these months.

The above result appears to be at odds with the generally accepted opinion that summers will become hotter and drier and winters milder and wetter in the UK and so intuitively the river flows should decrease during the summer but recover in the winter. It is appropriate to note here that although this study has focussed on the uncertainties associated with the climate model data, there are also uncertainties associated with modelling river flows, notably in the parameterisation as well as structure of the CATCHMOD model. These uncertainties would also be present in any other models as detailed in Wilby (2005). The lengthening of the summer dry period could be due to:

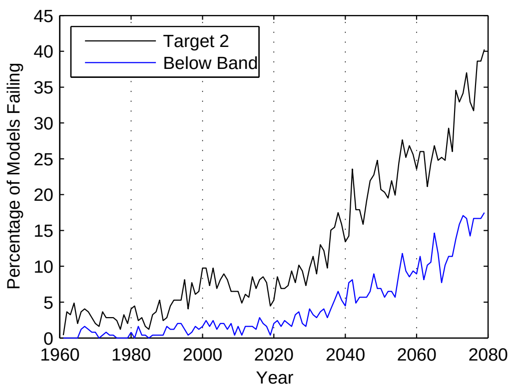
- The fact that the climate models show precipitation decreasing in both the summer and autumn and potential evaporation increasing. This means that summer low flows extend into the autumn and recover during the winter/spring period from January onwards. It is also important to note that the catchment's chalk geology will lead to a lag between rainfall and flow and this will be more pronounced following periods of drought. This is a result of increased soil moisture deficits building over the summer period.
- An artefact of the parameterisation and structure of CATCHMOD. In all climate change impact studies, understanding the limitations and assumptions of the various models is of great importance in determining the useful information that can be teased out of the results. For a formal analysis of the uncertainty in climate models and CATCHMOD see New *et al*. (2007) in Appendix I and Wilby (2005).

If the dry period occurred earlier in the summer, invertebrates with bi- or multivoltine life cycles would be largely unaffected because of the production of several generations through the breeding season. However, univoltine species may be more impacted.

In the scenarios described, low flows regularly extending from August to December would result in the loss of a high proportion of individuals recruited that year (for both uni- and multivoltine taxa). This would in turn lead to diminished over-wintering populations, with potentially catastrophic consequences for the following year's breeding and recruitment programme.

The extension of the dry period appears to be consistent with the climate model data but it is also important to keep the uncertainty in the hydrological modelling in mind.

(a) Runs that fail Target 2 and have daily flows that fall below flow warning band.



(b) Mean percentage of runs that fail Target 2 at least once in a given month for each decade

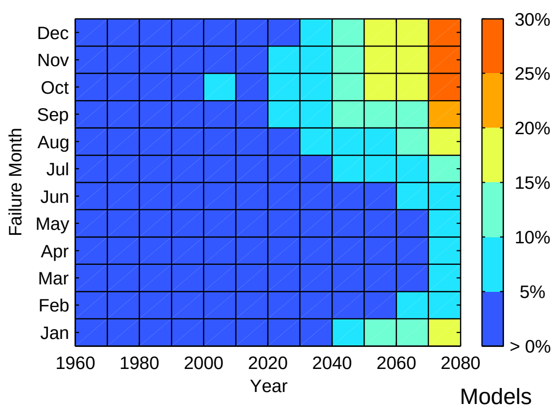


Figure I.5 Target 2.

Features

An interesting feature is that there are failures during the baseline period of 1961-1990. Failures are not found in the "observed" data and gauged records, but those shown in the figures represent the spread of flows that are generated by the plausible past climates given the variability of climate.

Impacts on ecology

Target 2 has been set at a level such that there is a buffer between the flow threshold and the level of flow below which there is likely to be an unacceptably high risk of an adverse impact on the invertebrate community (Atkins, 2007). In Figure I.5a, the failure of this lower threshold (below the flow warning band) has been plotted and it can be inferred that that the invertebrate community will be increasingly at risk. Indeed the figure shows that by the 2060s, about 10 per cent of runs have daily flows that fall below the flow warning band, indicating a high risk of adverse impact to the invertebrate community.

The increasing frequency of low flows occurring later in the year as shown in Figure I.5b point to the possibility of an increasing risk of many individuals being lost.

Notes

Target 2 is based on daily flows and it is important to note that the bias-correction procedure performed on the CPDN data does not preserve the day-to-day variability of the observed precipitation over long periods of time. This will obviously have a strong influence on the accuracy of the daily structure of simulated river flows (Hay *et al*., 2002). However, for the purposes of this target, the daily structure is unimportant. Indeed it is only important that the flow falls below the target at some point during the year.

Target 3

Graph explained

Target 3 comprises an annual flow threshold of summer Q95 of 237Ml/day which should not be breached at a frequency greater than one in six years, that is, a return period of six years. The number of runs that fail the flow threshold of Target 3 in a 30-year period is presented in Figure I.6. For each year, the number of failures in the previous 30 years is counted, for example in the year 2020, the period 1991-2020 is analysed for failures. No runs fail the target return period of six years (see Figure I.3) during the baseline period. However, a steady increase in the percentage of runs that fail through the twenty-first century can be seen, with over 50 per cent of runs failing by the 2050s. By the end of the 2070s, five per cent of runs fail about every year.

