10

Modelling Catchment-Scale Responses to Climate Change

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Introduction

The focus of the Euro-limpacs project was on responses of aquatic ecosystems (rivers, lakes and wetlands) to climate change, but these responses cannot be fully understood or predicted without considering the connections to other earth systems. Rivers, lakes and wetlands are connected to each other and to other water bodies such as groundwater and estuarine and coastal waters. Most of the water in these aquatic systems has passed through the terrestrial environment at some stage. A catchment-scale approach that considers these different environments is thus essential for predicting how European aquatic ecosystems might respond to climate change.

Typically, measurements of the aquatic and terrestrial environments and experimental manipulations are done in small ($<10\,km^2$) research catchments, in the laboratory or in small *in situ* tanks which represent the larger system to be studied. Management decisions are, however, typically made at much larger scales ($>1000\,km^2$), as in the EU Water Framework Directive, in which the River Basins are all large catchments. Furthermore, projections of future climates made by the models of atmospheric and oceanic circulation (General Circulation Models, GCMs) are produced at a coarse scale greater in size than many catchments. Models can help fill the gaps between the mismatch of scales between scientific measurement, management and climate projections. The complexity of the interactions between all these aquatic and terrestrial systems also necessitated a modelling approach: individual experiments and manipulations alone cannot consider this complexity or integrate the different processes.

Modelling catchment responses to climate change is a very demanding undertaking, requiring a number of tasks that are themselves very challenging. Firstly, in order to make predictions of the effects of climate change, it is necessary

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to produce climate change scenarios at the catchment scale. A credible methodology for converting the predictions of GCMs to the spatial scale required (known as downscaling) and of generating the resultant 'weather' needed by the models (e.g. daily precipitation and temperature) must be available. Secondly, models must be developed which connect catchment climates to variables that can be measured and which are features of interest in aquatic systems, such as water flows, water quality or the abundance of aquatic organisms. These models may involve detailed representations of catchment structure and function and their interactions with climate, or they may be more empirical. All models need to be tested to determine whether they represent observed data adequately, normally in an iterative cycle of testing and revision. Once a model is performing satisfactorily as judged by its ability to reproduce observations and conform to notions of how a catchment functions, a set of changed climates can be used to drive the model to produce a set of changed response variables. Thus, models can potentially provide an estimate of the effects of the changed climate on nitrate concentrations or fish biodiversity, for instance. Potential changes in catchment structure and function due to climate change must be considered during this process (e.g. the alteration of vegetation types in the catchment). Finally, the influence of changes in catchment management (e.g. novel crops or agricultural practices) can be assessed. These might, for instance, be due to changed climates, socio-economic factors or adaptive responses of catchment managers attempting to mitigate climate change effects.

This chapter outlines how this approach was used within Euro-limpacs, illustrates how the modelling process was applied in a range of case studies and describes how a consistent modelling approach for assessing flow and water quality across Europe was developed. The science of modelling was taken further by chaining models to simulate the response of flow and nitrogen at the catchment scale. Models that incorporate ecological effects have been developed for lakes, but for rivers these remain a research goal owing to the dynamic, complex nature of the river environment (Chapra 1997). The main focus of integrated modelling in the Euro-limpacs project was the development of catchment-scale models of flow and water quality. The applications described are a small sample of those undertaken. As the plethora of abbreviations and acronyms used in modelling work can rapidly become confusing, Table 10.1 is provided for explanation and reference.

The Euro-limpacs modelling strategy

Developing an integrated toolkit of models for catchment analysis and assessment has been central to the Euro-limpacs project, based on six key questions: (i) Can the impacts of climate change, land-use change and pollution be evaluated using modelling? (ii) How can models be used to assess likely effects of climate change on freshwater systems? (iii) Can models simulate the spatial/temporal variation in pollutant behaviour in freshwater systems? (iv) Can the uncertainty associated with these models be quantified? (v) Can socio-economic scenarios be incorporated into modelling assessments of climate change effects? (vi) How can models be best used to assist the management of surface waters influenced by climate

Table 10.1 List of abbreviations and acronyms

Abbreviation	*Meaning (if any)*	*Description*
AET	Actual Evapotranspiration	
CATCHMOD	Catchment Model	UK water balance model
CLUAM	Climate and Land-Use Allocation Model	
CGCM2	Canadian Global Coupled Model	GCM from the Canadian Centre for Climate Modelling and Analysis
CSIRO2	Commonwealth Scientific and Industrial Research Organisation	GCM from the CSIRO in Australia
EARWIG	Environment Agency Rainfall and Weather Impacts Generator	Model that generates weather data from downscaled GCMs in the United Kingdom
ECHAM4	European Centre Hamburg Model	GCM developed by the Max Planck Institute
GCM	General Circulation Model	Model used for understanding and predicting global-scale climate
GLUE	Generalised Likelihood Uncertainty Estimation	Technique for investigating model uncertainties
HadCM3	Hadley Centre Coupled Model	GCM from the Hadley Centre, UK Meteorological Office
HBV	Hydrologiska Byråns Vattenbalansavdelning	Scandinavian hydrological model
HER	Hydrologically Effective Rainfall	Rainfall potentially available to recharge rivers
HIRHAM	–	RCM developed for Europe by a number of meteorological institutes
INCA	Integrated Catchment Model	Suite of catchment models developed at the University of Reading for N, P, etc.
IPCC	Intergovernmental Panel on Climate Change	International Organisation for assessing Climate Change
MAGIC	Model of Acidification of Groundwater in Catchments	Acidification model, dealing mostly with soil and surface water (in spite of the title)
MIKE-11	Named after the model author	Hydrological model from the Danish Hydrological Institute
MPI	Max Planck Institute	German Research Institute
NAM	–	Rainfall-run-off model used with MIKE-11
RCM	Regional Climate Model	Model used for understanding and predicting climate at a smaller scale than a GCM
PET	Potential Evapotranspiration	
SDSM	Statistical Downscaling Model	UK model used for downscaling GCMs
SRES	Special Report on Emission Scenarios	IPCC report, which defined a number of standard greenhouse gas emission scenarios
TRANS	Transport	Hydrochemical model used with MIKE-11

Acronyms defined in the text and not used again are not covered in the table.

change? To address such questions, both new and existing techniques have been used. In this chapter, we describe these techniques before considering answers to the questions.

Downscaling

An essential first step in predicting the effects of future climates on aquatic ecosystems is to forecast what these climates are likely to be. On a global scale, future climate change is modelled using GCMs, which are mechanistic models of the climate system built on physical principles (IPCC 2007). Assumptions about greenhouse gas emissions, population growth and economic development have also to be made, and within Euro-limpacs, a standardized set of assumptions is used based on the Special Report on Emission Scenarios (SRES) of the IPCC (Nakićenović *et al*. 2000). These scenarios are explained in Chapter 3. GCMs are currently too coarse in resolution (~270 km × 270 km) for catchment-scale modelling, though finer-scale models are close to release. Methods are therefore required to 'downscale' the outputs from the GCMs to the appropriate scale for modelling effects. This is more problematic than might be imagined. There are two main approaches, variously called dynamic or model-based and statistical or empirical (Fowler *et al*. 2007). Dynamic downscaling uses regional climate models (RCMs) nested within the GCMs, which are used to provide input data and boundary conditions.

RCMs can simulate processes important on catchment scales and provide outputs on scales down to about 5 km. These are computationally expensive, however, and a more common approach is to use statistical downscaling methods. These rely on observed quantitative relationships between the small-scale climates and the large-scale climates. These relationships are then used to generate the large-scale or high-resolution climate from the GCM output, one major assumption being that the empirical relationships will remain the same in all projected climates, including those affected by enhanced greenhouse warming. Tisseuil *et al*. (2009) discuss further problems and refinements of statistical downscaling methods.

