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The impacts of climate change on hydrology in Ireland

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Summary A study of nine Irish catchments was carried out to quantify the expected impact of climate change on hydrology in Ireland. Boundary data from the European Centre Hamburg Model Version 5 (ECHAM 5) general circulation model were used to force the Rossby Centre Atmosphere Model (RCA3) regional climate model, producing dynamically downscaled precipitation and temperature data under past and future climate scenarios. This data was used to force the HBV-Light conceptual rainfall-runoff model to simulate stream flow in the reference period (1961–2000) and in the future (2021–2060) under the Special Report on Emissions Scenarios (SRES) A1B scenario. A Monte-Carlo approach to calibration was used to obtain 100 parameter sets which reproduced observed stream flow well. Use of an ensemble provided results in terms of a range rather than a single value. Results suggested an amplification of the seasonal cycle across the country, driven by increased winter precipitation, decreased summer precipitation and increased temperature. The expected changes in mean winter and summer flows as well as annual maximum daily mean flow varied depending on catchment characteristics and the timing and magnitude of expected changes in precipitation in each catchment.

Introduction

From the recent Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (IPCC, 2007), little doubt remains that the climate system has warmed in recent decades. Recent observations confirm increases in global mean temperatures, rising global average sea level and diminishing snow and ice cover. This warming, and the consequent rise in atmospheric water vapor have lead to an increase in mean precipitation over northern Europe as well as an increase in the frequency of heavy precipitation events over most land areas. It is expected that global average surface air warming will continue into the 21st century, and that hot extremes, heat waves and heavy precipitation events will continue to increase in frequency. The objective of this project was to examine how

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the predicted climate change will impact hydrology in Ireland.

In recent years, numerous studies have investigated the impact of climate change on hydrology and water resources in many regions (e.g. Arnell and Reynard, 1996; Bergström et al., 2001; Middelkoop et al., 2001; Gao et al., 2002; Menzel and Bürger, 2002; Pilling and Jones, 2002; Arnell et al., 2003 and Christensen et al., 2004). Charlton et al. (2006) investigate the impact of climate change on water supplies and flood hazard in Ireland using a grid-based approach, forcing the HYSIM model of Manley (1993) with statistically downscaled climate data from the Hadley Centre Climate Model, HadCM3 (Gordon et al., 2000). Murphy et al. (2006a) employ similarly downscaled data to force HYSIM, modeling individual basins rather than a gridded domain. As they discuss in Murphy et al. (2006b), parameter uncertainty is addressed by employing the GLUE methodology of Beven and Binley (1992) with Latin-Hypercube sampling (McKay et al., 1979) included as an alternative to Monte-Carlo simulations. The key differences between the study presented here and those of Charlton et al. (2006) and Murphy et al. (2006a) are the use of dynamically rather than statistically downscaled climate data to force the HBV-Light hydrology model (Seibert, 2005) and our use of Monte-Carlo simulations to account for parameter uncertainty.

Research carried out under the Community Climate Change Consortium for Ireland (C4I) project has emphasized developing dynamically downscaled climate data with which to investigate climate change and its impacts for Ireland (McGrath et al., 2005; Semmler et al., 2006). A feasibility study was performed by Wang et al. (2006) to explore the expected change in flood risk for the Suir catchment due to climate change based on these dynamically downscaled data. This study builds on the work of Wang et al. (2006) to develop a methodology that will be used with an ensemble of dynamically downscaled climate data (Semmler et al., 2006) to investigate the impacts of climate change on the hydrology of Irish rivers. Wang et al. (2006) used the HBV model (Bergström, 1992) from the Swedish Meteorological and Hydrological Institute (SMHI) which is usually calibrated using a manual trial and error approach. Here, it has been replaced by the HBV-Light model of Seibert (2005) because its interface allows Monte-Carlo simulations. Calibration using Monte-Carlo methods yields an ensemble of simulations allowing us to account for parameter uncertainty in our analysis. The second difference is that a significant bias has been identified and reduced in the dynamically downscaled precipitation data. Wood et al. (2004) discuss the occurrence of such biases, and the impact they can have on this type of study. Thirdly, the scope of the study has been expanded to include nine catchments (Fig. 1, Table 1) selected to ensure varying topography, geology, climatology and expected climate change. Finally, the focus has broadened from extreme flooding events to include changes in seasonal flows. Changes in winter and summer flows are of interest in their own right, but also allow us to make more reliable statements about flood risk.

In this study boundary conditions from a general circulation model are used to drive a regional climate model to produce dynamically downscaled precipitation and temperature data. These data are used to force a hydrology model which simulates run off during a reference period (1961–2000) and a future period (2021–2060) for a given future climate scenario. In the next section (Study methodology), details of the experiment, including the models and data used, and a precipitation bias correction scheme are provided. Dynamically downscaled temperature and precipitation data are presented to illustrate how climate is expected to change in Ireland in the future.

The structure of this paper then follows the stages of the study methodology, as a successful analysis of the impacts of climate change depends on the successful calibration and validation of the models. The HBV-Light conceptual hydrology model is forced with observed precipitation and

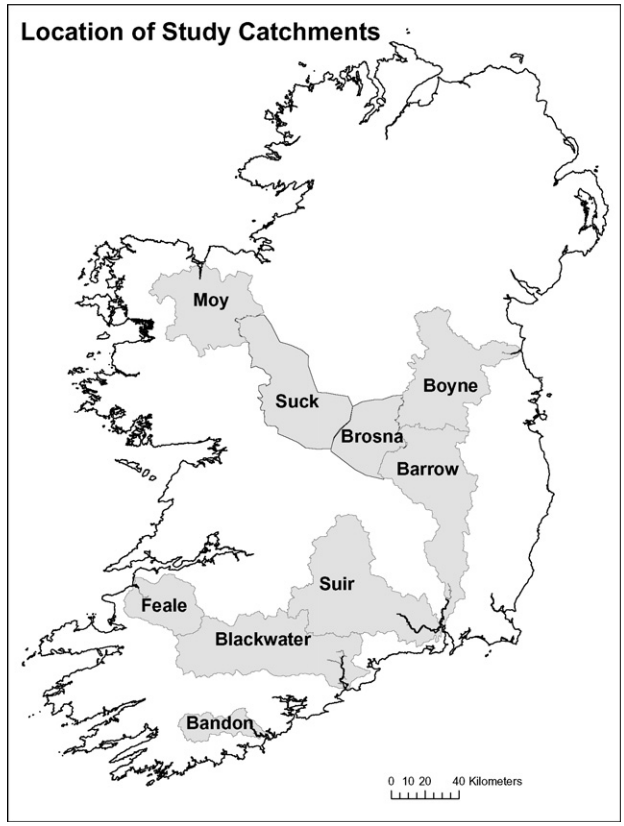

Figure 1 Locations of study catchments.

Table 1 Stream flow gauge station and location, catchment area upstream of the gauge station

Catchment	Stream flow gauge station	Latitude (°N)	Longitude (°E)	Area (km^2)
Moy	Rahans	54.10	−9.16	1803
Boyne	Slane Castle	53.71	−6.56	2452
Blackwater	Ballyduff	52.14	−8.05	2302
Suck	Bellagill	53.36	−8.24	1219
Brosna	Ferbane	53.27	−7.83	1210
Feale	Listowel	52.44	−9.48	648
Barrow	Royal Oak	52.70	−6.98	2381
Suir	Clonmel	52.35	−7.70	2138
Bandon	Curranure	51.77	−8.68	431

temperature data and calibrated using a Monte-Carlo approach. The performance of the hydrology model is then validated by forcing it with dynamically downscaled data for the reference period (1961–2000) and comparing the simulated stream flow to observations. When the hydrology model has been successfully calibrated and validated, the impact of climate change on hydrology is simulated by comparing simulated stream flow in the future (2021–2060) to that in the reference period. Finally, the conclusions of the study are presented and recommended future research activities are outlined.

Study methodology

Fig. 2 illustrates the study methodology for each catchment which requires the use of three models. A general circulation model (GCM) was first used to simulate global climate. The *European Centre Hamburg Model Version 5* (Roeckner et al., 2003) was used here in a coupled atmosphere ocean run (ECHAM5-OM1). Simulations were carried out by the model and data group at Max–Planck-Institute for Meteorology in Hamburg, Germany. The resolution of the GCM is on the order of hundreds of kilometers. This was too coarse to capture the fine scale variability in precipitation due to orography and land cover. So, these data were used as boundary condition data to drive a finer resolution Regional Climate Model (RCM).

The *Rossby Centre Regional Atmospheric Climate Model Version 3 (RCA3)* used here, was developed from the High Resolution Limited Area Model (HIRLAM) but includes improvements in the radiation scheme, the turbulence scheme and the cloud parameterization (Kjellström et al., 2005; Jones et al., 2004). A new land-surface scheme was developed and implemented in RCA3 (Samuelsson et al., 2006). In previous work (Semmler et al., 2006; Wang et al., 2006), the RCA3 model was run on a 0.12° (13 km) spherical, rotated latitude/longitude grid encompassing Ireland, and centered to include the Atlantic Ocean to the north, west and south of the country. The use of ECHAM5-OM1 boundary data with RCA3 to derive dynamically downscaled meteorological data on this grid has been validated by Wang et al. (2006) and Semmler et al. (2006). In this study, the precipitation and temperature data from these simulations were used to examine the impact of climate change on hydrology in nine catchments in Ireland.