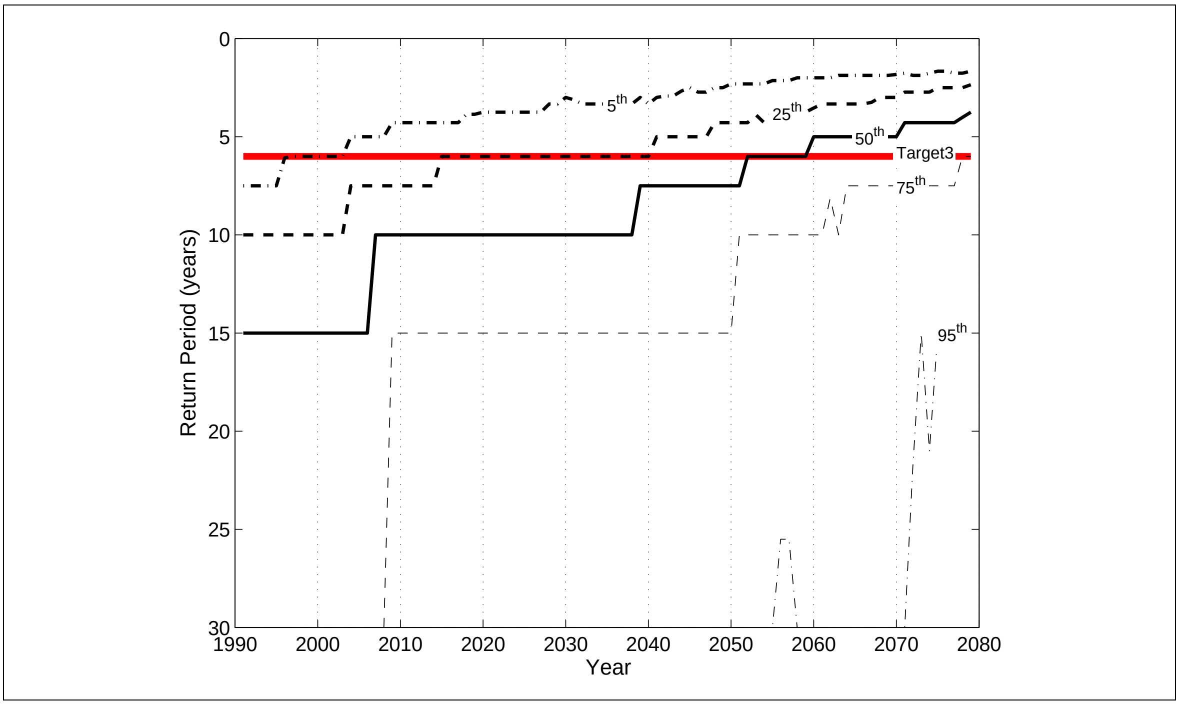


Figure I.6 Target 3: Percentiles of return period for the failure of flow threshold 3 for a 30-year moving window.

Features

Target 3 attempts to capture the frequency of low flow years and it is clear from Figure I.6 that they increase through the twenty-first century, meaning an increasing chance of consecutive low flow years.

Impacts on ecology

Although there is a lack of long-term datasets showing the effects of extended droughts, there is evidence that invertebrate communities can survive two years of low flows or drought (Wood and Armitage, 2004). Figure I.6, however, suggests that there may be droughts of much longer duration but unfortunately there is no data on the effects of these droughts on invertebrates. However, it is clear that by the end of the twenty-first century, the flows may not recover to the levels to re-establish taxa associated with chalk rivers. Indeed, by the 2050s, over 50 per cent of runs fall below Target 3, possibly meaning that the Environment Agency may have to consider that the invertebrate community will be permanently altered. Exley (2006) found little evidence to suggest that taxa preferring slow flowing water habitats were increased in abundance under low flow conditions. Under multi-year droughts, taxa preferring slower velocities would become established. Many species typical of chalk streams could be lost or diminished, however changes in biota in relation to flow variation and habitat structure are discussed in more detail by in forthcoming papers in a special issue of Freshwater Biology and Aquatic Conservation.

LIFE scores

Graph explained

Statistical relationships between LIFE scores and river flows were developed by Exley (2006). Spring LIFE is almost always higher than autumn LIFE in any given year, so modelling autumn LIFE (when chalk stream communities are more stressed) using a range of predicted flows would represent a worst case scenario and could be very informative. However, the CAMS flow targets were developed using the spring LIFE scores and previous year's summer Q95, and it is this relationship that has been looked at in this study.

Each member of the flow ensemble was converted to a LIFE score and a histogram of values plotted in Figure I.7, showing the range of LIFE scores for a particular year in the twenty-first century. The red line is a threshold developed using the Resource and Management framework (RAM) for the River Itchen (Environment Agency, 2002), below which there is the potential of flow stress developing. A LIFE score of 0.974 for this threshold was arrived at following detailed discussion between the Environment Agency and the Centre for Ecology and Hydrology, in advance of the production of the RAM framework (Exley, 2006).

