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Climate impacts on river flow: projections for the Medway catchment, UK, with UKCP09 and CATCHMOD

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Abstract:

The potential impact of climate change on areas of strategic importance for water resources remains a concern. Here, river flow projections for the River Medway, above Teston in southeast England are presented, which is just such an area of strategic importance. The river flow projections use climate inputs from the Hadley Centre Regional Climate Model (HadRM3) for the time period 1960–2080 (a subset of the early release UKCP09 projections). River flow predictions are calculated using CATCHMOD, the main river flow prediction tool of the Environment Agency (EA) of England and Wales. In order to use this tool in the best way for climate change predictions, model setup and performance are analysed using sensitivity and uncertainty analysis. The model's representation of hydrological processes is discussed and the direct percolation and first linear storage constant parameters are found to strongly affect model results in a complex way, with the former more important for low flows and the latter for high flows. The uncertainty in predictions resulting from the hydrological model parameters is demonstrated and the projections of river flow under future climate are analysed. A clear climate change impact signal is evident in the results with a persistent lowering of mean daily river flows for all months and for all projection time slices. Results indicate that a projection of lower flows under future climate is valid even taking into account the uncertainties considered in this modelling chain exercise. The model parameter uncertainty becomes more significant under future climate as the river flows become lower. This has significant implications for those making policy decisions based on such modelling results. Copyright © 2010 John Wiley & Sons, Ltd.

KEY WORDS climate change; water resources; ensembles; uncertainties; river flow

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INTRODUCTION

Modelling the possible impacts of climate change on river flows can provide planners and managers with the information they need to make evidence-based decisions about meeting demands for water resources, managing flood risks and protecting ecosystems in the future (EEA, 2007). However, alongside such climate impact assessments, robust decision-making requires careful consideration of the sources and relative magnitude of associated uncertainty. In water resources applications, this is particularly important as the uncertainties include not only external sources of uncertainty such as emission scenario or climate model (Hewitt and Griggs, 2004; Ekström *et al.*, 2005), but also uncertainties in input downscaling techniques, hydrological modelling structure and parameters, and river discharge observations (Wilby and Harris, 2006). Climate model based impact studies are inherently difficult because of the relatively weak climate change signal compared with observed variability and modelling uncertainty (Wilby *et al.*, 2008). However, such studies are essential in order to inform policy making and adaptation strategies (Stainforth *et al.*, 2007; EA, 2008, 2009a; Dessler and Parson, 2010).

The most extreme effects of climate change in terms of rates of warming combined with drier summers are anticipated in the south east of the UK (Norton and Byrne, 2004; Murphy *et al.*, 2009) with a marked drop in river flows expected in late summer and autumn in this area (EA, 2008). In addition, the south east is already under pressure in terms of available water resources, and proposed development in the regions will only increase this pressure as water supply demands increase (Norton and Byrne, 2004; EA, 2009b). Within the South East, the Medway catchment, in particular, is an area of strategic importance in terms of water resources as it is classified as 'seriously water stressed' (EA, 2008, p. 10) while exporting water out of the catchment to meet demand elsewhere in the region (EA, 2004). In this paper, climate change impacts on river flows in the Medway are assessed. The climate impact model used in this study is the conceptual hydrological model favoured by the EA of England and Wales known as CATCHMOD. The hydrological model is driven with ten ensemble projections of the future scenario A1B with the coupled

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HadCM3/HadRM3 model system over the time period 1960–2080 (early release UKCP09 scenarios—autumn 2008, which did not include ensemble member 'afixk'). The climate ensemble approach is known to provide a better understanding of the possible ranges of future conditions compared with use of single model realizations (Stainforth *et al.*, 2007; Murphy *et al.*, 2009). Here, we focus on the UKCP09 projections which seek to sample uncertainties arising from structural and parameter error and initial conditions of one GCM–RCM (detail provided in Murphy *et al.*, 2009). We acknowledge alternative approaches, such as the multi-model RCM ensembles of PRUDENCE (Déqué *et al.*, 2007) and ENSEMBLES (Hewitt and Griggs, 2004; van der Linden and Mitchell, 2009). Here, we would particularly like to note that, as our approach only uses one climate model and one scenario, our results can only be indicative, and we advocate future exploration of climate change impacts in the Medway with alternative approaches.