Comparison of dynamically downscaled precipitation data to gauge data during the reference period revealed biases of up to 78% in mean monthly and annual precipitation. Wood et al. (2004) demonstrate that failure to correct for bias in downscaled climate forcing data can yield implausible results from hydrological models. Experiments (not shown) found that using uncorrected precipitation data resulted in a bias of up to 50% and 200% in mean winter and summer streamflow respectively. A simple bias correction scheme was therefore necessary to provide a more reasonable validation of streamflow during the reference period. Downscaled precipitation data were sorted by month, and a cumulative distribution function (CDF) was calculated for each month and compared to observed precipitation data. The disagreement between the CDFs of simulated and observed daily precipitation was greatest in the summer, and indicated the occurrence of too many low intensity events. A cut-off rate was calculated so that setting all simulated values less than this value to zero corrected the number of dry days. The magnitude of this cut-off rate varied from around 0.5 mm day^{-1} in winter to over 2 mm day^{-1} in summer. The remaining bias was assumed to be evenly distributed over all days with rain and subtracted. The amount subtracted was typically about

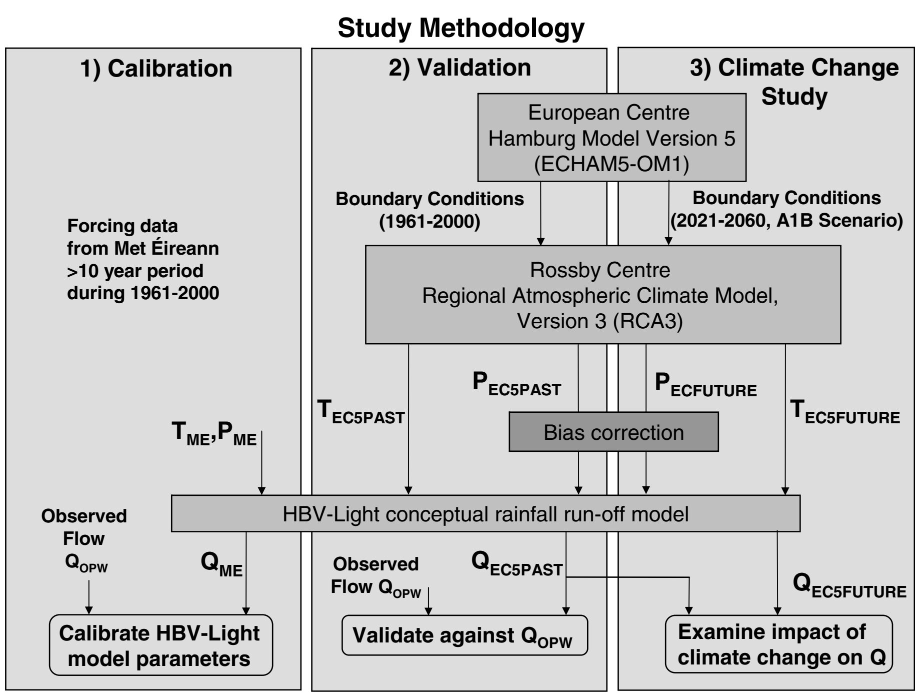

Figure 2 Study Methodology.

2.5 mm day^{-1}, though at some stations this was as high as 3.5 mm day^{-1} during the summer months. Higher values were typically associated with months and stations with fewer rain days. Implementing this simple scheme reduced the bias considerably and proved successful in capturing the seasonal cycle of mean monthly precipitation as well as its interannual variability. The parameters of the bias removal scheme were calculated using the data during the reference period, and were assumed valid for the future period too.

Finally, the dynamically downscaled precipitation and temperature data provided the required forcing data for the HBV-Light model (Seibert, 2005) which was used here to simulate stream flow in nine study catchments (Fig. 1, Table 1). The original HBV model, developed by SMHI (Bergström, 1992), is a rainfall-runoff model which includes conceptual numerical descriptions of hydrological processes at the catchment scale. Conceptual models are particularly suited to this type of study because they have a simpler model structure than physics-based model, and can thus be run for lengthy climate simulations. It includes soil and snow routines, evaporation, linear reservoir equations and channel routing. Groundwater recharge and actual evaporation are functions of actual water storage in a soil box, runoff formation is represented by three linear reservoir equations and channel routing is simulated by a triangular weighting function. Potential evaporation on day t, $E_{POT}(t)$, is calculated as

$$E_{pot}(t) = (1 + C_{ET}(T(t) - T_M))E_{POT,M} \quad (1)$$

where $T(t)$ is the temperature on day t, T_M is the monthly mean temperature and $E_{POT,M}$ is the monthly mean potential evaporation. C_{ET} is a correction factor obtained through calibration. Monthly mean values for potential evaporation and temperature were calculated from observations at the same synoptic stations used to provide temperature data during the calibration period.

The HBV light model (Seibert, 2005) used here has identical structure to the model of Bergström (1992), with two small changes. The first is inclusion of a spin-up period rather than requiring prescribed initial states, and secondly the MAXBAS routing parameter can assume non-integer values. It was used here because its interface permits Monte-Carlo simulations.

Fig. 2 illustrates the three stages in this study. In the first stage the HBV-Light hydrology model was calibrated by forcing it with observed precipitation and comparing the simulated streamflow against observations. The second stage was the validation stage, in which we demonstrated that the models described here can reproduce streamflow during the reference period (1961–2000) when forced with simulated precipitation and temperature data in this period. Finally, the hydrology model was forced with simulated precipitation and temperature data during the future period under a given climate scenario and the expected impacts of climate change on hydrology in the catchments were analyzed.

Expected climate change

For each of the nine study catchments, Fig. 3 shows the mean monthly temperature and precipitation in the reference period (1961–2000), the expected increase/decrease in these quantities in the period (2021–2060) compared to the reference period, as well as the expected change in interannual variability in these quantities between the two periods. Future simulations were based on the Special Report on Emissions Scenarios (SRES) A1B scenario (Nakicenovic et al., 2000), which assumes globalization with strong economic growth, and technological emphasis balanced across all sources (i.e. similar improvement rates apply to all energy supply and end-use technology). Interannual variability was calculated as the standard deviation across all years for each month.

In the reference period 1961–2000, the Blackwater and Bandon were the warmest catchments, while the Brosna was the coolest though the range of mean daily temperature across catchments is just 8.91–10.04 °C. There was a strong seasonal cycle in daily mean temperature. In all catchments, maximum daily mean temperatures occurred in July (from 13.7 °C in Moy and Suck to 14.5 °C in Boyne) and minimum daily mean temperatures occurred in January (from 3.8 °C in Brosna to 6.2 °C in Blackwater).

Interannual variability in the daily mean temperature for each month was calculated as the standard deviation in monthly average daily mean temperature across the 40 years of the reference period. Interannual variability in mean daily temperature (not shown) was highest in the Barrow and Suir, and lowest in the Blackwater and exhibited a strong seasonal cycle. It was highest in February, varying from 1.3 °C Blackwater to 1.8 °C in the Moy and Suck. Interannual variability in the summer months was approximately half that in the winter, and was lowest in May with little variation between the catchments.

Under the A1B scenario, temperature is expected to increase in all months in all catchments. The greatest increase is expected in the Barrow and Suir, and the lowest in the Blackwater, though the range across catchments is small. The greatest increase is expected in August (from 1.4 °C in the Moy and Suck to 1.65 °C in the Barrow and Suir). The smallest increase occurs in June and is on the order of 0.6–0.7 °C in all catchments.

In general, interannual variability increases between April and October. In winter, there is a decrease in November, December and February, while there is an increase of about 0.5 °C in January. The greatest decrease is in December (−0.07 °C in Blackwater to −0.19 °C in Boyne). Increased interannual variability in mean daily temperature affects potential evapotranspiration, which in turn influences summer low flows and autumn soil moisture.

During the reference period, mean annual precipitation as well as the timing and amplitude of the seasonal cycle were found to vary with geographical location. The wettest catchments were the Bandon (1679 mm) and Feale (1469 mm) in the southwest. In these catchments the minimum and maximum mean daily precipitation were simulated in July (3.13 mm/day, 2.62 mm/day) and December (6.11 mm/day, 5.08 mm/day) respectively. The Barrow (849 mm) and Boyne (941 mm) were the driest catchments. In the southeast the minimum was simulated earlier in June. In the west, the minimum was simulated in April and maximum in November. The Boyne showed a very irregular seasonal distribution with a minimum (2.2 mm/day) in February and maximum (2.86) in August.