The graph shows that in 2008, the distribution of LIFE scores is centred just above the value of one and as time progresses, the centre of the distribution shifts towards lower values of LIFE. The distribution also becomes narrower and skewed by the end of the century, with an increasing number of runs that have LIFE scores failing the RAM threshold.

Notes

The low LIFE scores in 2079 correspond to low summer Q95 flows. However, the linear relationship between LIFE and flow may in reality break down over a protracted period of drought. In these circumstances flow may be consistently low but a further deterioration in ecology occurs simply as a function of time (Extence, 2008).

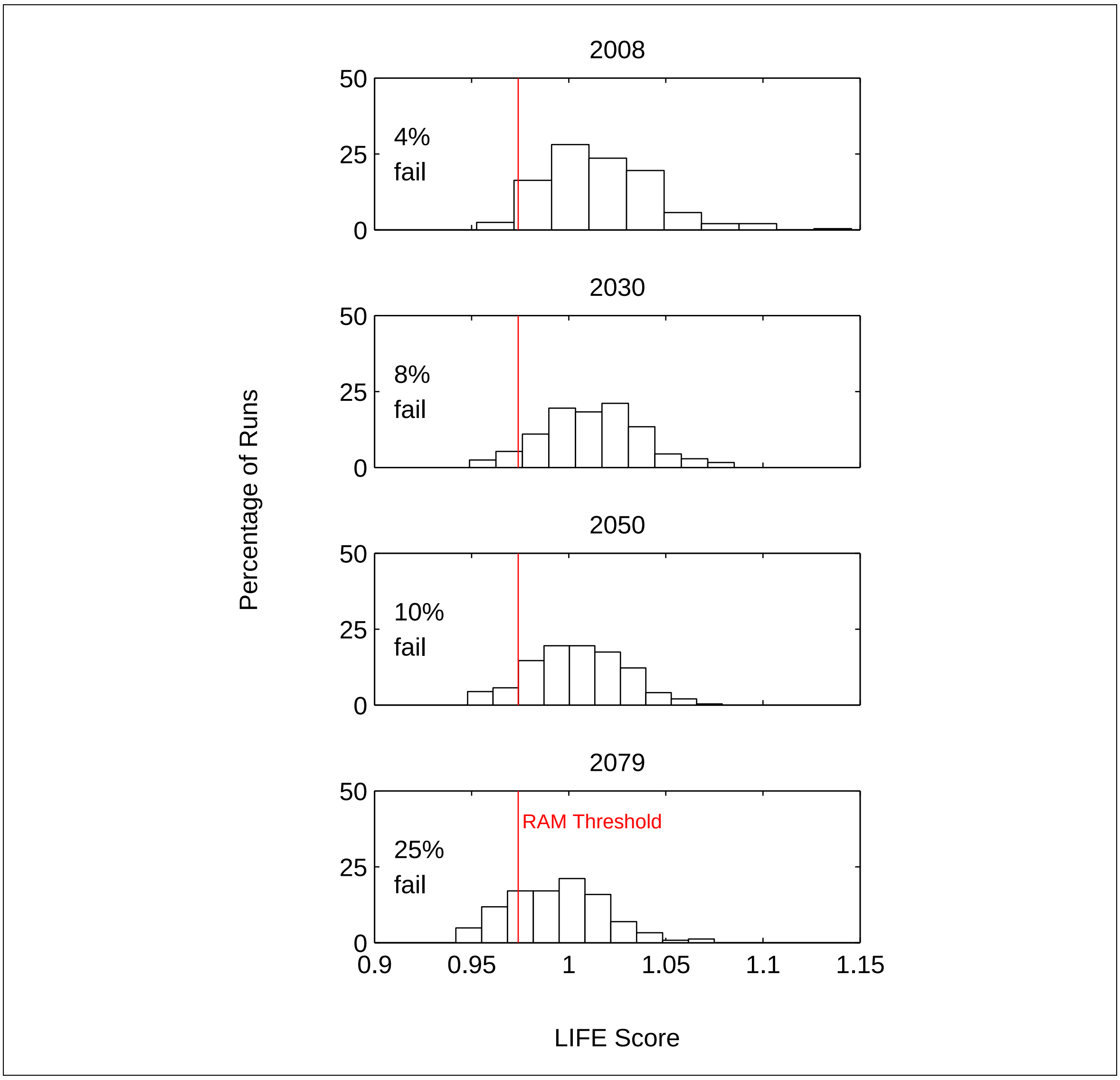


Figure I.7 Histograms of LIFE scores for given year in twenty-first century.