In Euro-limpacs, we standardized downscaling methods. Dynamically downscaled data across Europe were available from the EU-funded PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects, 2001–04) website (http://prudence.dmi.dk), for the periods 1961–90 and 2071–2100. The data were generated by nesting an RCM within two GCMs, but the output cell size (0.5° × 0.5°) was still too coarse for most catchment applications and required further downscaling using the Statistical Downscaling Method (SDSM; Wilby *et al*. 2002) with refinements based on 'local methods', as described by Wade *et al*. (2008). For instance, GCM and RCM temperature predictions are for the average altitude of a grid cell. To correct this to the altitude of a catchment, a lapse rate (the rate of change of temperature with altitude) based correction was proposed, preferably using a site-specific lapse rate or alternatively a 'standard' lapse rate of −0.6 °C per 100 m.

In some instances, it was appropriate to use a GCM cell different from that in which the site lies to build a relationship between GCM or RCM output and local conditions. For example, if the site is in a mountainous region, then a

GCM cell which is dominated by mountains is the most appropriate; this may be the cell which includes the site or an adjacent cell. The SDSM was apparently successful in some cases (Wilby *et al*. 2006; Whitehead *et al*. 2006), but in other applications, it failed to produce reliable reconstructions of the monthly mean rainfall totals and the seasonal patterns in rainfall for the control periods. It was therefore abandoned in favour of a standardized delta-method approach which used change factors derived from the GCMs and applied to individual catchments (Wade *et al*. 2008). For each month in a control period (1961–90), a factor consisting of the mean observed precipitation divided by the mean RCM-modelled precipitation was derived. These factors were then applied to the RCM-modelled precipitation for the period 2071–2100 to calculate catchment precipitation under a particular change scenario. For temperature, a similar procedure was applied except that the factor was additive rather than a ratio (Wade *et al*. 2008).

River Kennet case study

Table 10.2 shows an example of some results from a change factor analysis. The aim was to calculate flows in the river Kennet in southern England under a variety of climate change scenarios, as part of an attempt to model the effects of climate and socio-economic changes on the river (Skeffington 2008; see also Chapter 11). In this case, the climate scenarios were derived from the UK Climate Impacts Programme (UKCIP02, Hulme *et al*. 2002). In UKCIP02, the predictions of the HadCM3 GCM were dynamically downscaled to a 50-km grid in a double-step procedure using two regional climate models.

A selection from the SRES – the A1F1, A2, B1 and B2 scenarios (see Chapter 3) – was run for three periods, the 2020s, 2050s and 2080s, to give a number of scenario-period combinations. Due to computational limitations, only the A2–2080 combination was dynamically downscaled, the others being interpolated using pattern recognition (Hulme *et al*. 2002). The A2 and B2 scenario predictions for the Kennet catchment were used as inputs to the 'weather generator' programme EARWIG (Environment Agency Rainfall and Weather Impacts Generator: Kilsby *et al*. 2007), which generated daily values for meteorological parameters including temperature, rainfall and potential evapotranspiration. EARWIG works by fitting a sophisticated stochastic model of daily rainfall to observed data and using change factors calculated from the UKCIP02 scenarios to do the same for future climates.

Other climatic variables are calculated from rainfall using regression relationships: an approach that works well for the variables controlling river discharge (Kilsby *et al*. 2007). This calculated meteorology was then used to generate daily values for river discharge under different scenarios by feeding it through the hydrological model embedded in the INCA-N Model (Wade *et al*. 2002a). Temperature and potential evapotranspiration (PET) were used directly from EARWIG, but the INCA-N model also requires actual evapotranspiration (AET) and hydrologically effective rainfall (HER). These were calculated from EARWIG daily rainfall and PET using a simple spreadsheet model (Bernal *et al*. 2004; Durand 2004), which works by calculating a soil moisture deficit which must be satisfied before any HER occurs. It is clear from this account that even addressing relatively simple

Table 10.2 Observed and modelled meteorological and hydrological data for the river Kennet under various climate change scenarios

		*Observed**	*Modelled*			
Variable	*Units*	*1961–90*	*1961–90*	*2020s A2/B2*	*2050s B2*	*2050s A2*
Annual rainfall	mm yr^{-1}	759	759	778	757	758
Days with:						
<0.2 mm	%	56	54.7	55.5	57.7	57.3
<1.0 mm	%	67	66.1	65.9	67.4	67.2
Temperature						
Mean	°C	9.2	9.2	10.2	11.0	11.3
Mean daily min	°C	5.1	5.4	6.4	7.2	7.5
Mean daily max	°C	13.0	12.9	14.0	14.8	15.1
Max daily max	°C	33	31.2	33.6	38.1	38.5
Min daily min	°C	−16	−14.8	−12.0	−12.8	−13.5
PET†	mm yr^{-1}		536	641	728	750
AET‡	mm yr^{-1}		459	481	503	512
HER§	mm yr^{-1}		299	298	254	247
Discharge in river Kennet						
Annual mean	$m^3 s^{-1}$	9.60	9.83	9.87	8.38	8.15
Minimum	$m^3 s^{-1}$	0.93	2.12	1.76	1.29	0.74
Maximum	$m^3 s^{-1}$	46.7	46.6	61.8	59.3	48.9
5th percentile	$m^3 s^{-1}$	3.88	3.43	3.38	2.60	2.44
1st percentile	$m^3 s^{-1}$	2.37	2.65	2.39	1.99	1.62

*Meteorological data are catchment means from the UK Meteorological Office at http://www.metoffice.gov.uk/climate/uk/averages/ukmapavge.html#. Hydrological data are from the UK National River Flow Archive at http://www.nwl.ac.uk/ih/nrfa/webdata/039016/g.html. INCA-predicted discharge has been adjusted to take into account drinking water abstraction from the catchment.
†PET, potential evapotranspiration (calculated without restrictions due to water availability).
‡AET, actual evapotranspiration.
§HER, hydrologically effective rainfall (rainfall potentially available to recharge rivers).

questions requires a long chain of models with associated uncertainties, suggesting that there might be some benefit in developing methods to reduce the number of models needed. Tisseuil *et al*. (2009) had reasonable success in predicting river flows in a variety of river types in the Garonne Basin by direct downscaling from GCMs using a variety of statistical models.

The results of the Kennet study (Table 10.2) show that when comparing observed and modelled data for the validation period of 1961–90, EARWIG is successful in reproducing the observed mean and distribution of temperature and rainfall. Likewise, the INCA-N model successfully uses these data to reproduce the observed mean and distribution of discharge in the river, except that the observed absolute minimum values, due to the exceptionally dry period of 1975–6, are not simulated. The success at reproducing the observed data with minimal calibration gives some confidence in the future predictions (Table 10.2).

Rainfall increases slightly in the 2020s but decreases somewhat by 2050. PET, however, increases due to rising temperatures, until in the 2050 A2 scenario it is almost equal to rainfall. Fortunately for river flows, most of the decrease in rainfall and increase in PET occur in summer: this means that the change in AET is much smaller, as the soil moisture deficit will limit evapotranspiration. As the Kennet is a groundwater-dominated river, flow will continue through the summer droughts as at present, but low flows will become more common by the 2050s.