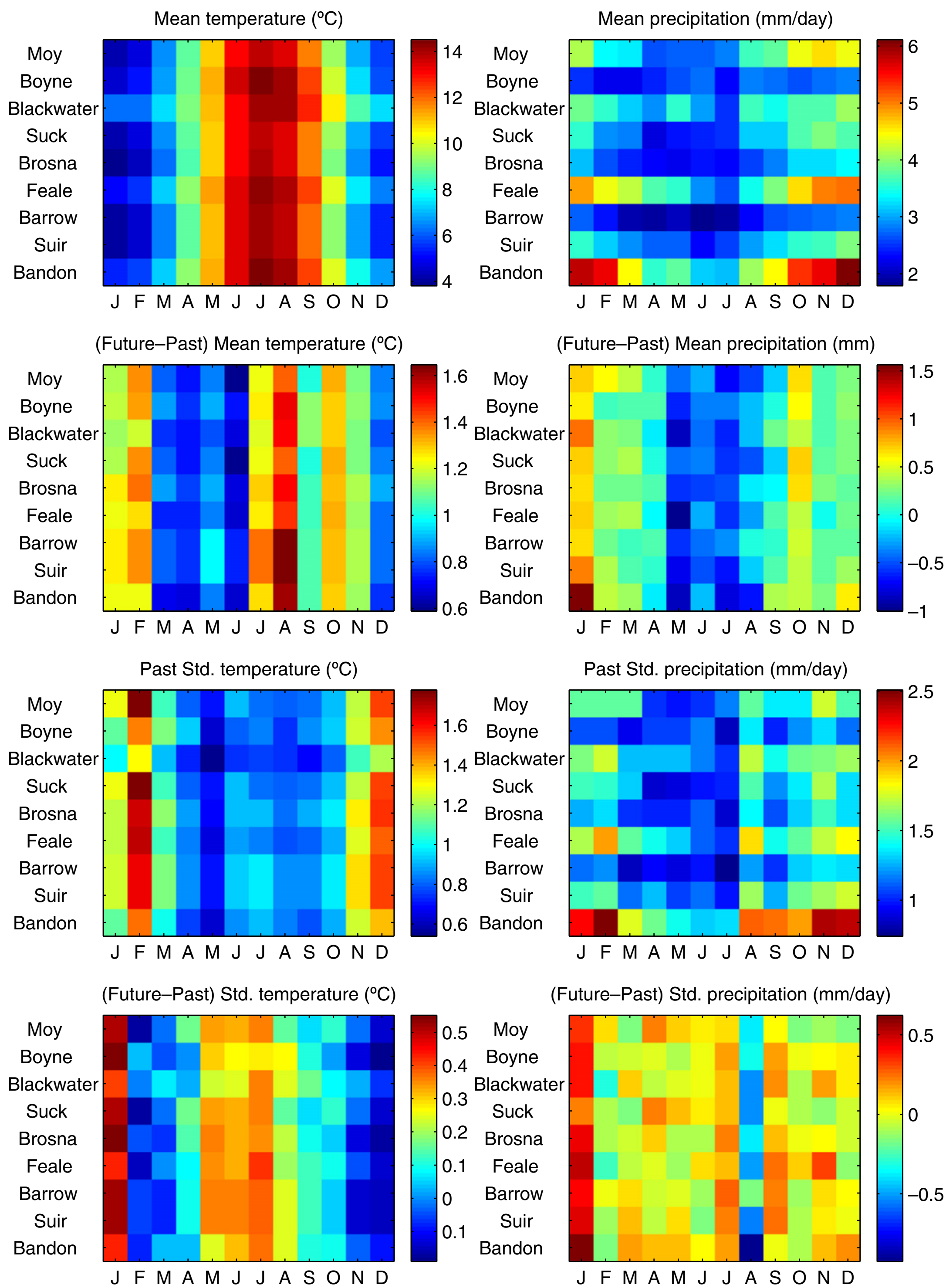

Figure 3 Expected change in temperature (left) and precipitation (right) due to climate change under SRES A1B scenario. Mean quantities (1961—2000) are shown in the top panel. The expected change in mean quantities is shown in the middle. The expected change in interannual variability is shown on the bottom.

Interannual variability in mean precipitation (not shown) was highest, and had the greatest amplitude in seasonal cycle in the wetter catchments. Minimum interannual variability was in April/May in the west (Suck (0.88 mm/day), Brosna (1.0 mm/day), Moy (0.98 mm/day)), and June/July everywhere else. Maximum interannual variability was in February in the southeast (Bandon (2.51 mm/day), Blackwater (1.76 mm/day) and Feale 2.00 mm/day)), but in November/December everywhere else. Again, the Boyne had a somewhat irregular cycle with the maximum interannual variability in August (1.36 mm/day).

Under the A1B scenario, a general increase in winter precipitation and decrease in summer precipitation is expected. The decrease in precipitation extends from April to August in the southwest, and May to September in the west, and May to July/August in the east and southeast. In all catchments the greatest increase is expected in January (from 0.62 mm/day in Boyne to 1.56 mm/day in Bandon). The largest decrease is generally expected in May (from −0.59 mm/day in the Barrow and Brosna to −1.0 mm/day in the Feale) but occurs later in July for the Moy and Suck.

Little trend was identified in the expected change in interannual variability in precipitation, which is expected to increase or decrease by up to 0.2 mm/day. However, all catchments showed an expected decrease in August (from −0.16 mm/day in the Barrow to −0.92 mm/day in Bandon) and an increase in January (from 0.2352 mm/day in Suck to 0.6232 mm/day in Bandon).

HBV-Light model calibration

A defining feature of any conceptual model, such as HBV-Light, is that its parameters are not physically measurable, and must be calibrated (Kavetski et al., 2006). The first step in this study was to calibrate the HBV-Light model by forcing it with observed precipitation and temperature data from Met Éireann, the Irish National Meteorological Service. Temperature data from the nearest synoptic station to the catchment was used, while precipitation data from 8 to 12 rain gauges in the catchment were used to derive a time series of mean areal daily precipitation using Theissen polygons. Simulated daily mean flow was compared to observed stream flow data from the Office of Public Works (OPW, 2007).

The HBV and HBV-Light model parameters are physically-based, but they are effective parameters for the catchment and may not bear any semblance to measurements from the field. In the User's Manual for the original HBV model (Bergström, 1992) it is recommended that the model be calibrated manually using a trial and error approach seeking the unique optimal parameter set that best simulates runoff during the calibration period. However, conceptual models are often over-parameterized, so that very different parameter sets can give similarly good results during calibration (e.g. Mein and Brown, 1978; Beven and Binley, 1992; Duan et al., 1992; Beven, 1993; Freer et al., 1996; van der Perk and Bierkens, 1997; Seibert et al., 1997). Furthermore, interactions between model parameters may result in them being inter-correlated (Jakeman and Hornberger, 1993 and Gaume et al., 1998). The run off may be sensitive to change in one uncertain parameter value, but the impact of the change may be compensated for by other uncertain parameters.

Badly-defined parameters introduce subjectivity in both manual and automatic calibration approaches. In a manual

Table 2 HBV-Light model parameter definitions, units and reasonable ranges for variables which were calibrated in this study

Parameter	Definition	Units	Minimum Value	Maximum Value
FC	Maximum value of soil moisture storage	mm	50	500
LP	Fraction of FC above which actual ET equals potential ET	–	0.3	1.0
BETA	Shape coefficient	–	1.0	6.0
CET	Correction factor for potential evaporation	C^{-1}	0.0	0.3
K0	Recession coefficient (upper box)	d^{-1}	0.05	0.5
K1	Recession coefficient (upper box)	d^{-1}	0.01	0.4
K2	Recession coefficient (lower box)	d^{-1}	0.001	0.15
MAXBAS	Length of triangular weighting function in routing routine	d	1	7
PERC	Maximum rate of recharge between the upper and lower groundwater boxes	mm d^{-1}	0	3
UZL	Threshold for Q_0 flow	mm	0	100

Table 3 Calibration period and HBV-Light calibration quality indicators for each catchment

Catchment	Calibration Period	Mean (R_{eff})	Max (R_{eff})	99th percentile
Moy	01/01/1974–12/31/1983	0.7682	0.9626	0.9471
Boyne	01/01/1980–12/31/1991	0.7355	0.912	0.8885
Blackwater	22/06/1965–21/06/1974	0.7081	0.8394	0.8246
Suck	01/07/1975–01/06/1984	0.7461	0.9235	0.9124
Brosna	01/01/1967–31/12/1976	0.7338	0.8992	0.8726
Feale	01/01/1975–31/12/1984	0.4861	0.7797	0.7276
Barrow	01/05/1972–30/04/1981	0.761	0.9229	0.9051
Suir	01/01/1975–31/12/1984	0.7341	0.8736	0.853
Bandon	16/02/1975–15/02/1984	0.5235	0.7314	0.7133

R_{eff} refers to the modified Nash-Sutcliffe efficiency parameter. For each catchment, 10,000 ensemble members were run in the calibration.

calibration, the user may choose initial values or try to limit the range of possible parameters based on their knowledge of the physical parameters of the catchment. Automatic calibration methods will yield different final parameter sets depending on starting point (Kite and Kouwen, 1992), and the user must then subjectively decide which is most reasonable.

Lindström (1997) argues that if several parameter sets yield the same run off in calibration, that any one of them could be used for the model application. This assumes that the simulated runoff using each of these parameter sets is 'similar'. Harlin and Kung (1992) demonstrate that sets of parameters which give similarly good results during a calibration period may yield different results in other time