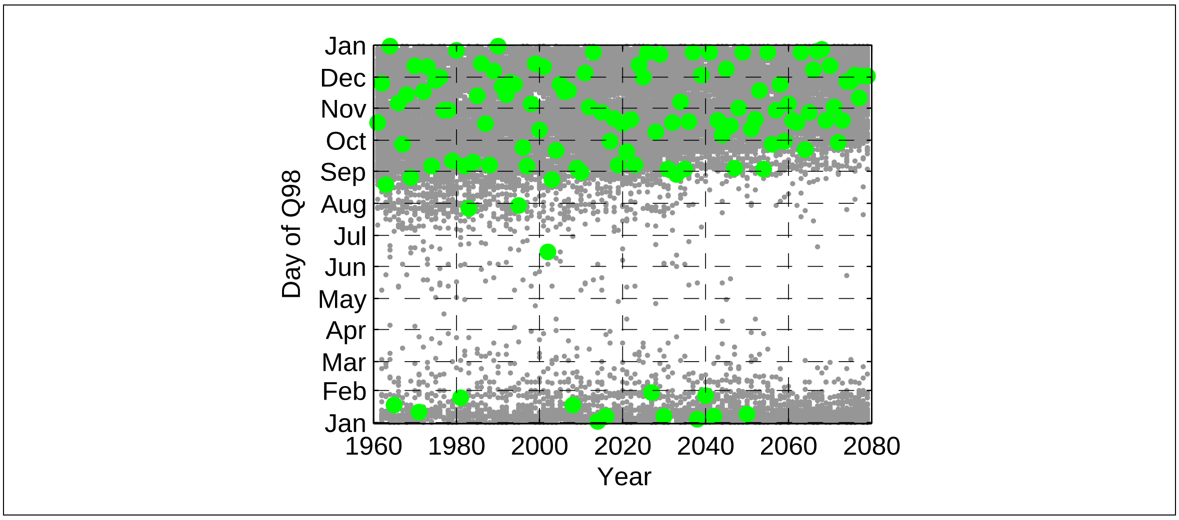


Figure I.8 Location of Q98 for each year with grey dots representing each ensemble run and green dots representing standard run.

Summer Q95

A large number of flow metrics were originally tested by Exley (2006) and it was summer Q95 that showed the most statistically significant relationships to LIFE score. For the past climate, times of low flow occurred frequently in September. However, as can be seen in Figure I.8, which shows the annual Q98 for the twenty-first century, the low flows tend to occur later on in the year by the 2070s, represented by the shift of the cluster of grey dots from August-January to October-January. The annual Q98 has been shown as it is equivalent to the summer Q95, if summer flows are less than winter flows. Should the temperatures also rise, thereby allowing invertebrates to breed and live later in the year, the definition of summer may need to be revised.

Ecological impacts matrix

The three targets that were drawn up during the CAMS process have been useful to test and have shown that it will be difficult to maintain a natural chalk stream invertebrate community in the future. However, it does reduce the statistical analysis to only three sets of values. To provide a richer story, a matrix is proposed for analysing the effects of the river on biodiversity which combines both the thresholds derived previously and expert opinion on how the ecology of the River Itchen will react to climate change. As the focus of the study has been on low flows, on one axis of the matrix is the duration of the low flow (or the number of consecutive years of low flow). On the other axis is the extent (or the value of the annual Q98). In each of the cells of the matrix is a qualitative description of the ecological status of the river, see **Error! Reference source not found.**. The matrix has been used to then analyse the percentage of ensemble members that experience each of the river ecology impacts at selected time horizons, colour-coded into five categories representing the percentage of runs that fall into each part of the matrix (see Figure I.9).

The figure shows that in the 2020s, there is a high risk of the invertebrate community being harmed in more than 50 per cent of runs, followed by a chance that recovery may not occur once higher flows return. By the 2070s, over 25 per cent of runs show high risk of damage to the invertebrate community with an equal percentage of runs showing that there will be either recovery or a permanent change in the community. As the twenty-first century progresses, the colours towards the top left of the matrix become bluer, and the middle to bottom right change towards orange, representing a growing risk of the invertebrates being harmed. However, in this set of simulations, the risk of a highly modified community remains less than five per cent.

	1 year only	2-4 consecutive years	> 5 consecutive years
Upper flow warning band (198 - 262Ml/day)	No adverse impacts on invertebrates and overall ecology of river remains healthy.	Some risk of invertebrate community being harmed but recovery possible.	High risk of community changing with some chance of recovery.
Lower flow warning band (157 - 198Ml/day)	Some risk of invertebrate community being harmed but recovery possible.	High risk of invertebrate community changing but with high chance of recovery.	High risk of community changing with some species remaining.
Below flow warning band and RAM threshold (< 157Ml/day)	Invertebrate community harmed and some risk no recovery.	High risk of invertebrate community changing permanently to slow flow-type communities.	Highly modified community more typical of arid environments could develop, including species with adaptive strategies enabling survival over extended periods of drought. Iconic species such as salmon, lamprey, otter no longer present.

Table I.1 Climate change impacts assessment matrix for ecology of River Itchen.