Though these results appear credible and self-consistent, other attempts to model the same system have yielded a range of results. Arnell and Reynard (1997) predicted a decrease in run-off of 21% (range +24% to −37%) in the Lambourn, the major tributary of the Kennet, by 2050 given climate models then available and a range of hydrological assumptions. Limbrick *et al*. (2000) modelled hydrological changes in the Kennet due to climate change, using earlier versions of the Hadley Centre models (HadCM1 and HadCM2) as climate drivers and the hydrological model incorporated in INCA. The average reduction in annual flows by 2050 was 19%, similar to that described here (15%–17%), as were many of the seasonality features, such as a reduction in minimum flow of 46% (51% here). Whitehead *et al*. (2006) used INCA, and the HadCM3 model as climate driver statistically downscaled to the Kennet, to explore the implications for flow and N concentration. In contrast to this study, to Arnell and Reynard (1997) and to Limbrick *et al*. (2000), they predicted an *increase* in mean flow rates of 2%–5% by 2050. Wilby *et al*. (2006) used statistically downscaled GCM data and a more sophisticated hydrological model, CATCHMOD, coupled with INCA, to study N concentration and flow. For the HadCM3 model, this predicted a small (c. 5%) decrease in median flow in 2050 for the A2 storyline, and an even smaller increase (c. 2%) in median flow for the B2 storyline. Both Whitehead *et al*. (2006) and Wilby *et al*. (2006) used three different GCMs to generate climate drivers, with strongly contrasting results. In particular, the CGM2 model predicted large increases in mean flow by 2050 of about 35% (Whitehead *et al*. 2006) or 80% (Wilby *et al*. 2006), in contrast to the 'dry' Hadley Centre model. Clearly, the implications of these differences are large.

Statistical models

The quantification of the relationships between the distribution of biota and environmental conditions is a central theme of ecology, and there are existing methodologies available for predicting the effects of climate change on species in freshwaters. One common approach involves modelling the current distribution of an organism in relation to habitat variables, in particular temperature and flow regime, predicting changes in the habitat variables due to climate change, and using the model to predict the change in species distributions. A large number of studies of this type have been carried out (e.g. Berry *et al*. 2002; Mohseni *et al*. 2003), and the techniques being used are rapidly developing (e.g. Rushton *et al*. 2004). There are, however, problems with the approach. One is how to validate and test such models (Vaughan & Ormerod 2005). Another is that different models applied to the same data may predict significantly different impacts (e.g. Lawler *et al*. 2006). One technique for evaluating such models is to use ensemble forecasting (Araújo & New 2007) by applying several different models to the same problem and evaluating areas of agreement and disagreement. As described below, Buisson *et al*. (2008) adopted such an approach to model the future distribution of 35 fish species in French streams.

Seven different statistical techniques were used. Fish presence–absence data were extracted from the Office National de l'Eau et des Milieux Aquatiques (ONEMA) for 1110 sites distributed over the whole country. The sites chosen were judged to have minimal human disturbance, and the data were obtained by standardized electrofishing techniques. Data from fish species present in more than 25 sites were retained for study, amounting to 35 species (see Table 10.3). These data were then related to climatic and environmental variables. Three variables were used to describe climatic conditions: mean annual precipitation, mean annual air temperature and annual air temperature amplitude, derived from the difference between mean air temperature of the warmest month and mean air temperature of the coldest month. Future values for each of these three descriptors were derived for the 2080s from three GCMs: HadCM3 (Hadley Centre for Climate Prediction and Research, the United Kingdom), CGCM2 (Canadian Centre for Climate Modelling and Analysis) and CSIRO2 (Commonwealth Scientific and Industrial Research Organisation, Australia). Predictions of future climate were made for each of these using four greenhouse gas emission scenarios. These were scenarios A1, A2, B1 and B2 from the IPCC SRES (Nakićenović *et al*. 2000). Thus, 84 separate modelling runs were performed for each fish species: seven species distribution models × three GCMs × four emission scenarios.

The study also recognized that climatic variables are not the only ones to affect fish distribution: rivers and streams have a variety of habitats, and a large lowland river will clearly be different from a small headwater stream even if the climate is the same. Some of this habitat variation is correlated with information that can be obtained from databases and thus can be taken into account in the analysis. In this study, three derived variables were used to represent habitat variation: (i) elevation above sea level; (ii) a parameter representing position on the upstream–downstream gradient, derived from catchment area and distance from the source and (iii) stream velocity derived from width, depth and slope at the sampling site. As these derived variables are likely to be correlated with the climatic ones (e.g. high elevation with low annual air temperature), the deviations from the expected values at each site were used in the analysis to give six independent variables.

The species distribution models were then calibrated for each species using a randomly selected 777 river sites from the database. The remaining 333 sites were used to validate the calibration in an iterative process, and when these were satisfactory, predictions of probability of occurrence of each species at each of 1110 sites were converted into presence–absence values using a threshold maximizing the sum of two measures: sensitivity (i.e. the percentage of presence correctly predicted) and specificity (i.e. the percentage of absence correctly predicted). The calibrated models were then used to predict fish species distributions for 2080 for each of the 12 scenarios. The future probabilities of occurrence were transformed into presence–absence values by using the same threshold values as for current predictions.

Table 10.3 Analysis of agreement between projections of fish species' presence or absence in France for 2080

	Fish species				Source of variability (%)[§]		
*Code**	*Genus*	*Species*	*English name*[†]	*Consensus*[‡] *(%)*	*SDM*	*GCM*	*GES*
Les	*Leuciscus*	*souffia*	Varione	48	38	48	15
Lec	*Leuciscus*	*cephalus*	Chub	69	30	54	16
Ana	*Anguilla*	*anguilla*	Eel	68	56	14	30
Bar	*Barbus*	*barbus*	Barbel	62	55	35	9
Cht	*Chondrostoma*	*toxostoma*	SW European Nase	44	80	7	12
Alb	*Alburnoides*	*bipunctatus*	Spurlin	54	49	48	3
Leg	*Lepomis*	*gibbosus*	Pumpkinseed	55	85	11	4
Sas	*Salmo*	*salar*	Salmon	52	70	24	6
Lel	*Leuciscus*	*leuciscus*	Common dace	65	62	35	3
Bam	*Barbus*	*meridionalis*	Southern barbel	45	96	0	4
Rur	*Rutilus*	*rutilus*	Roach	69	48	48	4
Sce	*Scardinius*	*erythrophthalmus*	Rudd	45	58	40	2
Cyc	*Cyprinus*	*carpio*	Carp	59	89	8	3
Tht	*Thymallus*	*thymallus*	Grayling	42	41	55	4
Amm	*Ameiurus*	*melas*	Black bullhead	41	77	22	1
Gog	*Gobio*	*gobio*	Gudgeon	70	95	2	3
Blb	*Blicca*	*bjoerkna*	White bream	50	67	30	3
Tit	*Tinca*	*tinca*	Tench	58	61	36	2
Sal	*Sander*	*lucioperca*	Zander	45	88	11	1
Cac	*Carassius*	*carassius*	Crucian carp	45	93	2	5
Chn	*Chondrostoma*	*nasus*	Sneep	50	61	38	1
Rha	*Rhodeus*	*amareus*	Bitterling	58	44	55	1
Ala	*Alburnus*	*alburnus*	Bleak	70	88	11	1
Esl	*Esox*	*lucius*	Pike	65	79	20	0
Gaa	*Gasterosteus*	*aculeatus*	Three-spined stickleback	31	76	23	1

Bab	*Barbatula*	*barbatula*	Stone loach	62		94	6	0
Lol	*Lota*	*lota*	Burbot	36		88	12	0
Abb	*Abramis*	*brama*	Common bream	63		97	2	1
Gyc	*Gymnocephalus*	*cernuus*	Ruffe	59		94	6	0
Pup	*Pungitius*	*pungitius*	Nine-spined stickleback	41		87	8	5
Php	*Phoxinus*	*phoxinus*	Minnow	56		62	35	2
Pef	*Perca*	*fluviatilis*	Perch	61		52	33	15
Lap	*Lampetra*	*planeri*	Brook lamprey	46		39	44	18
Cog	*Cottus*	*gobio*	Bullhead	41		79	5	16
Sat	*Salmo*	*trutta fario*	Brown trout	63		61	24	15

Species are arranged in order of the magnitude of change predicted, the most positive first.
*Code is the three-letter code used to identify species in Fig. 10.1.
†English names from Froese and Pauly (2009).
‡Consensus is the measure of agreement between the 84 model combinations used for the fish projections.
§Source of variability in the model projections for each species: SDM, species distribution model; GCM, global climate model; GES, greenhouse gas emission scenario.