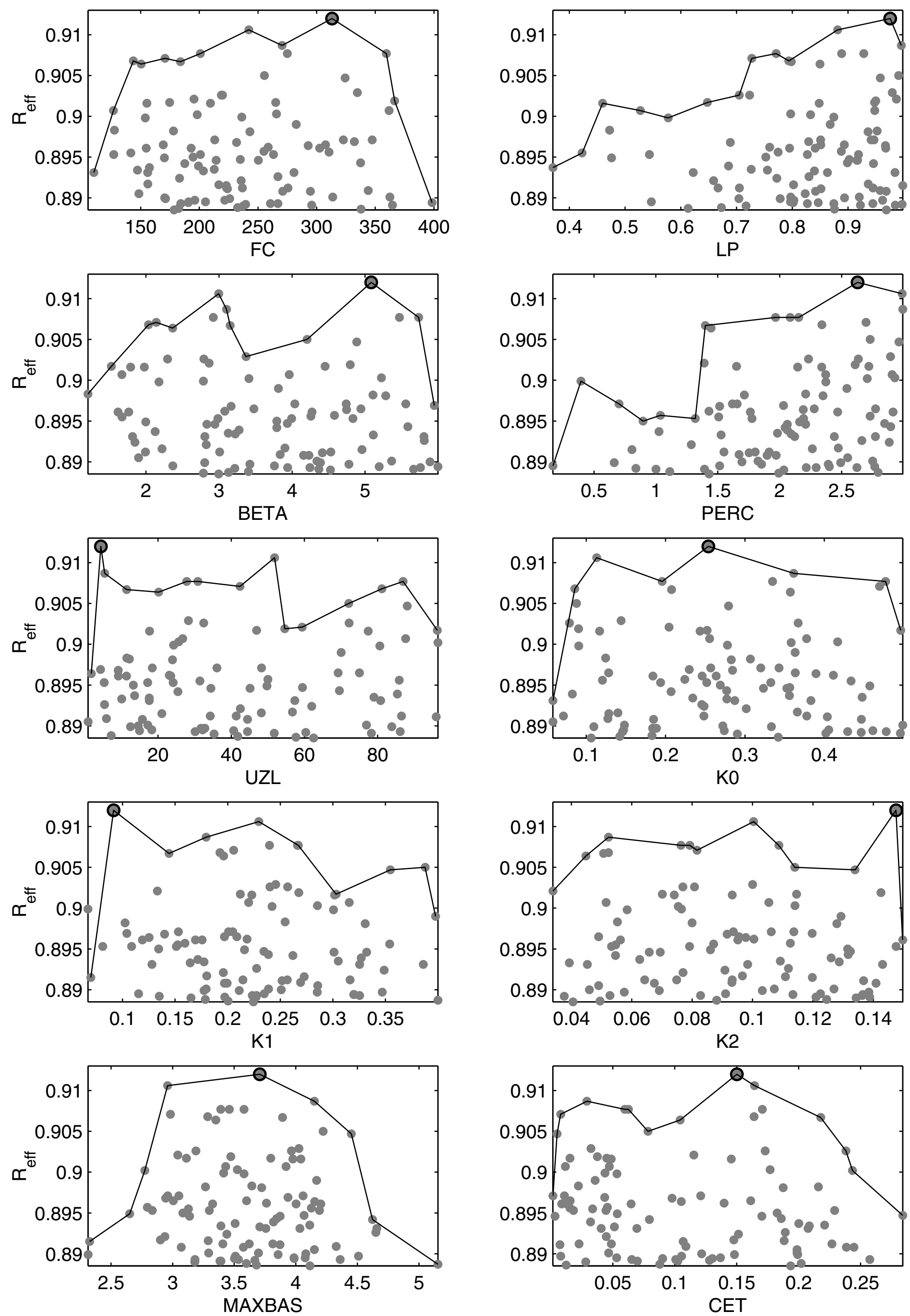

Figure 4 Values of R_{eff} for the best 100 HBV-Light parameter sets from calibration of the Boyne catchment. The 'best' value for each variable is highlighted with a black circle.

periods. This occurs because model parameters determine the states of the various submodels, i.e. the soil routine, snow routine, routing routine etc., and so the states of the various submodels may differ depending on choice of parameter set. This is particularly significant in a climate impact study as the changes in weather conditions will impact some subroutines more than others. For example, the impact of the change in temperature will be determined by the parameters of the evaporation parameterization and soil moisture routine. Seibert (1997) argues that using a Monte-Carlo approach to calibration allows the interaction between parameters to be taken into account as whole parameter sets vary rather than varying individual parameters. Furthermore, simulations yield an ensemble of possible results so expected changes can be expressed as a range rather than a single result.

Table 2 contains a list of the parameters calibrated, their abbreviated name in the model, units and a reasonable range for each parameter derived from a literature review (Booij, 2005; Seibert, 1997, 1999). In this study, an ensemble of 10,000 parameter sets was generated by sampling from a uniform distribution within the full range of physically reasonable values for each parameter from Table 2. For each parameter set, HBV-Light was used to simulate runoff and the quality of the calibration was assessed using the Nash-Sutcliffe efficiency, R_{eff}.

The period during which the HBV-Light model was calibrated for each catchment is given in Table 3. The periods were determined by the limited duration of contemporaneous precipitation and streamflow data in each catchment. The best 100 parameter sets (i.e. the 99th percentile) were selected for the climate simulations. Table 3 shows the mean R_{eff} value calculated across all 10,000 parameter sets, the maximum (''best'') R_{eff} value obtained and the 99th percentile value for each catchment. Only values above the 99th percentile were used in the climate simulations

Table 4 Mean and median (italics) HBV-Light parameter values across best 100 ensemble members for each catchment

	FC	LP	BETA	CET	K0	K1	K2	MAXBAS	PERC	UZL
Moy	277.3	0.64	3.75	0.137	0.261	0.078	0.085	3.31	1.77	81.4
	273.9	*0.62*	*3.97*	*0.137*	*0.259*	*0.08*	*0.089*	*3.48*	*1.81*	*86.6*
Boyne	234.1	0.82	3.68	0.107	0.273	0.227	0.093	3.63	2.04	41.6
	223.6	*0.85*	*3.78*	*0.099*	*0.273*	*0.223*	*0.093*	*3.61*	*2.13*	*34.9*
Blackwater	184.5	0.8	2.54	0.137	0.24	0.266	0.102	2.87	1.67	61.6
	175.4	*0.84*	*2.15*	*0.131*	*0.214*	*0.267*	*0.105*	*2.92*	*1.75*	*62.9*
Suck	131.4	0.74	3.69	0.135	0.256	0.195	0.1	5.62	1.4	65
	121.2	*0.75*	*3.63*	*0.123*	*0.259*	*0.186*	*0.105*	*5.66*	*1.48*	*64.2*
Brosna	285	0.75	4.21	0.116	0.265	0.193	0.072	3.17	2.11	45.4
	279.2	*0.77*	*4.24*	*0.098*	*0.269*	*0.188*	*0.069*	*3.18*	*2.2*	*38.11*
Feale	217.1	0.75	2.83	0.153	0.353	0.293	0.079	2.45	1.1	12.8
	182.5	*0.78*	*2.3*	*0.157*	*0.357*	*0.313*	*0.085*	*2.43*	*0.97*	*7.92*
Barrow	265.1	0.82	3.59	0.113	0.271	0.234	0.1	4.04	1.67	52.9
	258.6	*0.84*	*3.59*	*0.107*	*0.263*	*0.225*	*0.102*	*4.02*	*1.71*	*51.4*
Suir	256.1	0.81	3.66	0.142	0.257	0.193	0.098	3.1	1.76	52.9
	256.9	*0.83*	*3.7*	*0.163*	*0.254*	*0.196*	*0.103*	*3.08*	*1.89*	*50.6*
Bandon	95.2	0.72	3.69	0.179	0.282	0.296	0.097	2.94	1.2	41.5
	85.1	*0.73*	*3.53*	*0.187*	*0.292*	*0.317*	*0.1*	*2.91*	*1.01*	*35.1*

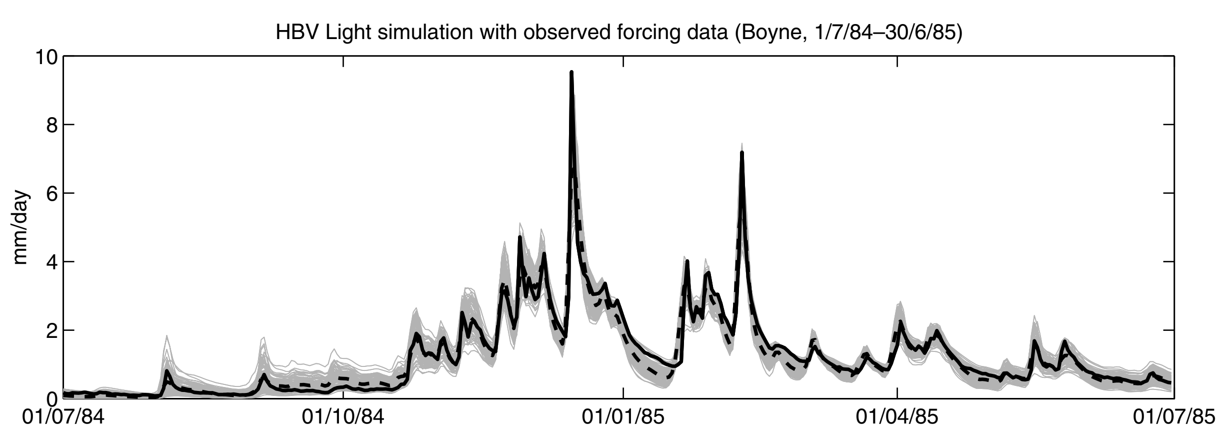

Figure 5 Comparison of observed and simulated streamflow in the River Boyne during the period (01/07/84–30/06/1985). Simulated flow was obtained by forcing HBV-Light with the observed meteorological data.

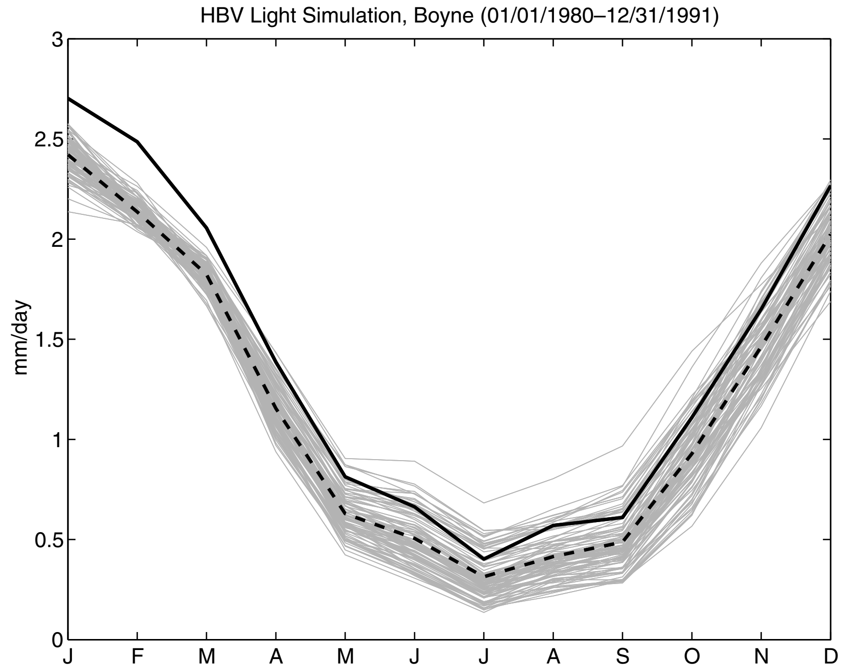

Figure 6 Comparison of the observed and simulated seasonal cycle of streamflow in the Boyne catchment during the calibration period. The HBV-Light was forced with the observed meteorological data.