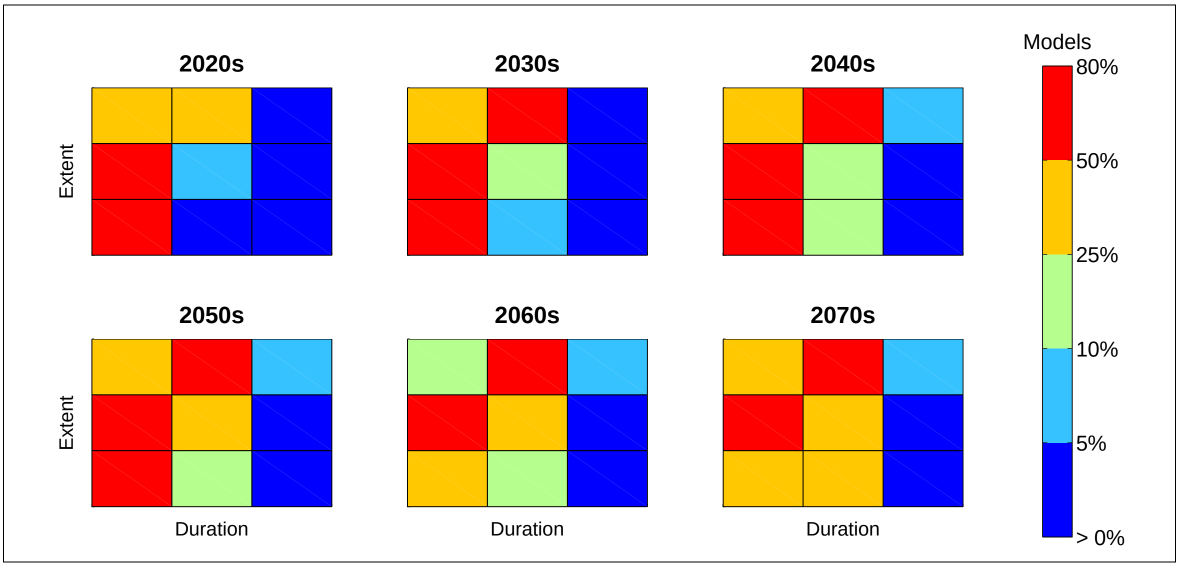


Figure I.9 Matrices of climate change impacts on ecology of River Itchen through twenty-first century.

Relevance to management decisions

Abstractions

The overall picture so far appears to show drastic changes in the flow and consequently the invertebrate community. This picture will be worsened should abstractions also be included, and although not considered in the CATCHMOD modelling, it was deemed necessary to provide at least a simple analysis of the effects of abstractions. By using simple regression relationships to examine the effects of water abstractions, graphs similar to Figure I.6 for testing Target 3 have been plotted in Figure I.10. The three scenarios considered in order of increasing volume of abstraction are:

- Historical abstractions.
- Business-as-usual scenario where only 2002 abstractions are used.
- Fully licensed scenario.

It is clear from Figure I.10 that for all abstraction scenarios, Target 3 is failed throughout the whole of the twenty-first century; that is, the summer Q95 flow falls below the flow threshold of 237Ml/day with a return period of less than six years. It can be seen that the fifth percentile moves closer towards a return period of one year as more water is abstracted and as time progresses. For example, in 2010, five per cent of the models show a return period of 1.5 years for historical abstractions, 1.3 years for business-as-usual and 1.1 years for fully-licensed, but by 2070, all abstraction scenarios show a value one year. This result is not surprising as it is well known that the Itchen is over abstracted at a level that is not sustainable in the future. All the figures show is that the return period decreases at a reduced rate as an increasing amount of water is abstracted from the river, in other words, the frequency at which the flow threshold is breached increases at an increasing rate.