To evaluate agreement between the model runs, a 'consensus' parameter was calculated as the first axis of a principal components analysis of the predictions for each species. The mean consensus between models was 57% (Table 10.3), but values for each species differed considerably. It ranged from 31% for *Gasterosteus aculeatus* (three-spined stickleback) to 70% for *Gobio gobio* (gudgeon). Generally, the rarer species had lower consensus values. Table 10.3 also shows the sources of variability in projections for each fish species. For the entire data set, 70% of the variability was due to the species distribution models, 24% to the GCMs and only 6% to the emission scenarios. However, the pattern varied somewhat between species, and for some, such as the chub (*Leuciscus cephalus*), the choice of GCM was a more important source.

Given the dominant role of the species distribution model in the fish species projections, a single GCM (HadCM3) combined with a single emission scenario (A1FI) was arbitrarily chosen to assess the potential impacts of climate change on stream fish assemblages (see Buisson *et al*. 2008). These predictions are shown in Fig. 10.1 as changes in the probability of occurrence of each species. Buisson *et al*. (2008) found that all 35 fish species would be positively or negatively affected by climate change. On average, changes in the probability of occurrence ranged from −36.6% for *Salmo trutta fario* (brown trout) to +44.6% for *Leuciscus souffia* (varione). Those gaining the most appear to be warm-water species or those with a large range of thermal tolerance. Most negatively affected were two cold-water species – *Cottus gobio* (bullhead) and *Salmo trutta fario* (brown trout). On average, however, the 35 fish species would change their probability of occurrence by +5.6% by 2080, indicating a slightly positive response to climate change. Even though a species increases overall, local extinctions in some areas might occur, compensated by colonizations of new sites. For some species, the changes in spatial distribution were calculated and are illustrated for three representative species in Fig. 10.2: *Barbus barbus* (barbel), *Esox lucius* (pike) and *Salmo trutta fario* (brown trout).

Barbel, *Barbus barbus*, a rheophilic species relatively common in French streams, was predicted to expand its range greatly under climate change. The consensual model did not predict any extinctions and forecast that it could colonize a large number of areas where it does not currently occur, for example, NW France, the Pyrenees, the Massif Central and the Jura Mountains. Pike (*Esox lucius*), a predatory species living among dense vegetation, was predicted to move to new suitable habitats mainly in eastern France and in mountainous areas, whereas it could suffer from local extinctions in the western part of France where it currently occurs in many sites. Finally, brown trout *Salmo trutta fario*, a species characteristic of cold and well-oxygenated streams, was predicted to be the most severely affected by climate change. By 2080, its distribution would be restricted to the most upstream sites of the mountainous regions and some streams of NW France. The results thus predict that cold-water species living in headwater streams would suffer the most deleterious effect of climate change as their potential distributional area reduced, while other fish species occurring currently downstream would be able to expand their range upstream.

Overall, these results were consistent with those obtained in North America, which predicted a decrease in salmonid distribution and contrasting results for

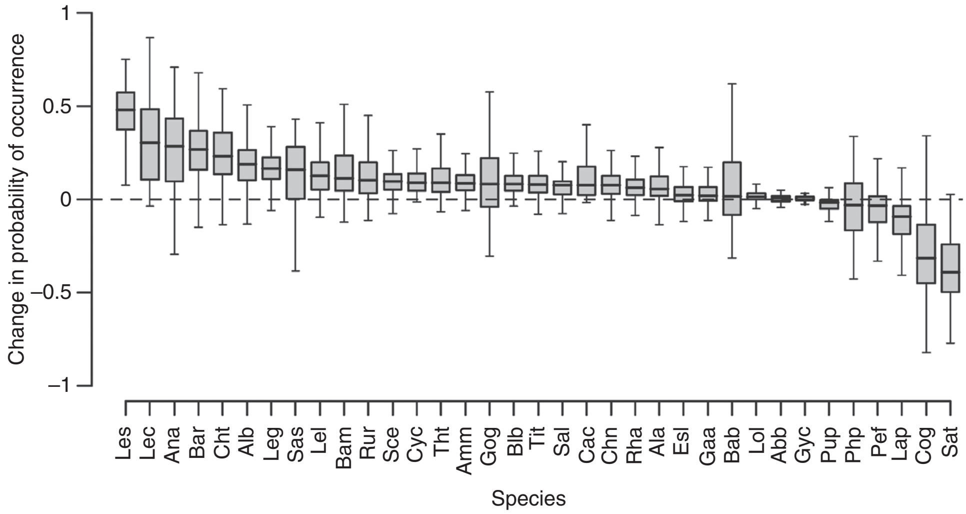

Figure 10.1 Changes in the probability of occurrence for each of 35 fish species in France predicted for 2080 using the scenario HadCM3 A1FI. Each box and whisker plot represents 84 model runs: the median is the line within the box; the edges of the box are the first and third quartiles, and the whiskers are the upper and lower extremes. See Table 10.3 for species codes.

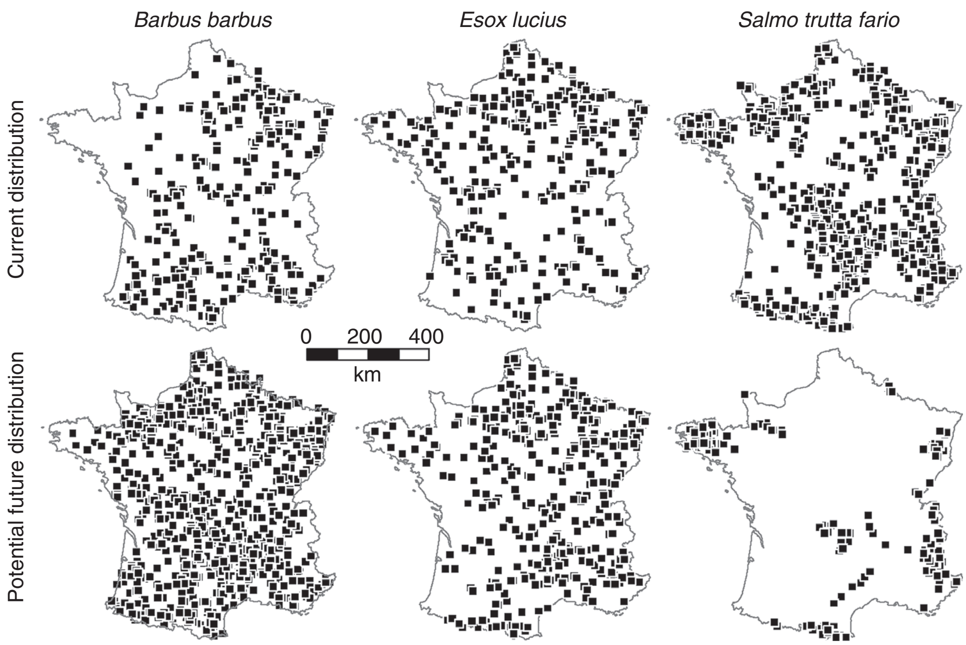

Figure 10.2 Predicted distributions in French rivers of three fish species: *Barbus barbus* (barbel), *Esox lucius* (pike) and *Salmo trutta fario* (brown trout) at the present day and in 2080.

cool- and warm-water species (e.g. Mohseni *et al*. 2003). Nevertheless, compared with other taxa for which the impacts of climate change could be very detrimental (e.g. Thomas *et al*. 2004, 2006), this assessment for French stream fish species was rather positive, as most fish were predicted to expand their distributional area rather than reduce it. This may result from the scarcity of cold-water species in French fish assemblages compared to cool- and warm-water species which have a larger range of tolerance.