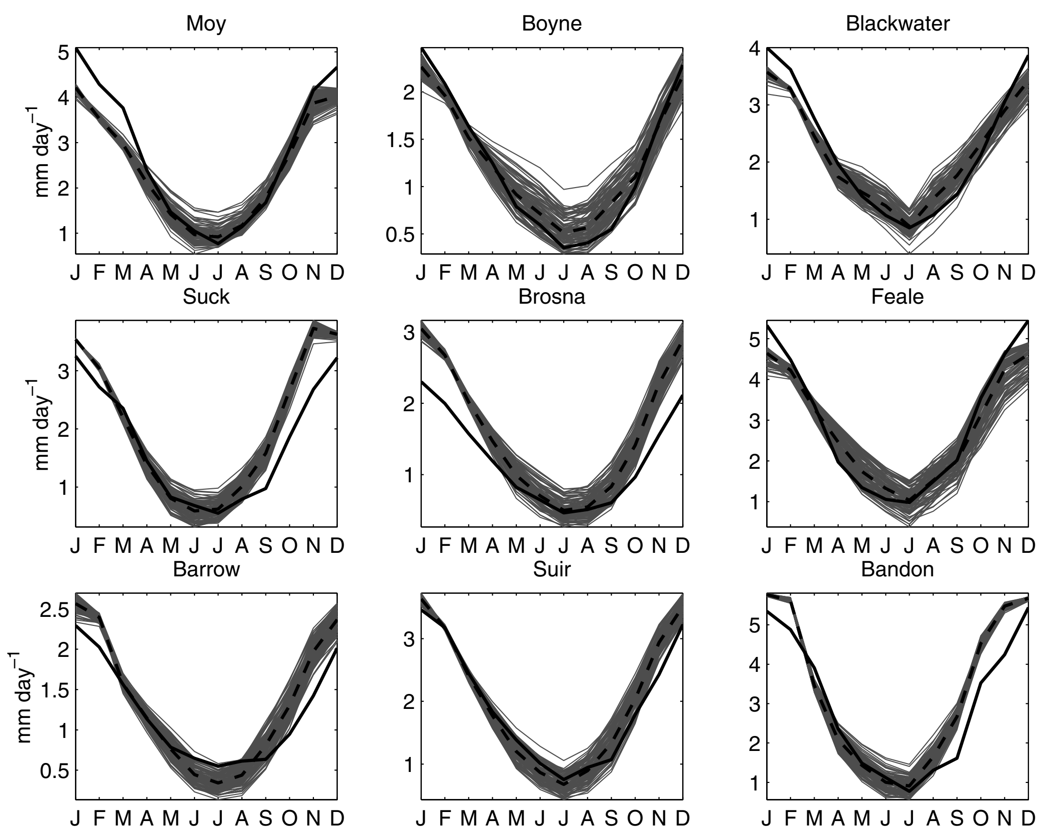

Figure 7 Validation of seasonal cycle of stream flow in each of the nine study catchments during the reference period (1961—2000). Simulated ensemble members are shown in grey, with the ensemble mean as a black dashed line. Observations are shown as a solid black line.

presented in the following sections. The best and worst calibrations were obtained in the Moy and Bandon catchments, where the 99th percentile values were 0.9471 and 0.7133 respectively.

Calibration results for the Boyne catchment shown in Fig. 4 demonstrate the merits of using a Monte-Carlo approach. Usually, when the HBV model is calibrated using a trial and error approach, one parameter is varied within a certain range, while all other parameters are held constant. A parameter was considered sensitive if it yielded very different stream flows at different values. Furthermore, the parameter was considered well-defined if the quality of the calibration deteriorated as the parameter value deviated from some optimum value. For each of the parameters calibrated, Fig. 4 shows the values of the best 100 parameter sets and the R_{eff} value associated with that calibration. Clearly, excellent simulations ($R_{\mathrm{eff}} > 0.9$) were possible over wide ranges of most model parameters.

From Seibert (1997), it is the upper boundaries of the scatter plots that are of real interest, as for any value of a given parameter, poor simulations may occur due to the values of the other parameters. For a well-defined parameter, the upper boundary should have a distinct peak while in ill-defined parameters the upper boundary will have a broad plateau. In the Boyne catchment LP, PERC and MAXBAS were the best defined parameters. It is noteworthy that the list of well-defined parameters was found to vary by catchment.

For each parameter, the mean and median values calculated across the 100 ensemble members used in the climate simulations are shown in Table 4. These values do not represent the optimal parameter set, but merely provides a way of qualitatively comparing the catchments.

Large values of FC and BETA are associated with more damped and even hydrographs (e.g. Brosna, Moy, Suir, Boyne, and Barrow). However, steep slopes and the absence of extensive aquifers can explain large values of BETA in the smaller river catchments like the Bandon, because BETA can also be interpreted as a measure of the extension of relative contributing area (Seibert et al., 2000). Low values of CET are associated with more damped and even hydrographs (e.g. Boyne, Barrow and Brosna). The recession coefficients (K0, K1 and K2) can be expected to decrease with increasing catchment size because of a more damped and even hydrograph in a larger catchment. This is at least true for K1 which has its highest values in the Bandon and Feale, and much lower values in larger catchments such as the Boyne and Suir. Flow from the lower groundwater box is limited to PERC, so small values (e.g. Feale, Bandon) result in a larger response from the upper groundwater box. MAXBAS can be expected to increase with increasing catchment size because of the increasing channel length (e.g. Suck, Boyne, and Barrow).

Fig. 5 shows the simulated streamflow in the the river Boyne for a year during the calibration period for the best

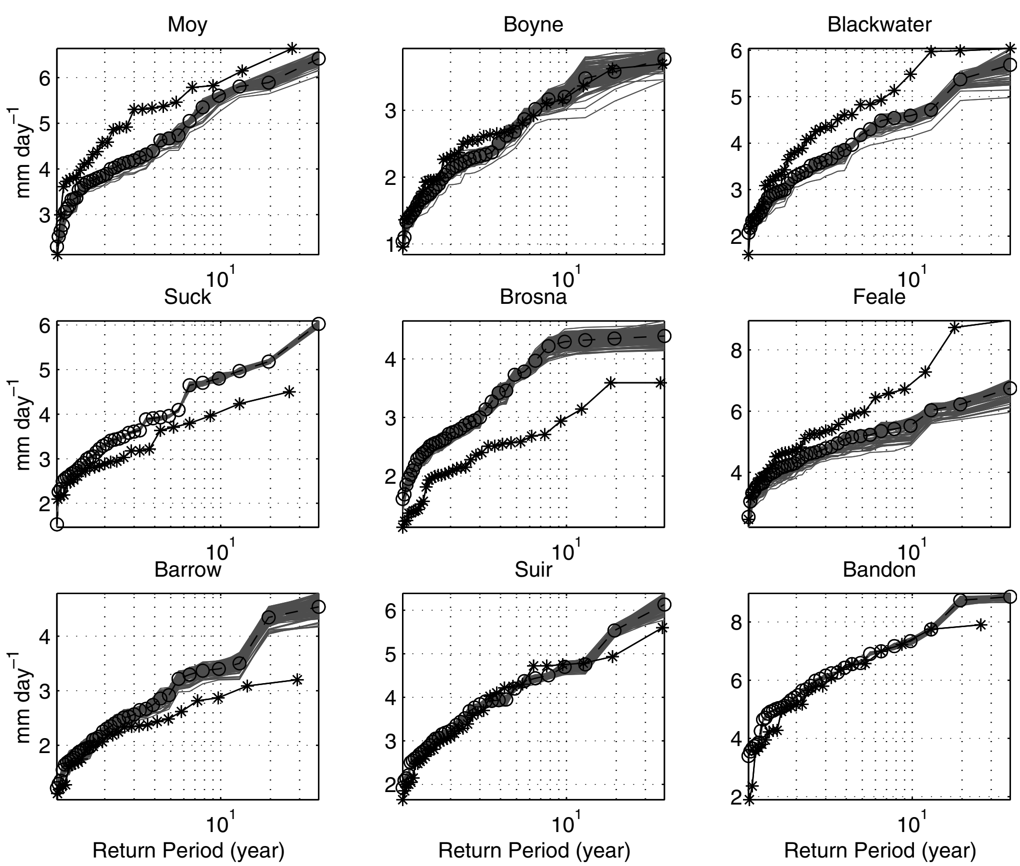

Figure 8 Validation of simulated mean winter flow during the reference period (1961–2000). Daily mean flow is averaged over winter (DJF) for each year. Ensemble members are shown in grey, the ensemble mean as a black circle, and observations are shown as black asterisks.

100 ensemble members, using the observed meteorological data to force the HBV-Light model. Fig. 5 demonstrates that the model is capable of reproducing the observed flow quite well. Ensemble spread is low relative to the dynamic range of values. The observations fall within the ensemble on almost all days. It can be seen however, that there were some discrepancies between the simulated and observed flow, particularly during the winter peaks which are often underestimated. Fig. 6 compares the simulated and observed seasonal cycle of streamflow calculated from the full calibration period. Clearly, even when forced with 'good' calibration data, the HBV-Light model is not perfect. In both Figs. 5 and 6, observations are generally closer to the upper limit of ensemble spread, with large events, and consequently winter flows underestimated.

Validation of past climate (1961—2000)

Calibration produced 100 parameter sets which produced satisfactory agreement between simulated and observed flow during the calibration period. However, this does not guarantee that simulated flow in other time periods, or forced with other data, will agree with observations. When the HBV-Light model parameters for a catchment were found, the stream flow generated using the past climate data (1961—2000) was validated against observations. Boundary conditions from the ECHAM5-OM1 model during the reference period 1961—2000 were used to drive the RCA3 model to produce the dynamically downscaled precipitation and temperature data required to run the HBV-Light model. The simulated flow was compared to the observed flow for the reference period. In any catchment, parameter uncertainty caused the flow predictions to vary considerably. Uhlenbrook et al. (1999) argues that model predictions, particularly in applied studies should be given as ranges rather than as single values, so all 100 ensemble members are shown here.