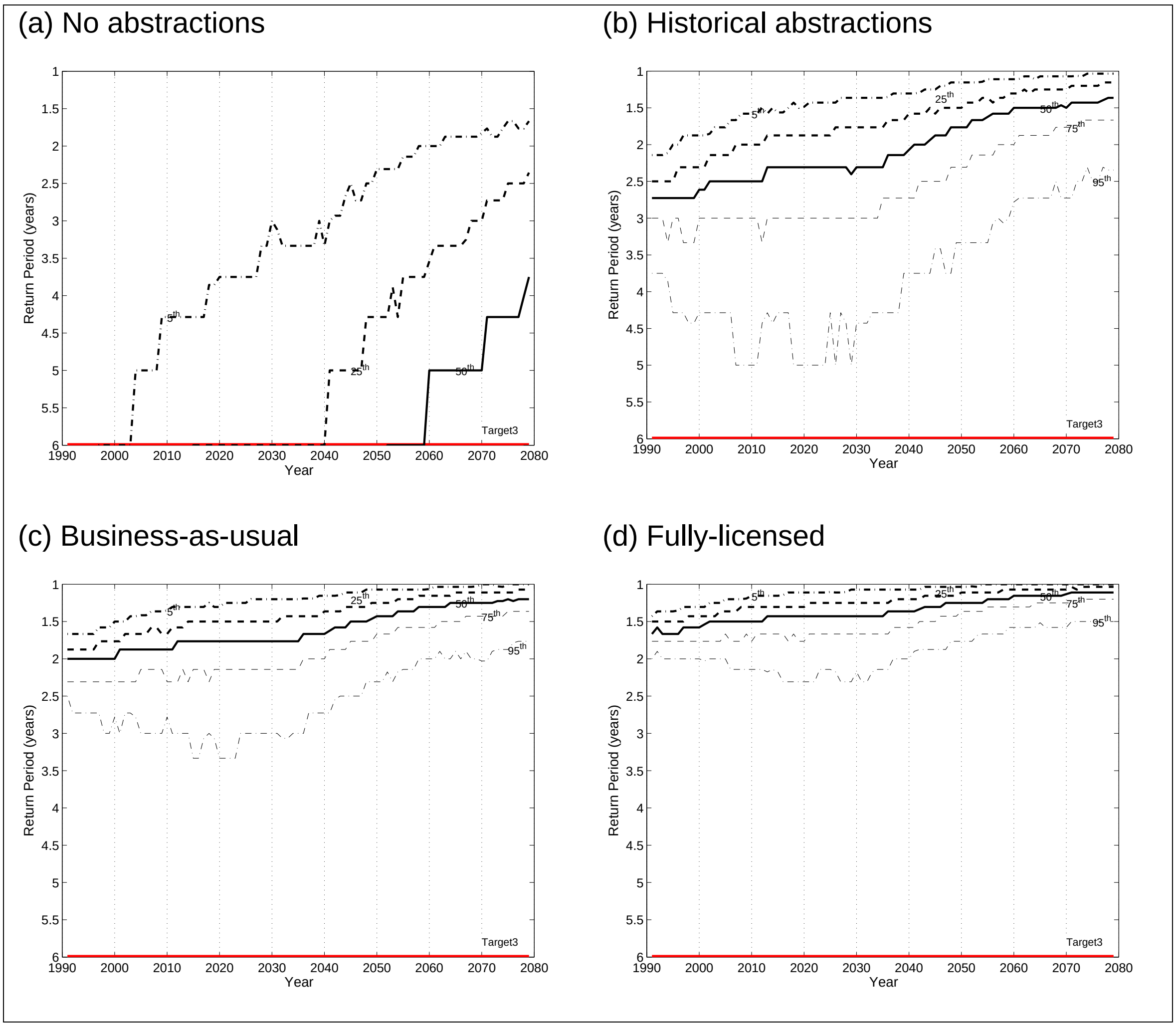


Figure I.10 Return period of summer Q95 flows less than Target 3's flow threshold with percentiles.

Adapting to climate change

Assessing adaptation strategies

The scenarios described so far are not the whole story. Should large changes in flow arise in the future it is likely that some form of action will be taken to mitigate or adapt to the impacts of climate change. In terms of river ecology, there are a number of possible ways to adapt, including channel modification and habitat restoration which have been shown to affect the sensitivity of LIFE scores to flow (Dunbar *et al*., 2006 and Dunbar and Mould 2008). Unfortunately, there is little quantitative data to calculate the effects of these measures. However, the effects of river support, that is, augmenting river flow by pumping from the groundwater aquifer, can be modelled. This has been carried out using CATCHMOD simply by removing water from the chalk aquifer and releasing it as river runoff. In effect, this process "borrows" water from the winter flows, assuming that the groundwater aquifer refills during the winter.

Graphs Explained

The annual augmented flow required each year to sustain daily flow such that it does not reach the flow threshold of Target 1 or near the top of the flow warning band, that is, a value of 262 Ml/day, is plotted in Figure 0.3. Each grey dot represents the total augmented flow for each year for each CATCHMOD run. For years where there is no augmentation, a dot is not plotted, hence the broken lines for the percentile plots, for example the 25th percentile shows one value for 2026 and 2030 but no values in between, meaning that no augmentation was required for at least 25 per cent of the runs during this period. The results show that up to the mid-2020s, only 5 per cent of the runs require augmentation, but by the 2060s, 50 per cent of the runs need additional flow. As time progresses the amount of flow augmentation increases, for example in the mid-2040s the flow required by 50 per cent of runs is of the order of 10Ml/year, however by the 2070s this increases by one order of magnitude to over 100Ml/year.

As the augmentation borrows water from future baseflows, changes in the high flows (Q2) have been plotted in Figure I.12. The results show a decrease in the high flows once augmentation starts, although there is some delay which relates to the amount of augmentation that is supplied to the river, for example although 25 per cent of runs require augmentation every year from about the 2020s, it is only by the early 2040s that a corresponding number of runs show decreasing high flows. However, for about half of the runs, there is very little effect on the high flows.

Impacts on ecology

The aim of the augmentation is to support the river ecology, so that it can retain its ecological status. However, by augmenting the flow, the high flows are also reduced which can be important for scouring the river bed and removing silt to the benefit of the invertebrate community. Therefore at some point further augmentation may need to be curtailed in order to maintain high flows. However, it must be noted that the degree of habitat modification may also be important, as less river support may be needed if appropriate river restoration is undertaken (Dunbar *et al*., 2006, Dunbar and Mould, 2008).

Impacts on decisions

As mentioned previously, abstractions have not been included in this analysis. However, it is clear from Figure 0.3, that there will be conflict between pumping groundwater to augment flows to achieve and maintain good ecological status of the river and allowing users to abstract the quantities of water under their current abstraction licences.