Dynamic models

A fuller understanding of the potential effects of climate change on aquatic ecosystems can be obtained using dynamic, mechanistic models. Dynamic models allow model components to change with time: mechanistic models attempt to capture all the important processes as connected systems of equations. Dynamic, mechanistic models should be able to represent the transient changes in the pollutant stores in catchments and represent the response of biogeochemical cycles to altered precipitation and temperature inputs. Thus, they are eminently suited to modelling climate change effects. The disadvantages of these models are well known (e.g. Chapra 1997): they can require large amounts of data, which may not be available, they require a full knowledge of the important processes and how they are connected, they are difficult and time-consuming to write and programme and uncertainty is a major issue if a model aims for complete understanding of a system (see below). Nevertheless, they represent the best hope for accurate predictions of climate change effects, and building and improving them is a priority for research.

The most widely used dynamic models in the Euro-limpacs project have been the INCA models. The INCA (INtegrated CAtchment) models are dynamic computer models that predict aspects of water quantity and quality in rivers and catchments (Whitehead *et al*. 1998a, b; Wade *et al*. 2002a). They are designed to represent the factors and processes controlling flow and water quality dynamics in both the land and the in-stream components of river catchments, whilst minimizing data requirements and model structural complexity (Whitehead *et al*. 1998a, b). INCA can produce daily estimates of discharge, stream water concentrations and fluxes over a period of many years at any point along a river's main channel. The model provides a number of tools to aid understanding of the system, and statistics to allow comparison with observed data can be generated.

The original INCA-N model was developed and used to model nitrogen in catchments (Wade *et al*. 2002a, Wade 2006). The INCA framework has now been extended to phosphorus (INCA-P, Wade *et al*. 2002b, c), particulates (INCA-SED, Jarritt & Lawrence 2007), dissolved organic carbon (INCA-C, Futter *et al*. 2007a, 2008), mercury (INCA-Hg, Futter *et al*. 2007b) and macrophyte and epiphytic algal dynamics (Wade *et al*. 2002b; Whitehead *et al*. 2008). A notable example is the application of the INCA-N model to the Garonne river system in France (Tisseuil *et al*. 2008), at 62,700 km^2 the largest river basin modelled so far. The spatial and temporal dynamics in the stream water nitrate concentrations were described and related to variations in climate, land management and effluent point sources using multivariate statistics. In conjunction with the hydrological model HBV (Hydrologiska Byråns Vattenbalansavdelning), the INCA-N model was used to understand which factors and processes control the flow and N dynamics in different climate zones and to assess the relative inputs from diffuse and point sources across the catchment. The simulations suggested that, in the lowlands, seasonal patterns in the stream water nitrate concentrations were dominated by diffuse agricultural and point-source effluents with an estimated 75% of the river load in the lowlands derived from arable farming. The model proved able to simulate observed seasonal nitrate patterns at large spatial ($>300\,km^2$) and temporal ($\geq$ monthly) scales using available national data sets. The model was equally good at simulating observations in the upper, mid and lower reaches of the Garonne. This application of the linked HBV and INCA-N models to a major European river system showed that it was possible to simulate observed behaviour in a catchment commensurate with the largest basins to be managed under the Water Framework Directive.

The success of the model in simulating observed nitrogen behaviour in catchments allows its use to project changes in nitrogen fluxes in future as a result of climate change. As described above, summer flow rates in the river Kennet in SE England are likely to fall in the future as drought periods become more extreme. Extending the modelling to simulate nitrate-N, Whitehead *et al*. (2006) used the INCA-N model to show that the droughts might trigger a release of nitrate from the soils and this nitrate would be exported to the river, as illustrated in Fig. 10.3. With climate change predictions downscaled from the HadCM3 model and the A2 emissions scenario, nitrate-N concentrations increased to values close to the EU drinking water limit of $11.3\,mg\,l^{-1}$. Falling flow rates and rising nitrate levels could affect water supply and put in doubt plans to improve the water quality and ecology of such a sensitive chalk stream as the Kennet. A series of adaptation strategies was investigated using the model to assess the effectiveness of potential mitigation strategies. For example, reducing agricultural fertilizer use by 50% in the catchment gave the biggest improvement, lowering nitrate concentrations to levels not seen since the 1950s. Reducing atmospheric sources of oxidized and reduced N by 50% reduced the nitrate by about $1\,mg\,l^{-1}$ compared with the baseline scenario. Constructing water meadows along the river (which is parameterized in the model as an increase in the in-stream denitrification coefficient) would be more beneficial, significantly slowing down the rising levels of nitrate. A mixed strategy of a combination of all three approaches – reducing fertilizer, reducing N deposition by 25% and constructing half the number of wetland areas alongside the river system – also generated significant reductions in nitrate. The realism of these simulations depends on how well the model represents reality, and different approaches to the same system have yielded different results. For example, other GCM simulations predicted an increase in flow rather than the decrease shown in Fig. 10.3. Another study using the same climate and emission scenario but different INCA parameterization predicted a decrease in stream nitrate by 2050 rather than an increase (Skeffington 2008). Nevertheless, the results give some impression of the likely effects of management options, and also show the long response times before any improvement occurs. More explicit modelling of groundwater transport in chalk catchments predicts even longer response times (Jackson *et al*. 2007).

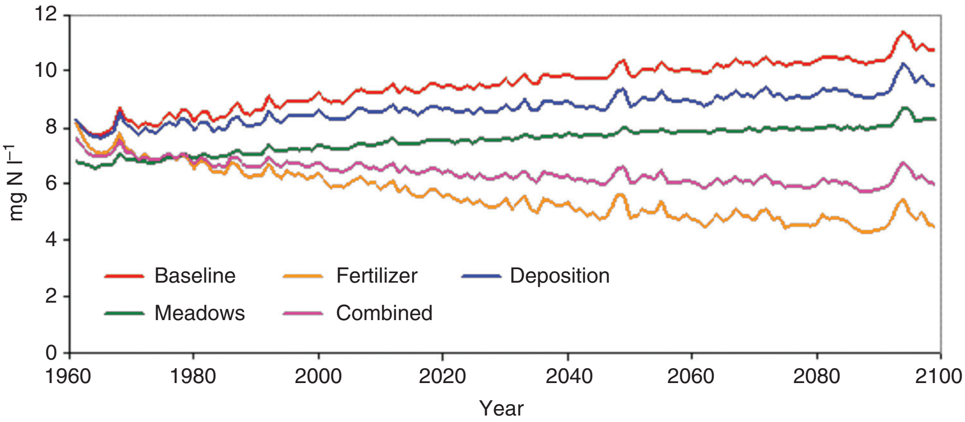

Figure 10.3 The effects of climate change, simulated by the INCA-N model, in the river Kennet for 1960–2100, together with the effects of various adaptation strategies. These were 'fertilizer', reduce N fertilizer input by 50%; 'deposition', reduce atmospheric N deposition by 50%; 'meadows', increase denitrification fourfold by constructing water meadows; 'combined', apply all three strategies but at half the rate.

These reductions also need to be seen in context. Inorganic nitrogen concentrations in rivers draining pristine catchments are often very low (<0.2 mg N l^{-1}; e.g. Perakis & Hedin 2002). The Kennet catchment has been at least partly agricultural land since the Bronze Age, and hence, it is likely to be a long time since conditions were uninfluenced by humans. However, the modelling estimates for the Lambourn (the major tributary of the Kennet) suggest that even in the 1920s, before the widespread use of artificial N fertilizers in the catchment, stream nitrate concentrations were only about a ninth of those currently observed. From Fig. 10.3, this would imply about 1 mg N l^{-1} for a 1920s nitrate concentration in the Kennet. Therefore, even the most effective mitigation option is unlikely to cause a return to pristine conditions.