In Fig. 7 an ensemble of the seasonal cycle of mean monthly flow in each catchment is validated against observed stream flow data. The seasonal cycle was generally well captured, particularly in the Suir catchment. Ensemble spread was higher in summer than winter due to parameter uncertainty. In winter, precipitation was sufficiently high that the soil column was generally saturated. In the summer, the evaporation parameters determine how quickly the soil column dries out due to evaporation while the soil parameters ensure variability in how much storage there is as well as how quickly water is redistributed to the groundwater storage layers. In summer, the observed monthly stream flows generally fell within the ensemble, but in winter all ensemble members were generally biased with respect to the observed. Winter flows were well captured in the Suir and Boyne, just slightly over- and under-estimated respectively. Winter flows were considerably overestimated

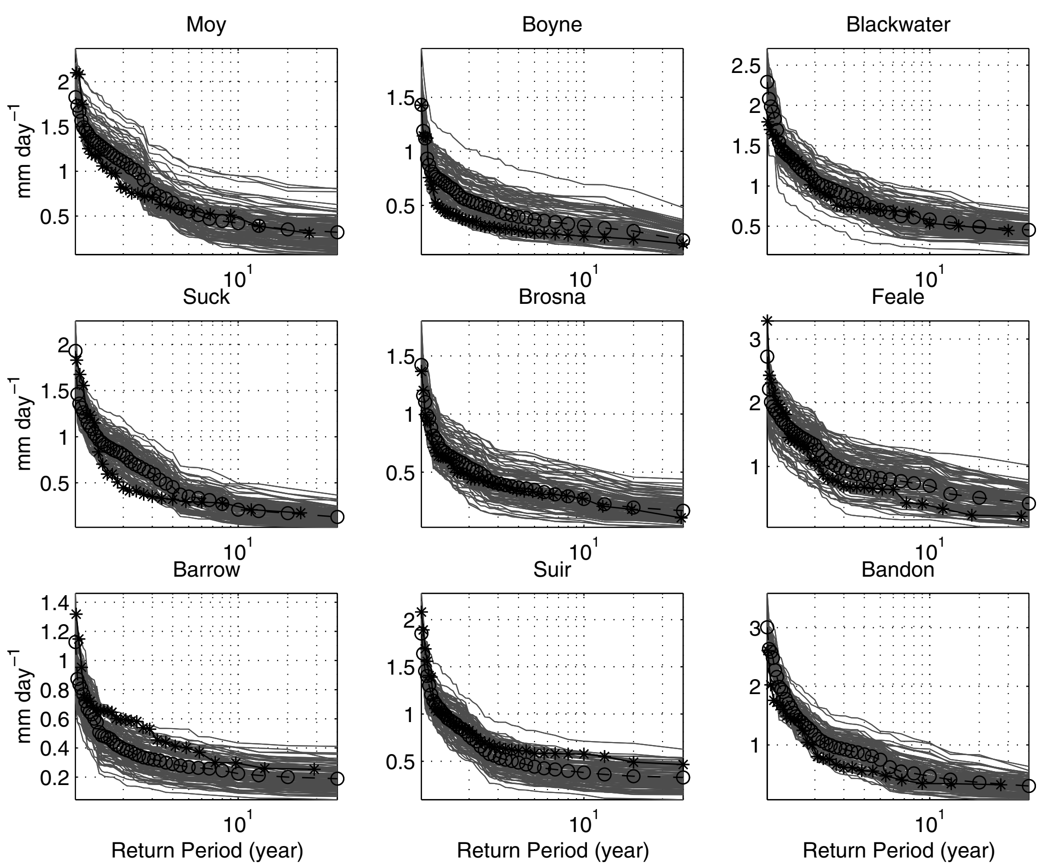

Figure 9 Validation of simulated mean summer flow during the reference period (1961—2000). Daily mean flow is averaged over summer (JJA) for each year. Ensemble members are shown in grey, the ensemble mean as black circles, and observations as black asterisks.

in the Suck, Barrow, Brosna and Bandon and significantly underestimated in the Moy, Blackwater and Feale. Summer flow was generally better modeled than winter flow, with the only serious discrepancies in the Boyne (overestimated) and the Barrow (underestimated). Differences between simulated and observed streamflow are due to the imperfect HBV-Light model (Figs. 5 and 6), as well as errors in the downscaled forcing data from the ECHAM5-OM1/RCA3 simulations.

In Fig. 8 the modeled mean winter (DJF) stream flow is plotted as a function of return period for each of the catchments and compared against observations from the OPW. If some winter flow Q_{20} has a return period of 20 years, then mean winter flow is likely to exceed this amount on average once every 20 years. Equivalently, in any year there is a 5% chance that mean winter flow will exceed this amount. This quantity was very reliably estimated, with excellent agreement in the Suir, Boyne and Bandon catchments. Risk was overestimated in the Suck, Barrow and Brosna. Recall from Fig. 7 that these were the catchments in which mean monthly flows were overestimated in winter. Risk was underestimated in the Moy, Blackwater and Feale, the catchments in which summer monthly flows were underestimated. Ensemble spread was typically just 10–15% of the range of all values indicating that the effects of parameter uncertainty are pretty insignificant in this quantity. However, in the biased results the observations typically fell outside the ensemble. Errors were as high as 50% (Brosna).

Fig. 9 shows the modeled mean summer (JJA) stream flow as a function of return period. If some summer flow Q_{10} has a return period of 10 years, then summer flow will only be less than this value once in 10 years, or equivalently there is a 10% chance that in any given year the mean summer flow will be less than this amount. Ensemble spread was generally much greater than for the mean winter flow case, due again to the greater impact of parameter uncertainty on summer flows. In all catchments, observations fell within the ensemble spread, though the spread in this case was much larger than in the case of the winter flows. Agreement was generally good, though risk was underestimated in the Boyne, Suck and Feale and overestimated in the Suir and Barrow.

The annual maximum daily mean flow is plotted against return period in Fig. 10. The most striking difference between this and Fig. 8 is that ensemble spread is significantly greater here. This indicates that while parameter uncertainty had little impact on our ability to simulate mean winter flow, it had a large influence on simulations of single events such as the annual maximum daily mean flow. This makes sense as a mean over 90 days will integrate some of the differences in model parameters because it is an averaged quantity. The maximum value depends on the states of the model and its various subroutines on a single day.

Despite the large spread, observations fell outside the ensemble in half of the catchments (Suck, Barrow, Brosna,

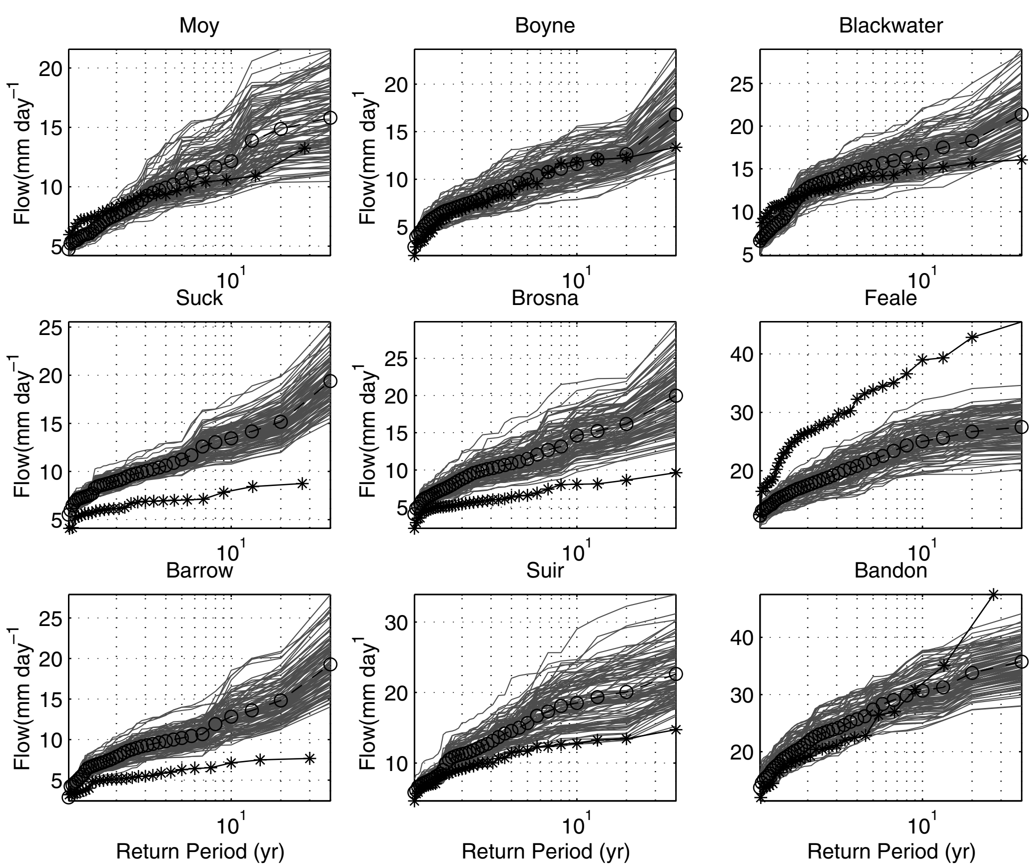

Figure 10 Validation of simulated annual maximum daily mean flow during the reference period (1961–2000). Ensemble members are shown in grey, the ensemble mean as black circles and observed values as black asterisks.

Feale).The best results were obtained for the Boyne and Bandon, which from Fig. 8 were the most reliable simulations of mean winter flow return period. Despite excellent agreement with observations in Figs. 7 and 8, simulated annual maximum daily mean flow in the Suir was overestimated in Fig. 10. In general, with the exception of the Feale, risk was generally overestimated. This occurred despite results from Fig. 7 indicating that half of the catchments overestimated and half underestimated mean winter flow.