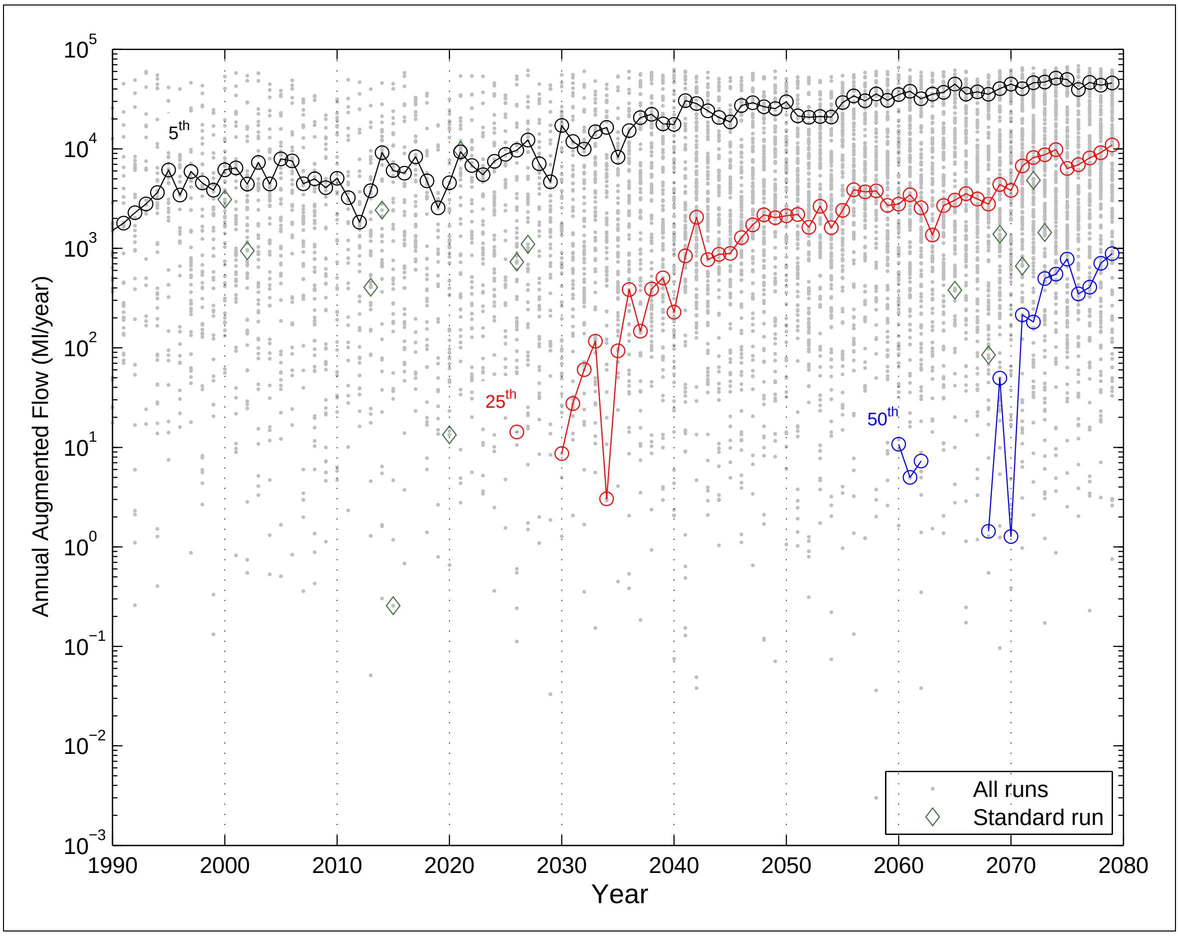


Figure I.11 Time series of volume of annual augmented flows to maintain healthy ecological status. Individual grey dots represent total augmented flow in one year for one CATCHMOD run. Green diamonds mark the results for the standard run. The black, red and blue lines represent the total annual augmented flow that 5%, 25% and 50% of the ensemble exceeds respectively.

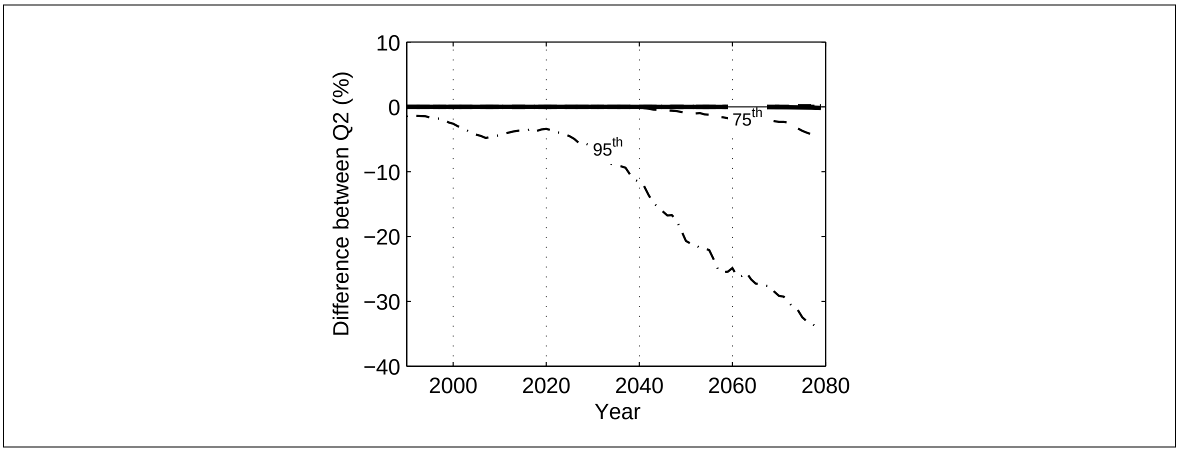


Figure I.12 Percentiles of differences in high flows (annual Q2) between river flows with and without augmentation (curves smoothed by moving average with window of 10 years).