Dynamic models other than the INCA models have been used and developed in the Euro-limpacs project. Andersen *et al.* (2006) analysed climate change impacts on hydrology and nutrient dynamics in the 113.5 km^2 Gjern River Basin in Denmark with the NAM-MIKE11-TRANS model chain and with regional climate model HIRHAM predictions used for meteorological prediction. HIRHAM predicted a non-significant increase in mean annual precipitation of 47 mm (5%) and a significant ($p < 0.001$) increase in mean annual air temperature of 3.2°C (43%) between the control (1961–90) and the scenario (2071–2100) periods. The precipitation-run-off model (NAM) used these data to forecast that the mean annual run-off from the river basin would increase by 27 mm (7.5%, $p < 0.05$) between the control and the scenario periods. Changes in the extremes were larger: run-off during the wettest year in the 30-year period increased by 58 mm (12.3%). The most dramatic change in hydrological regime was modelled for the headwater Gelbæk stream draining an 11.1 km^2 loamy catchment. Large (40%–70%) and significant ($p < 0.05$) reductions in run-off during late summer (August to October) were predicted. Conversely, the simulation of run-off in the neighbouring headwater Dalby stream draining a 10.5 km^2 sandy, groundwater-dominated catchment suggested almost no change in monthly run-off during the summer. Other results from groundwater-fed catchments (e.g. Jackson *et al*. 2007) also suggest that the effects of climate change will be apparent more quickly in systems with impermeable geology or loamy or clay soils where the hydrology is more responsive than in those catchments underlain by permeable geology or sandy soils where the groundwater will buffer short-term variations. An increase in flood plain inundation from an average of 34 to 51 days per year was predicted for the Gjern catchment. Total N exported from the river basin increased by 7.7% even though N retention in the river system was forecast to increase. This was more than counterbalanced by an increase in the transfer of N from land to surface waters.

Linking models

Many specialized ecosystem models are available which give robust and detailed predictions in a limited scientific field. With climate change, the possible environmental impacts are diverse and interconnected and involve the responses of a myriad of processes in whole catchments. Integrated management strategies will be needed to tackle the problems, and to model responses on a catchment scale individual models also need to be integrated (e.g. Andersen *et al*. 2006; Evans *et al*. 2006). However, linking models poses a number of challenges. The use of the output of one model as the input to the next requires that the models operate on the same spatial and temporal scale and on about the same level of complexity.

For most applications, it is not necessary to programme hard links between the models so that they operate as a single entity. This is difficult as individual models were rarely designed with this in mind, and input and output data formats are unlikely to be compatible. Nevertheless, it is essential for some applications such as those involving multiple model runs, for example, Monte Carlo analysis (see "Uncertainty" Section) or the creation of response surfaces. Manual adjustments of the outputs of one model so that they are suitable as inputs to the next allow independent models to be linked reasonably easily but are time-consuming and can involve considerable skill and scientific judgement. Much more work remains to be done, particularly so that the aspirations of the Water Framework Directive for integrated resource management over whole river basins can be addressed. An example of the approach and potential of linking models to simulate processes at the catchment scale is provided by the study of Kaste *et al*. (2006) on the Bjerkreim catchment in Norway.

The Bjerkreim River Basin (685 km^2) has an average run-off of 2430 mm yr^{-1} and discharges into an estuarine area (58°28′N; 5°59′E) near Egersund in south-western Norway. The land cover is dominated by non-forested, mountainous areas (~60%) and is typical of the inner south-western parts of Norway. Water surfaces, peatlands and heathlands make up about 20% of the area, while forests and agricultural land cover 15% and 5%, respectively (Kaste *et al*. 1997). Nitrogen deposition in the Bjerkreim area is the highest in Norway, 15–23 kg N ha^{-1} yr^{-1} (wet + dry) due to both high precipitation rates and relatively high N concentrations (Tørseth & Semb 1997). The main threats to aquatic ecosystems in the catchment are acidification and nitrogen enrichment, with substantial leaching of atmospheric-derived N from soils to surface waters already happening. The question addressed in this study was whether climate change was likely to alter the situation so that more (or less) nitrogen leached into the water, and whether nitrate concentrations in the rivers, lakes and receiving coastal waters were likely to increase or decrease and, if so, by how much.

Data from two GCMs – ECHAM4 from the Max Planck Institute, Germany, and HadAm3H from the Hadley Centre, the United Kingdom, driven with two scenarios of greenhouse gas emissions (IS92a and A2, respectively) – were dynamically downscaled (see above) to a spatial resolution of $55\,km^2 \times 55\,km^2$ and a temporal resolution of 6h using a model related to that used to perform weather forecasting in Norway. The downscaled predictions for control periods were adjusted to match observed data in the catchment before being used to make climate change prognoses. These were for different periods: 2030–49 for the MPI IS92a scenario and 2071–2100 for the Hadley A2 scenario (hereafter called 'MPI' and 'Had', respectively). Predicted changes in nitrogen deposition due to presently agreed legislation were also included in the forecast scenarios. The climate change data were then used to drive four models linked to assess the effects on hydrology and nitrogen concentrations and fluxes in the river and its coastal fjord (Kaste *et al*. 2006; Fig. 10.4). These models were the hydrological model HBV (Sælthun 1996), the water quality models MAGIC (Cosby *et al*. 2001) and INCA-N (Whitehead *et al*. 1998a, b; Wade *et al*. 2002a) and the NIVA Fjord models (Bjerkeng 1994). The flow of data between models is shown in Fig. 10.4. HBV was used to predict flows and other hydrological variables needed to run INCA, MAGIC to calculate N retention in INCA, INCA to calculate stream nitrate concentrations and the Fjord model to assess the biological consequences in coastal waters. The HBV, INCA and MAGIC models were calibrated initially to small sub-catchments within the main catchment area, before extending the calibration to the whole Bjerkreim basin. After calibration, the models were tested against observed data from a control period, in which they performed acceptably, though the means were simulated better than the seasonal patterns, and extreme events and unusual meteorological conditions were more difficult still to simulate (Kaste *et al*. 2006).

The two downscaled climate scenarios projected a temperature increase in the study region of about 1 °C with MPI and about 3 °C with Had, and both predicted increased winter precipitation. Projections of summer and autumn precipitation were quite different between the two models, however: a slight increase with MPI and a significant decrease with Had. Because different models were used for different periods, it was not possible to determine whether this was a model effect or a function of time. Because of higher winter temperatures, the HBV model predicted a dramatic reduction of snow accumulation in the upper parts of the catchment for both the climate change scenarios. This, in turn, led to higher run-off during winter and lower run-off during spring snowmelt. With the Had scenario, run-off in summer and early autumn is substantially reduced as a result of reduced precipitation, increased temperatures and, thereby, increased evapotranspiration. MAGIC and INCA models predicted no major changes in

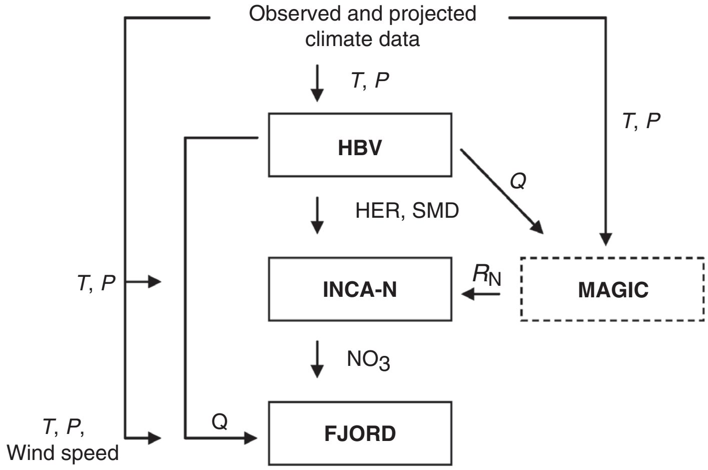

Figure 10.4 Data transfer scheme between models used to model the Bjerkreim River in Norway. The flow of data is indicated by arrows. *T*, temperature; *P*, precipitation; *Q*, water flow; SMD, soil moisture deficit; R_N, nitrogen immobilization as a percentage of input. Other abbreviations in Table 10.1. (From Kaste *et al*. 2006.)