For the UK, there are several important climate impact studies for water resource applications (e.g. Arnell, 2003; Wilby, 2005; Cameron, 2006; Vidal and Wade, 2006; Wilby and Harris, 2006; Bell *et al.*, 2007; New *et al.*, 2007; EA, 2009a), many of which take explicit consideration of the uncertainty associated with results. In most cases, the climate input uncertainty is considered large compared with the predictive uncertainty of the hydrological model, and climatic variability is found to lead to future variability in catchment hydrology and river flow. Here, the impacts of climate change on river flows in the Medway catchment are explored by making use of the early release UKCP09 climate projections to assist in making informed water resources decisions in the region.

The Medway region is expected to have a decrease in mean annual runoff: Arnell and Reynard (1996) used data based on UK Climate Change Impacts Review Group (CCIRG) climate change scenarios and their estimates of percentage change in runoff varied between +2 and −27% by 2050. Norton and Byrne (2004) used UKCIP02 data, with change factor downscaling, to calculate relative changes in flow for low and high emission scenarios; they found little change in winter and early spring flows but significantly reduced flows in summer and autumn. Kay *et al.* (2006) also used UKCIP02 data, with a high resolution RCM, to investigate projected changes in rainfall and obtain estimates of flood frequency; their results suggest a relative decrease in annual average rainfall and flood frequency under climate change.

In this paper, two research questions of importance are addressed, the first of which is essential for understanding the second: (i) hydrological model performance and uncertainty in predictions and (ii) climate impacts on river flow (with uncertainty). Thus, first the CATCHMOD model performance and predictive uncertainty are assessed with simulation results based on observed rainfall and compared with observed flow data (1990–1996). Then RCM projections (1950–2080) are used to drive CATCHMOD to produce projections of river flow and discuss the projected climate impacts on river flow for the Medway. The novelty of our research in comparison to previous Medway studies is that here we combine the most up to date UKCP09 projections with continuous hydrological modelling (rather than simpler change factor analysis) and examine the relative magnitude of the uncertainties considered in this climate impact modelling.

METHODOLOGY

Study area: the Medway catchment

The study catchment is that of the River Medway above Teston (Figure 1) in the Thames region of south-east England, where CATCHMOD is routinely applied for water resources planning. It has an area of 1210 km^2 and is predominantly rural with mixed geology of sandstones and clays and minor aquifers providing some consistent baseflow (Norton and Byrne 2004). There are significant artificial influences on runoff in the catchment, including three reservoirs. The EA have provided this study with their best available record of naturalized flows at Teston, calculated by adjusting observed flows to account for artificial influences and spanning the period