In Fig. 10, all ensemble members were forced with the same precipitation data, but the response of the various subroutines varied depending on the model parameters. So, assuming that the peak precipitation occurs on the same day in each ensemble member (which is the case), the ensemble spread was due entirely to parameter uncertainty. The discrepancy between the observations and the ensemble members occurred because the single precipitation event which gave rise to the observed maximum was not simulated with the same magnitude or at the same time in the climate model. In short, it is unreasonable to expect the experiment set-up to reproduce single events such as annual maximum daily mean flow as reliably as it can reproduce averaged quantities such as seasonal flows.

Climate change impacts on hydrology

In this section, the impact of the expected climate change under the A1B scenario was examined by comparing streamflow simulated using forcing data from the ECHAM5-OM1/RCA3 during the reference (validation) period (1961–2000) and a future period (2021–2060).

Fig. 11 shows the expected change in monthly stream flow (as a percentage of the simulated flow in the reference period). These results suggest an amplification of the seasonal cycle in stream flow in all catchments. Due to the predicted increase in winter precipitation, stream flow is expected to increase by up to 20% from October to April. The greatest increase in flow is generally in January, except in the Moy (February/March) and Suck (January/March). Due to the combination of reduced summer precipitation, increased temperature and consequent increased evaporation, stream flow is expected to decrease by up to 60% from May to September.

The impact of parameter uncertainty was very different in winter and summer. Recall that ensemble spread was greater in summer as storage was influenced by the parameters from the evaporation parameterization, and the soil moisture routine and stream flow were affected by the run off routine. In winter, the soil is close to saturated in all ensemble members and evaporation is low due to the lower temperatures. While in winter, all ensemble members indicate approximately the same expected increase in streamflow, the impact of parameter uncertainty during the summer months is such that the expected decrease in summer months is between 20% and 60%.

The expected change in mean winter flow (DJF) under the A1B scenario is plotted in Fig. 12. The greatest increase

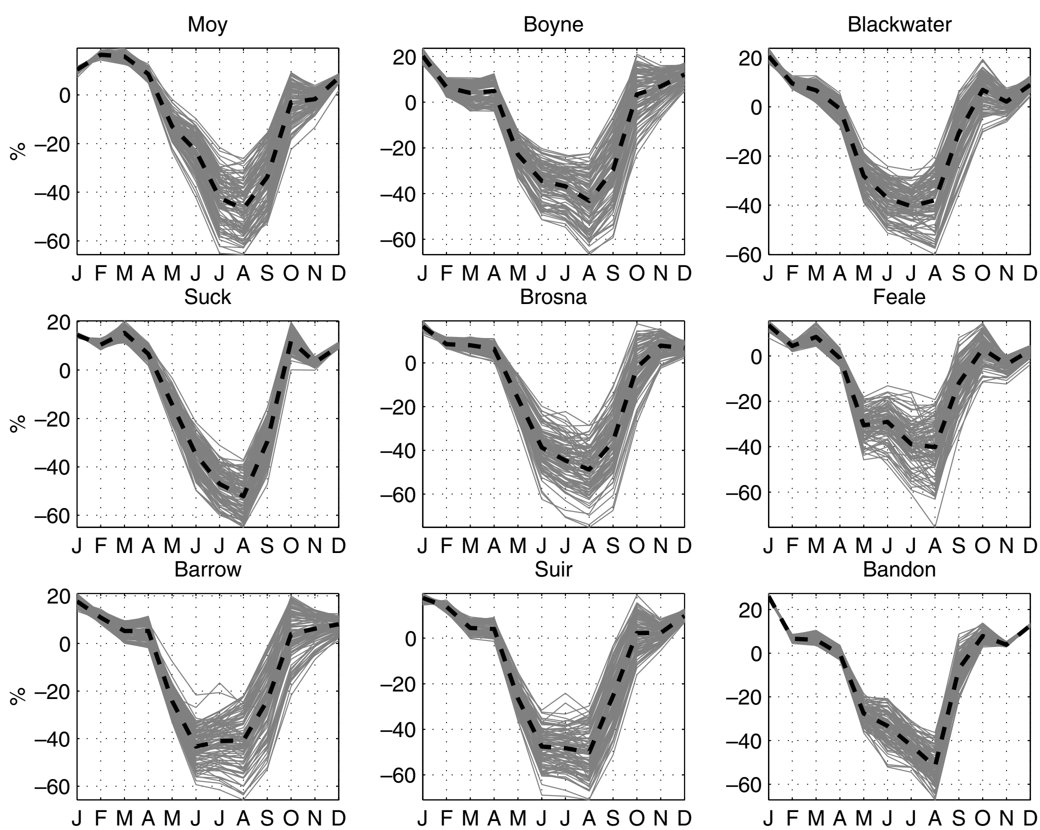

Figure 11 Change in simulated monthly mean daily flow due to climate change under the SRES A1B scenario. Ensemble members are shown in grey, with the ensemble mean shown as a black dashed line.

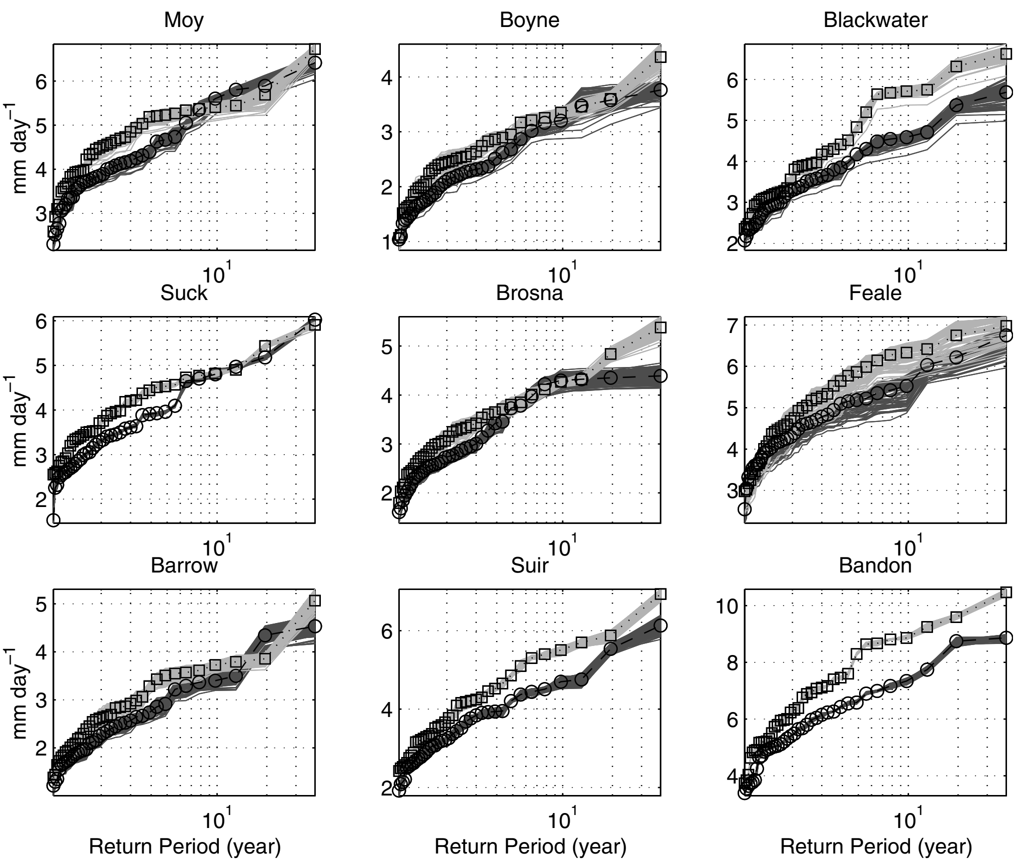

Figure 12 Change in simulated mean winter flow due to climate change under the SRES A1B scenario. Daily mean flow is averaged over winter (DJF) for each year. Ensemble members in the reference period (1961–2000) are shown in dark grey with the mean as black circles. Ensemble members in the future period (2021–2060) are shown in light grey, with the ensemble mean shown as black squares.

in risk is expected in the Blackwater and Bandon catchments, where the flow associated with a 40-year return period in the past is expected to have a return period of 9.8 and 8.5 years respectively in the period 2021–2060. Recall that these were the wettest catchments in the reference period (1961–2000), and were expected to have the biggest increase in mean precipitation and interannual variability in January precipitation.

The risk of extremely high winter flows is expected to almost double in the Feale and Suir, and will increase in the Boyne also. While precipitation is expected to decrease in November in the Feale, the catchment response is dominated by the Q_0 response, and so the impact of the December and January increase will be more pronounced than in other catchments. Mixed results were obtained for the Moy, Suck, Barrow and Brosna, where the flow associated with some return periods in the past are expected to have a greater return period in the future. These catchments are characterized by damped and even hydrographs so the response to a change in precipitation will be on a longer time scale than faster responding catchments.

Fig. 13 shows that a significant increase in the risk of extremely low summer flow is expected in all catchments and at all return periods. The greatest increase in risk is in the Suir and Barrow catchments where the greatest increase in temperature is predicted. It is noteworthy that in the past simulations, there is little interannual variability in summer flow in these catchments so that the flow with a 40-year return period is only slightly less than that with a return period of five years etc. In the future, a further reduction in the interannual variability is expected because possible stream flow values are limited by the lower end of the dynamic range.

The return period associated with annual maximum daily mean flow in the past and future are compared in Fig. 14. A definite increase in annual maximum daily mean flow at all return periods is apparent only in the Bandon and Blackwater catchments. For events with past return periods less than 20 years, an increase in risk is also expected in the Boyne and Suck. No change is expected in the Barrow, Feale, Suir and Moy, and a marginal decrease in risk is expected in the Brosna.