References

ATKINS, 2007. River Itchen SAC: Stage 4 Review of Consents. Site Action Plan: Appendix B, Environment Agency Report.

BYRNE, A., 2006. Modelling the Hydrological Effects of Climate Change on the River Itchen, Local Area Hydrology, Environment Agency Report.

CROSSWAITE, S., 2008. Fact Files: The River Itchen, Environment Agency.

DUNBAR, M. and MOULD, D., 2008. Distinguishing the Relative Importance of Environmental Data Underpinning flow Pressure assessment (DRIED-UP) 2. Environment Agency Report.

DUNBAR, M., YOUNG, A. and KELLER, V., 2006. Distinguishing the Relative Importance of Environmental Data Underpinning flow Pressure assessment (DRIED-UP). Environment Agency Report: 67.

ENVIRONMENT AGENCY, 2002. Resource Assessment and Management Framework. Report and User Manual (Version 3). R&D Technical Manual W6-066M. , Environment Agency, Bristol.

EXLEY, K., 2006. River Itchen Macro-Invertebrate Community Relationship to River Flow Changes. Environment Agency Report.

EXLEY, K., 2008. Private communication.

EXTENCE, C.A., BALBI, D.M. AND CHADD, R.P., 1999. River flow indexing using British benthic macroinvertebrates: A framework for setting hydroecological objectives, *Regul River*, pp. 543-574.

FUNG, C.F., LOPEZ, A., NEW, M., WATTS, G., EXTENCE, C. AND ORR, H., 2009. The implications of using large ensembles of climate scenarios for the management of river ecology in a chalk stream in the South of England. *River Research and Applications*, In preparation.

HALCROW, 2004. Climate Change Modelling Scenarios, Doc No: H(PR)03 Rev: 1, River Itchen Sustainability Study, Environment Agency Report.

Hay, L. E., CLARK, M.P., WILBY, R.L., GUTOWSKI, W.J, LEAVESLEY, G.H., PAN, Z., ARRITT, R.W. and TAKLE, E.S. 2002: Use of Regional Climate Model Output for hydrologic simulations. Journal of Hydrometeorology, **3**: 571-590.

HAY, L. AND CLARK, M., 2003. Use of statistically and dynamically downscaled atmospheric model output for hydrologic simulations in three mountainous basins in the western United States. *Journal of Hydrology*, 282(1-4): 56-75.

HULME, M., JENKINS, G.J., Lu, X., TURNPENNY, J.R., MITCHELL, T.D., JONES, R.G., LOWE, J., MURPHY, J.M., HASSELL, D., BOORMAN,P., MCDONALD,R. and HILL,S. (2002) Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report, Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK. 120pp.

LOPEZ, A., FUNG, C.F., AND NEW, M., 2009. From climate model ensembles to climate change impacts: A case study of water resource management in the South West of England. Water Resources Research, Submitted.

NEW, M., LOPEZ, A., DESSAI, S. AND WILBY, R., 2007. Challenges in using probabilistic climate change information for impact assessments: an example from the water sector. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, **365**(1857): 2117-2131.

PANOFSKY, H.A.A.B., G.W., 1968. Some applications of Statistics to Meteorology. The Pennsylvania State University Press.

UK CLIMATE IMPACTS PROGRAMME (UKCIP), 2008. UKCIP Scenarios Gateway. Available from: www.ukcip.org.uk [accessed 14th January 2009]

WILBY, R.L., 2005. Uncertainty in water resource model parameters used for climate change impact assessment. *Hydrological Processes*, **19**(16): 3201-3219.

Wood, P.J.and ARMITAGE, P.D.2004. The response of the macroinvertaebrate community to low-flow variability and supra-seasonal drought within a groundwater dominated stream. Archiv Fur Hydrobiologie, **161**(1): 1-20.

WOOD, A.W., LEUNG, L.R., SRIDHAR, V. AND LETTENMAIER, D.P., 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs, *Climatic Change*, **62**: 189-216.

l

We are The Environment Agency. It's our job to look after your environment and make it **a better place** – for you, and for future generations.

Your environment is the air you breathe, the water you drink and the ground you walk on. Working with business, Government and society as a whole, we are making your environment cleaner and healthier.

The Environment Agency. Out there, making your environment a better place.

Published by:

Environment Agency
Rio House
Waterside Drive, Aztec West
Almondsbury, Bristol BS32 4UD
Tel: 0870 8506506
Email: enquiries@environment-agency.gov.uk
www.environment-agency.gov.uk