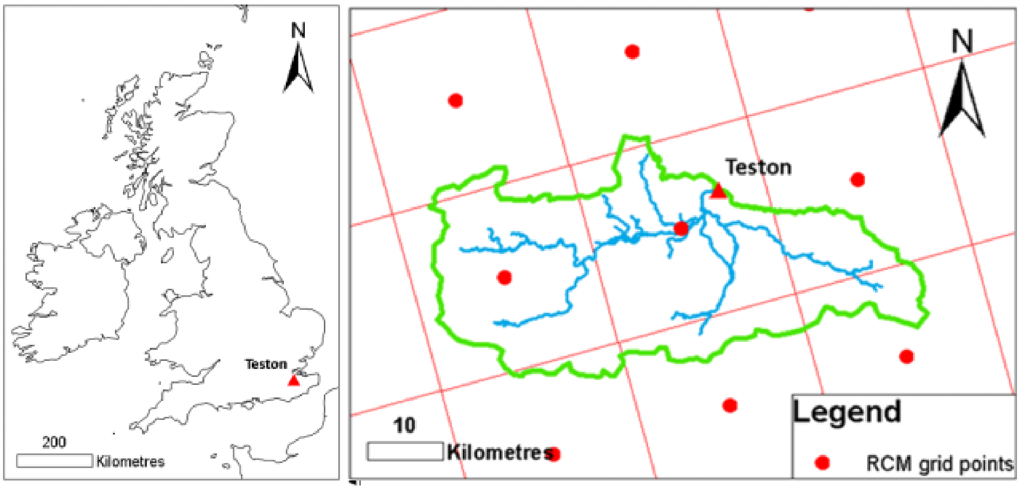

Figure 1. The Medway catchment above Teston and RCM grid

10 April 1990 to 14 July 1996. The rainfall record for the catchment had been previously produced by the EA using data from 11 rain gauges with the Thiessen polygon method. The PET record had been constructed using PENSE, the EA's in-house system for calculating PET based on the Penman–Monteith equation (Norton and Byrne 2004). No quantitative estimation of uncertainty accompanies this data. A record of observed daily temperature at Edenbridge (latitude 51·203 longitude 0·137, approximately 30 km west of Teston) was extracted from the UK Met Office's MIDAS database.

CATCHMOD simulations

CATCHMOD is a relatively simple catchment hydrology model with a long history. It is easy to use and understand, and has few parameters as it is conceptually based (Table I). In the UK, it has been adopted by the EA and a number of water companies for water resources modelling and has been employed in previous climate change impact studies (Diaz-Nieto and Wilby, 2005; Wilby, 2005; Vidal and Wade, 2006; New *et al.*, 2007). It is described in detail elsewhere (EA, 2005; Wilby, 2005) and thus only a summary of the model follows.

In our use of CATCHMOD, catchment response is modelled as one hydrological zone using conceptual soil moisture and catchment storage modules (unsaturated and saturated zones and channel) to model total runoff (Figure 2). It is also possible to partition the catchment into several hydrological zones in CATCHMOD, but initial tests found no significant variation in results but an increase in required computer power, and so this option was rejected. Records of abstractions and returns can be used to calculate adjusted channel flow. There are five parameters and four initial conditions which must be specified (Table I). Minimum and maximum values for each parameter are specified based on the EA guidance for plausible ranges (EA, 2005) and current calibrated values for the Medway in use by the EA at the time of writing.

Rainfall and PET data supplied by the EA were used to drive 100 000 Monte Carlo simulations. The parameters and initial conditions were randomly sampled, assuming uniform distributions, from the ranges specified in Table I. The naturalized flow record was used to calculate 'goodness-of-fit' or 'performance' for each run, using Nash–Sutcliffe (NS) efficiency (Nash and Sutcliffe, 1970) for flow 'as is' (NS), which is suitable for medium to high flows and log of flows (NS–log), suitable for low flows. Root mean square error (RMSE) and mean absolute error (MAE) were also calculated for comparative purposes. The entire naturalized flow record was used for calculating performance. The NS and NS-log performance measures were combined with a simple weighting function according to percentile of flow, with NS-log being important and thus 100% weight for the lowest flows and NS 100% for the highest flows. The NS and NS-log were also tested using a shaping factor which has the effect of accentuating the weight given to better simulations (Freer *et al.*, 1996). There is an (unsurprisingly) nonlinear relationship between the NS and NS-log values that were calculated.

Table I. Plausible ranges for parameters and initial conditions. Ranges are defined based on current EA guidance documentation and discussion with current EA staff using CATCHMOD

Description of parameters and initial conditions	Code	Minimum	Maximum
Direct percolation (%)			
A fixed fraction of precipitation that bypasses the soil horizon even during periods of soil moisture deficit	DP	0	45
Potential drying constant (mm)			
Value of deficit above which evaporation occurs at a reduced rated	PDC	0	150
Gradient of the drying curve	Slope	0	0·6
Linear storage constant (days)			
Represents temporary storage in the unsaturated zone	C_r	0	30
Nonlinear storage constant (days km^{-2})			
Represents storage in the saturated zone/aquifer	C_{qu}	0	5000
Initial soil moisture deficit in upper store (mm)	D1	0	100
Initial soil moisture deficit in lower store (mm)	D1	0	100
Initial outflow from upper catchment store (mm day^{-1})	R1	0	10
Initial outflow from lower catchment store (m^3 s^{-1})	Q1	0	10