Conclusions and discussion

Nine Irish catchments have been studied to investigate the impact that climate change will have on their hydrology. Boundary conditions from the ECHAM5-OM1 general circulation model were used to drive the RCA3 regional climate model to produce dynamically downscaled precipitation and temperature data, required by the HBV-Light conceptual rainfall-runoff model.

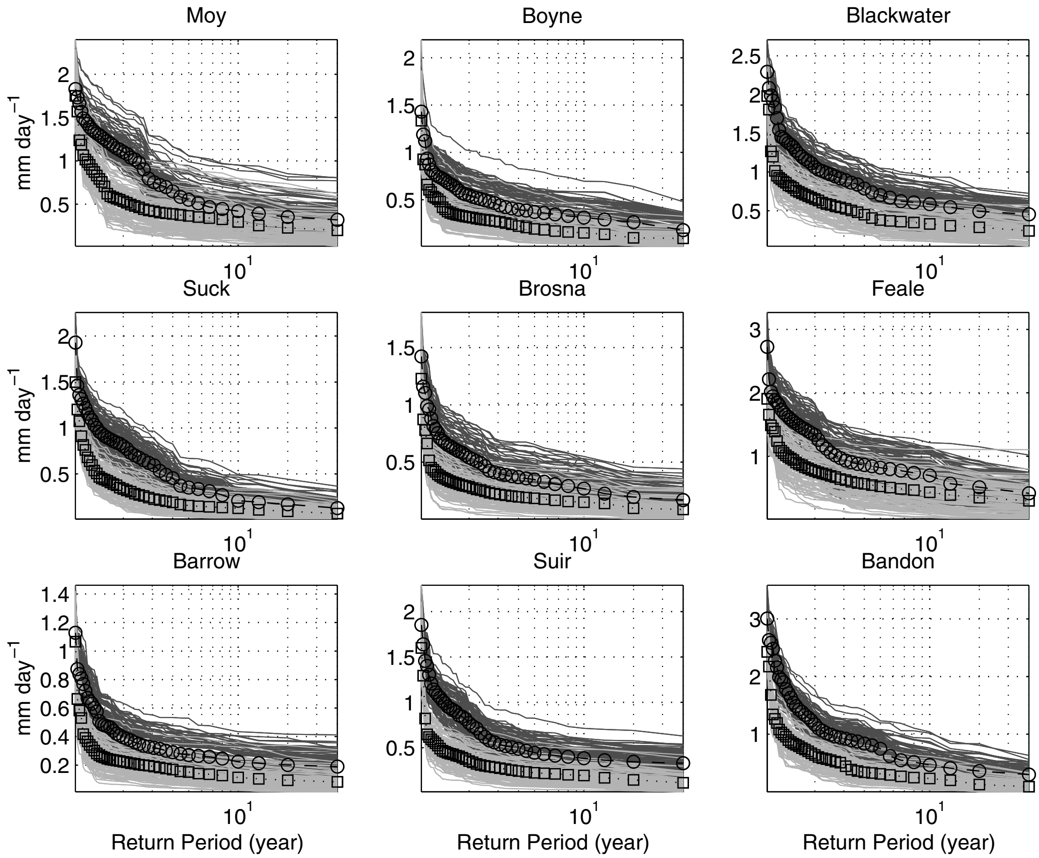

Figure 13 Change in simulated mean summer flow due to climate change under the SRES A1B scenario. Daily mean flow is averaged over summer (JJA) for each year. Ensemble members in the reference period (1961—2000) are shown in dark grey with the mean as black circles. Ensemble members in the future period (2021—2060) are shown in light grey, with the ensemble mean shown as black squares.

A Monte-Carlo approach to calibration was used, in which the 99th percentile of an ensemble of 10,000 parameter sets were selected for use in the impact study. Use of this approach allows the inclusion of parameter uncertainty in the study, and provides a range of possible values rather than a single value. This allows us to include a statement on our confidence in the outcome.

The HBV-Light model was validated for a reference period (1961—2000) to ensure that stream flow was modeled correctly. A persistent positive bias in the downscaled precipitation was accounted for and removed to improve the agreement between modeled and observed stream flow. It was shown that the impact of parameter uncertainty on the validation of seasonal (winter and summer) flow was less significant than in the annual maximum daily mean flow. This is intuitive as the seasonal flows are integrated values rather than single events which result from a combination of antecedent flow, the magnitude of a single storm event and a response determined by uncertain parameters.

Comparisons of simulated flow from the future (2021—2060) and the reference period suggest an amplification of the seasonal cycle with increased winter precipitation leading to a rise in winter (DJF) stream flow, and the combination of increased temperature and decreased precipitation causing a reduction in summer (JJA) stream flow. Change to the seasonal cycle will have an impact on water supply management and design. Increased winter flows, coupled with the predicted increase in extreme precipitation events lead to an elevated risk of flooding. This is particularly significant in the southwest of the country, and those catchments with fast response times. The decrease in summer stream flow will impact water availability, water quality, fisheries and recreational water use. Given the magnitude of the predicted decrease in summer flows, further research on these sectors and their ability to respond to the predicted change is warranted.

During the validation stage of this study, a significant bias was identified in the dynamically downscaled precipitation data from the ECHAM5-OM1/RCA3 simulations. A simple procedure was implemented to identify and reduce this bias, allowing us to reliably reproduce past streamflow. However, the simulated change in future precipitation and consequently streamflow are influenced by choice of bias correction scheme. In the long-term, the prevalence of regionally distributed bias in precipitation from large-scale models needs to be addressed. Meanwhile, future work should investigate refining the bias correction scheme to improve the reliability of our simulated streamflow estimates.

The use of an ensemble of parameter sets in this study allowed us to examine the impact of parameter uncertainty in the calibration stage on the outcome of the validation and impact study. However, further improvements to our calibration procedure could be made. Future studies will examine whether sampling a larger portion of parameter

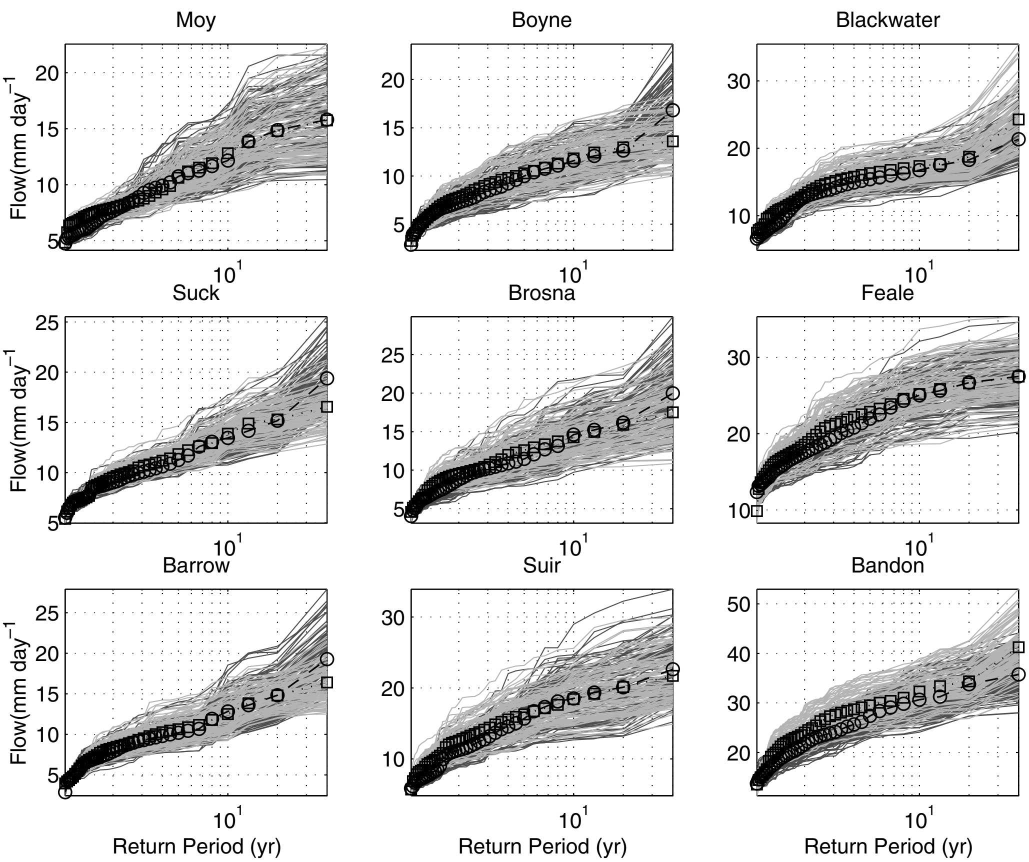

Figure 14 Change in simulated annual maximum daily mean flow due to climate change under SRES scenario A1B. Ensemble members in the reference period (1961—2000) are shown in dark grey with the mean as black circles. Ensemble members in the future period (2021—2060) are shown in light grey, with the ensemble mean shown as black squares.

space through a larger initial ensemble size could produce improved calibrations e.g. in the Feale and Bandon catchments. Sensitivity to choice of performance metric will also be explored; Nash-Sutcliffe efficiency was the sole criterion by which performance was measured. Sensitivity of experiment outcome to calibration using other measures such as RMSE, coefficient of determination, or a combination thereof will be examined.

Parameter uncertainty is by no means the only source of uncertainty in this study. As discussed by Semmler et al. (2006) and Murphy et al. (2006a) for example, there is a 'cascade' of uncertainty associated with climate impact studies. Parallel research activities such as those discussed by Semmler et al. (2006) are focused on generating an ensemble of climate simulations based on different GCMs and multiple future climate scenarios. The ultimate goal is to use this ensemble as forcing data for the framework developed here to provide Irish engineers, planners and policy-makers with a meaningful ensemble of projected changes in streamflow with which to plan for the future.

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