nitrate concentrations and fluxes with the MPI scenario but a significant increase in concentrations and a 40%–50% increase in fluxes with the Had scenario (Fig. 10.5). These results arose from balances between the effects of climate change on nitrogen processes within the catchment. With the MPI scenario, the reduced N deposition was largely compensated by a temperature-driven increase in N mineralization (16%) such that the total available N in the system was nearly constant. With the Had scenario, however, N mineralization increased by nearly 40% compared to the control period. This was partly compensated by reduced N deposition and increased uptake by vegetation but counteracted by a reduction in the basin's ability to retain N.

Among the N retention processes included in the INCA-N model, two opposing factors operate at the same time. First, the long-term accumulation of N in the system leads to a decreased C : N ratio in the organic soil layer, which increases the risk of N leaching. Secondly, the increased temperature promotes vegetation growth and hence uptake of N. The net effect of all these processes was that at the Bjerkreim river outlet, the INCA-N model simulated a 4% decrease in mean NO_3^- concentration but a 4% increase in the mean *flux* with the MPI scenario. This is because the increased temperature accelerated aquatic N retention processes and thus reduced NO_3^- concentrations, whilst increased precipitation and thus stream water flow increased the total NO_3^- export from the basin. With the Had scenario, the stream water NO_3^- concentrations and fluxes were predicted to increase by approximately 50% and 40%, respectively. Here, the predicted decrease in annual flow reduced the NO_3^- export potential relative to the MPI scenario.

A possible consequence of increased nitrate concentrations is that the acidification of the river could increase, thus offsetting ongoing recovery from acidification due

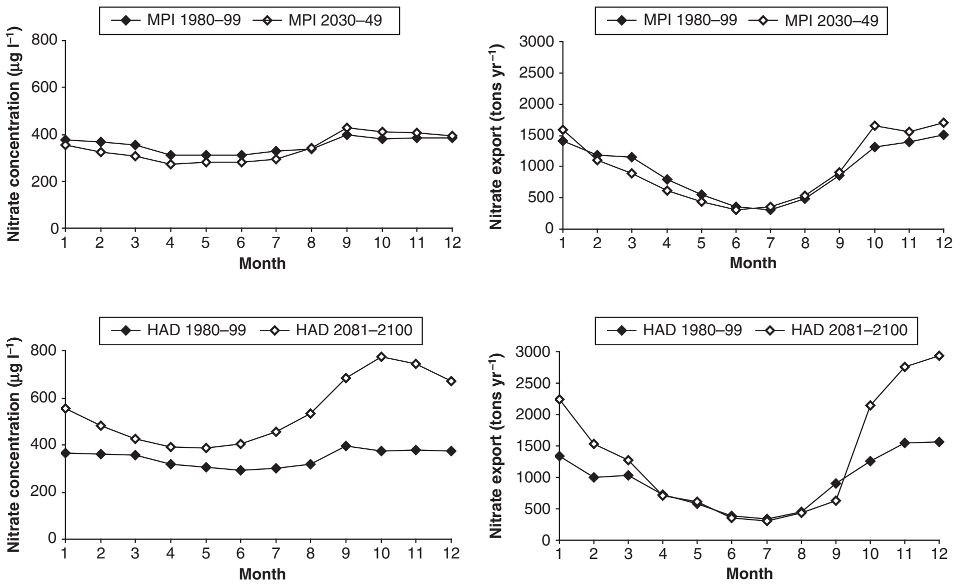

Figure 10.5 INCA-N-simulated NO_3 concentrations and fluxes at the Bjerkreim River outlet in 2030–49 and 2081–2100, based on the MPI and Had scenarios, respectively. (From Kaste *et al*. 2006.)

to reductions in acid deposition (see Chapter 7). The increased N loading may stimulate the growth of N-limited benthic algae and macrophytes along the river channels and lead to undesirable eutrophication effects in the estuarine area. Simulations made by the Fjord model indicate that primary production in the summer in the estuary might increase by 15%–20% with the Had scenario. Since this scenario does not entail any increase in NO_3^- fluxes during summer (Fig. 10.5), the production increase may be a result of a longer residence time of the surface layer due to reduced freshwater inputs. It thus seems that the changes in run-off patterns may have a greater effect on algal production than the changes in nutrient conditions *per se*.

The linked-model approach presented here involved several sources of uncertainty. Among these were uncertainties related to (i) scaling of input data; (ii) climate and N deposition scenarios; (iii) model parameterization and calibration; (iv) model structure/ability to simulate key processes and (v) transfer of data with inherent uncertainties between models. All models involved proved to be fairly robust in reproducing current data, but the number of processes which have to be simulated to make predictions mean that the model results should be regarded as possible outcomes and not forecasts, especially beyond 2050.

However, some of the responses predicted by the models are founded in experimental and observational data. For instance, both laboratory- and large-scale experiments have suggested that decomposition and N mineralization show a faster response to a temperature increase than the corresponding N retention processes, at least during an initial phase of the warming process (Kirschbaum

1995; van Breemen *et al*. 1998). This is illustrated in this study by the increase in the N mineralization rate in response to the MPI and Had scenarios for air temperature and precipitation in the Bjerkreim River Basin. Decades with elevated atmospheric N inputs have increased the stores of N in soil, and empirical data have demonstrated a negative correlation between NO_3^- leaching rates and the C : N ratio of soil organic matter (Gundersen *et al*. 1998; MacDonald *et al*. 2002).

Even given current legislation on reducing N deposition, the MAGIC model simulated a slight decrease in the C : N ratio of soil organic matter in the Bjerkreim catchment by 2100. This implies a gradual increase in NO_3^- leaching rates even with no climate change. With the MPI and the Had climate scenarios, the decrease in C : N ratios and thus increase in NO_3^- leaching rates were more pronounced, offsetting the gains from reductions in N deposition. The extent to which this might happen depends on several uncertain factors. Among these are (i) the size of the N pool available for mineralization; (ii) the amount of additional carbon sequestered due to climate change and thereby affecting the soil C : N ratio and (iii) the actual temperature responses of the various N sink and source processes. Additionally, there are still large uncertainties associated with future NO_3^- leaching as a response to decreasing C : N ratios in catchment soils. The empirical model of Gundersen *et al*. (1998), which is included in MAGIC, is based on a large spatial data set, and we currently lack sufficient long-term data on C : N ratios and NO_3^- leaching to confirm the model on a temporal scale.

Overall, this study has shown that the results of linking different models can lead to helpful insights about the effects of climate change on water flows and nitrate leaching in catchments, which are not necessarily clear from running the models alone. Though the results are uncertain and not to be taken as a firm forecast, they highlight possible outcomes and also suggest future research that could be used to improve the model predictions.

Uncertainty

All model predictions are uncertain to some degree, and quantifying and preferably reducing uncertainty is one of the priorities for climate change modelling (e.g. Wilby 2005). The meteorological models used to drive climate change predictions are themselves uncertain, and this can have major impacts on predictions of water quality. For instance, Whitehead *et al*. (2006) and Wilby *et al*. (2006) used three different GCMs to predict changes in flow in the river Kennet for 2050: the results ranged from a 19% decrease to an 80% increase. To add to these, there are the uncertainties associated with water quality modelling structures, parameters and observations.