Uncertainty analysis

The GLUE methodology (Beven and Binley, 1992) was used to estimate predictive uncertainty. A binary classification system, based on the NS efficiency, was used to separate results from the Monte Carlo simulation into 'behavioural' (NS $\geq$0·6) and 'non-behavioural' (NS$<$0·6) outputs, and the same criteria for NS-log. The threshold of 0·6 is necessarily subjective, but later we evaluate this decision statistically (see Section on CATCHMOD Model Performance). The behavioural sets were then used to produce likelihood-weighted predicted flow distributions using the method of Beven and Freer (2001).

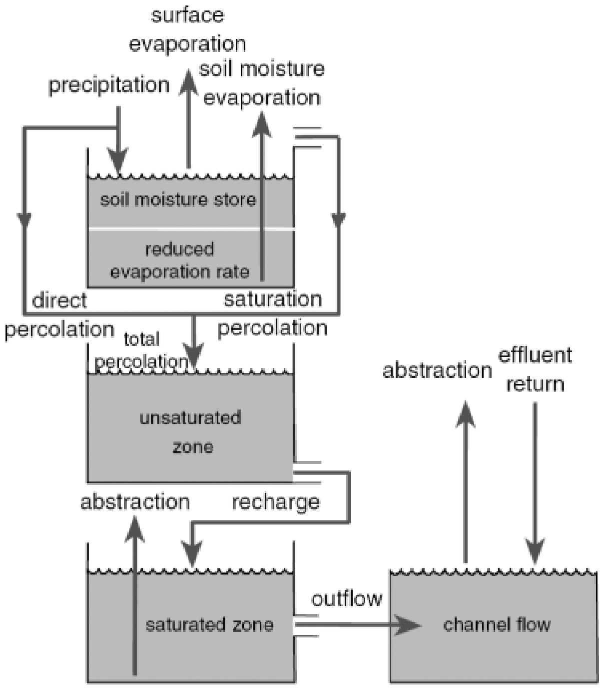

Figure 2. CATCHMOD structure. Reproduced from Wilby (2005, p. 3204)

Note that an assumption of negligible uncertainty from observed data (rainfall, PET, naturalized flow) and model structure is made, although it is acknowledged that such uncertainty may affect results, although based on the authors' experience the most important uncertainties are likely to be derived from the model parameters and the climate inputs. It is also assumed that GLUE as a non-Bayesian technique can represent the required uncertainty (Beven *et al.*, 2008). Although, there is an ongoing debate regarding whether or not Bayesian analysis provides a more robust or objective alternative to GLUE analysis (Mantovan and Todini, 2006; Beven *et al.*, 2008), fundamentally this may not matter, as long as some estimate of uncertainty is transparently provided. Results of GLUE are always conditional on the subjective elements of the methodology (Beven and Freer, 2001): and as noted above our methodology does not account for observational uncertainty (measurement errors), model structural uncertainty (the sensitivity analyses carried out here will expose structural dependencies for this case study) or any change in our uncertainty estimates distribution between the observed and the projected data sets or change under future climate (non-stationarity). In particular, we note that the behavioural models selected in the GLUE analysis may possibly be less behavioural when they are forced with (uncorrected) RCM output. We also acknowledge that several alternatives to our combined NS and behavioural threshold approach exist for GLUE, such as the limits of acceptability approach (Blazkova and Beven, 2009).

Regional climate projections

Daily mean temperature and precipitation data from ten early release UKCP09 ensemble climate projections were provided by the UK Met Office (autumn 2008). These are identical to the final UKCP09 projections (Murphy *et al.*, 2009; http://ukclimateprojections.defra.gov.uk/) apart from the absence of ensemble member 'afixk'. The data are taken from ensemble outputs of the HadCM3 GCM (Collins *et al.*, 2006), assuming scenario A1B emissions, which were used to drive the HadRM3 RCM. More information on the HadRM3 experiments for UKCP09 can be found in Murphy *et al.* (2009). The climate projection data is already dynamically downscaled by the RCM and supplied at a resolution of $\sim$25 × 25 km. In this study, we have used the RCM data without further downscaling as the RCM output scale is comparable to the input data scale for the hydrological model (subsequently adjusted with the Thiessen Polygon method to the catchment shape). The nature of the structural error (bias) between the RCM outputs and observed precipitation data for the Medway catchment is explored in Figures 3 and 4, in order to consider whether correction for such error is appropriate. In Figure 3, uncorrected precipitation projections from the ensemble RCM control period for the Medway catchment as compared with observed precipitation data are shown in monthly percentage boxplots. From Figure 3, it can be seen that, as an ensemble, there is a tendency for a small overestimation of RCM precipitation in spring/early summer and a tendency for a small underestimation of precipitation in autumn. During August and September, further analysis reveals that the bias is mostly in the largest events. We note that this bias is significantly smaller to that seen in analysis for other catchments such as the Severn and the Tay (unpublished work by authors).

In Figure 4a, the annual cumulative ensemble RCM control period precipitation is shown against the observed. The overall dry bias is observable in this figure, although the spread of the ensemble is quite large. As an ensemble, the annual precipitation values show that the observed and modelled distributions are similar (note that *t*-test analysis flags three individual ensemble members which systematically underestimate precipitation and have statistically significant differences in their distributions to the observed at the 0·05 level).

A structural error correction (bias correction) was applied to the RCM ensemble precipitation in order to determine what improvements this might give for precipitation projections (Figure 4b). The correction technique was a distribution based scaling (Yang *et al.*, 2010), in which the distributions for the lower part of the distribution was corrected with a gamma distribution and the upper part with a GEV distribution, which has been found to be highly suitable for climate impact modelling of river flows. Part of the correction is to ensure that the climate change signal, i.e. the change comparing future climate periods with the control climate, is not affected by the error correction (under the assumption of bias stationarity). Figure 4b shows the best results of using this technique. The ensemble distribution can be brought somewhat closer to observed and consequently the ensemble spread is reduced. The improvement in the

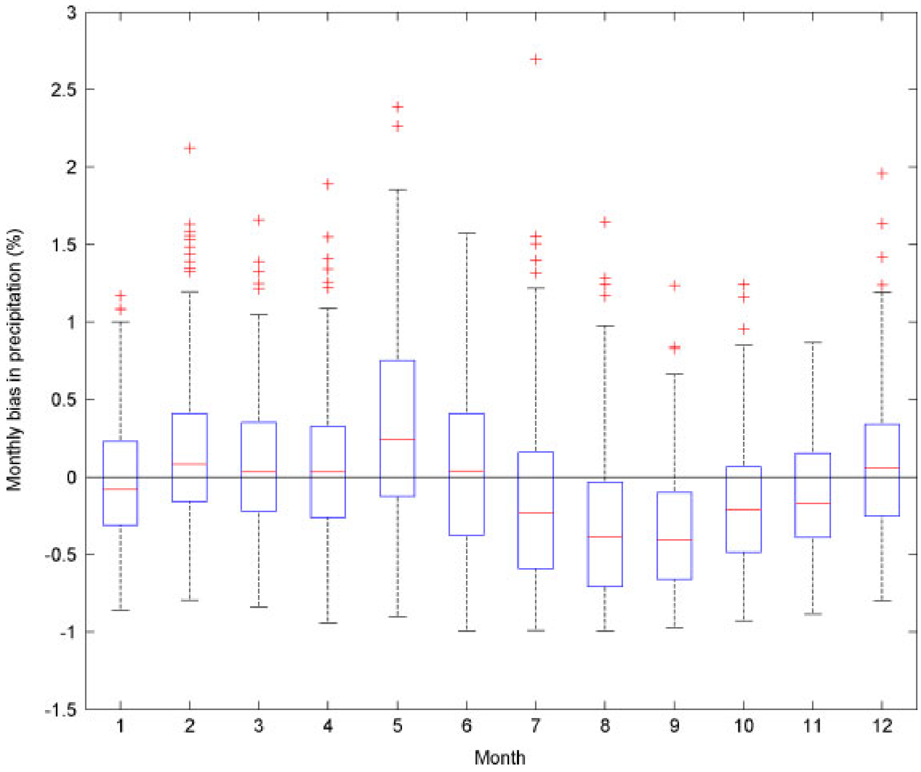

Figure 3. Uncorrected monthly precipitation difference between the control period ensemble RCM output and observed data for the Medway catchment