Though a good model can be calibrated to observed data, its predictions are rendered uncertain because of doubts over whether the model structure and parameters are good representations of the modelled system. It may be possible to calibrate a large number of different structures and parameters to fit the observed data equally well, but these differences lead to very different outcomes when projected into the future. This is known as the ‘equifinality problem’ (e.g. Beven 2006). There are various methods of estimating and reducing the degree of equifinality so that the number of possible model structures and parameters is reduced. One is to reduce the number of processes in the model, but this conflicts with the requirement for model realism. Water quality modelling is particularly difficult because the large spatial scale required means that it is hard to constrain model parameters. For instance, a water quality model may require the nitrogen concentration in the catchment soil, which is potentially measurable. But given that there will be a wide range of N concentrations in the catchment soils, which should be used? The mean of a large number of observations? Or should soils along flowpaths or close to rivers be given more weight? Or measurements from the upper parts of soil profiles which may have more direct hydrological influence? Experience shows that often models behave best with parameters that cannot be related to measured values in any obvious way.

There are, however, methods for estimating and reducing model uncertainty, and these have been extensively used in the Euro-limpacs modelling programme. One of these is Monte Carlo analysis (e.g. Rubinstein 1981). This is a well-established technique in which instead of running a model once with what is considered the best set of parameters to generate a single result, the model is run many times (typically thousands) with different values for input parameters selected from their potential ranges according to some scheme. The output is then a probability distribution which can be used to generate statistics such as confidence intervals. Moreover, the parameters with most influence on the uncertainty of the final result can be identified (known as sensitivity analysis) and the information used to identify optimum targets for research aimed at reducing uncertainties. The results of Monte Carlo analysis when applied to models can be surprising and counterintuitive. For example, the calculation of critical loads, the deposition thresholds used in pollution control policy, involves models which have 10–20 uncertain parameters. Monte Carlo analysis showed that the uncertainty in the calculated critical loads was typically less than the uncertainty in *any* of the input parameters (Skeffington *et al*. 2007). This behaviour is to be expected where parameters are independent and subject mainly to random errors.

Monte Carlo analysis has been applied to all the INCA models to identify key parameters and place confidence limits on model predictions (Wade *et al*. 2001; Cox & Whitehead 2004; Wilby 2005; Rankinen *et al*. 2006; Jarritt & Lawrence 2007). The results give an idea of the kind of variability that can be expected from water quality climate change simulations. For example, Fig. 10.6 shows the error bounds for predictions of phosphorus concentrations in the river Lambourn in the 2050s, using the INCA-P model (Whitehead *et al*. 2008). The 95% confidence bounds show a relatively narrow band of uncertainty during lower-flow summer months when conditions have been more stable. However, in winter months, the uncertainty increases as flow conditions become more variable and storms generate more run-off of water and nutrients.

One key achievement in the project has been to develop and apply a generalized Sensitivity and Uncertainty Analysis Tool, which uses a variant of Monte Carlo analysis called generalized sensitivity analysis. The specific method applied is that developed by Hornberger and Spear (1980). The Monte Carlo realizations are divided into those that best fit the observed data and the rest. The best results are

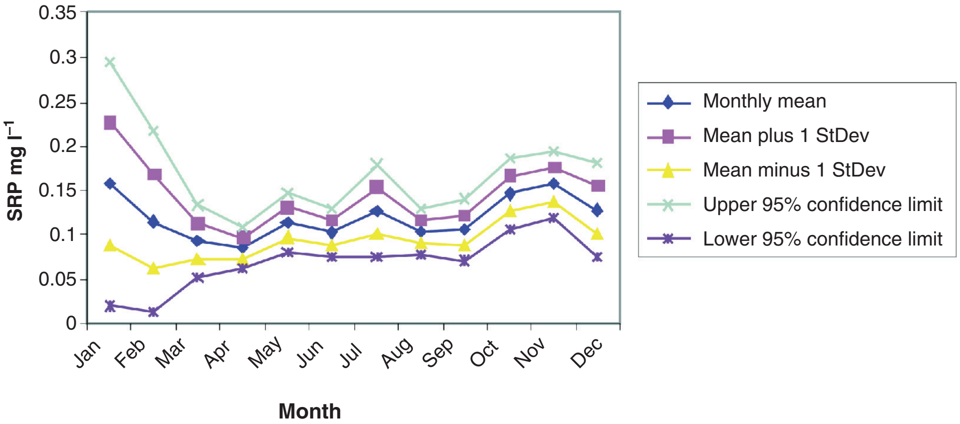

Figure 10.6 Soluble reactive phosphorus concentrations simulated by the INCA-P model for the 2050s in the River Lambourn, together with uncertainty bounds.

used to fit confidence intervals to model predictions. The tool can also be used for sensitivity analysis using Kolmogorov–Smirnoff statistics to produce a list of input parameters ranked in order of their importance in distinguishing good from bad simulations. It is being systematically applied to simulation results produced in the Euro-limpacs project from catchments across Europe in order to assess patterns in overall uncertainty, but this activity was not complete at the time of writing.

Conclusions

The ultimate goal of the catchment modelling in the Euro-limpacs project was to provide a pan-European assessment of the likely impacts of climate change on the flow regimes and water quality of river systems representative of key climate types across Europe. For a comprehensive assessment of water quality, a range of water quality parameters needed to be considered. Those considered were nitrogen, sediment, phosphorus, indicators of acidification (such as pH, alkalinity and acid neutralizing capacity), carbon and mercury. We are still some way from the ultimate goal, but we have made significant progress in three areas.

First, new catchment-scale models have been developed and existing ones improved leading to an improved capability in understanding how different factors and processes are integrated in response to climate or land-use management changes. Each of the INCA family of models has been harmonized in the sense that the versions for each of the different water quality indicators have the same structural representation of the key hydrological stores and pathways. The only differences between the models are the inputs and the biogeochemical cycle incorporated for each water quality measure. Thus, a toolkit of models now exists for a range of key pollutants with a common representation of catchment structure and hydrology.

Secondly, a methodology has been developed to convert outputs of temperature and precipitation from GCMs to values appropriate for use in the catchment-scale models. This standardized method for downscaling can be used with the INCA family of models to assess the likely impacts of climate change on freshwater quality (see “The Euro-limpacs modelling strategy” Section).

And thirdly, a semi-automated sensitivity and uncertainty tool has been developed that can be used to assess the effect of different parameter values on model performance and quantify the spread of modelled outcomes when making projections of future flow and water quality conditions.

The techniques of converting GCM output to meaningful inputs for catchment-scale models and the techniques of sensitivity and uncertainty analysis are not new, and other methods of uncertainty analysis are widespread. The novelty is the creation of a methodology that can now be consistently applied to river systems across Europe to assess changes in the flow and water quality for a broad range of water quality indicators, derive precipitation and temperature inputs to models in a clearly defined way and use a common methodology in sensitivity and uncertainty analysis that can be applied allowing comparison of the results at the pan-European scale.

The questions posed in the introduction can be mainly answered affirmatively. Models are never going to provide exact and unequivocal predictions of the effects of climate change on freshwater ecosystems. But the models developed during the Euro-limpacs project have been able to make useful predictions, qualified as they are by estimates of uncertainty. Models have also been used to explore plausible outcomes, to identify fruitful areas for further research so that future predictions will be less uncertain, to increase understanding of processes and to explore management options. Predictions concerning hydrology seem to be better founded than those concerning water quality, and ecological predictions are the most uncertain of all, reflecting a trend of increasing complexity and reduced understanding. There is still much research to do before we are close to being able to predict the effects of climate change on aquatic ecosystems.

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