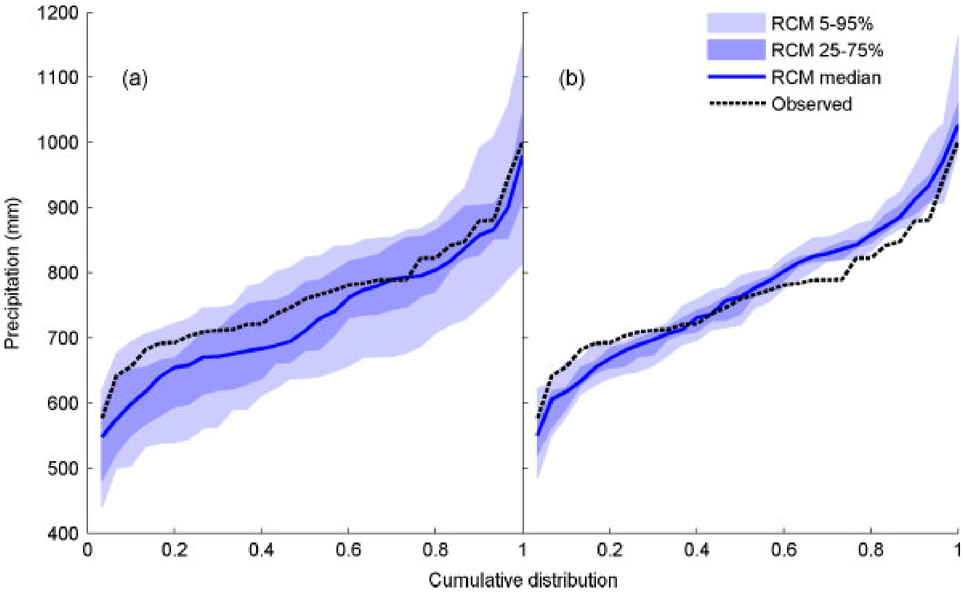

Figure 4. Annual cumulative precipitation for observed and ensemble RCM control period (a) uncorrected and (b) corrected

distribution is however relatively small, and not equal through the distribution, with some parts now having an increased estimation. We also highlight that for a case such as this where only short time series of high resolution observational data are available, this type of error correction is not necessarily appropriate. The application of the correction may in fact add to the uncertainty in the projections. There is substantial further work to be done in order to find robust solutions for structural error correction of precipitation (Terink *et al.*, 2010; Maraun *et al.*, 2010). As we are not confident of the benefits of bias correction, for this case the subsequent analysis has been performed using uncorrected precipitation.

River flow projections

The GLUE analysis provides a likelihood distribution for the resulting behavioural models, which could be related back to the specific sets of parameters and initial conditions which were used for each model run. An assumption is made that the likelihood of these parameter/initial condition sets found during the period with observed data is appropriate for use with the climate projections. The reader should take care to bear this assumption in mind, i.e. the distribution of results of the observed period should be compared with the climate projection results.

If time, computer processing power and data storage were no object then the catchment model could have been run again with every single set of behavioural parameters and initial conditions, but this time driven by 150 years of rainfall and temperature data derived from climate model output, to produce a likelihood-weighted projected flow distribution for the period 1950–2080. However, running the catchment model the $\sim 1 \times 10^6$ times that would be required to produce a likelihood-weighted projected flow distribution was not a viable option due to computational constraints. The approach adopted was therefore to run the catchment model, driven by climate model output, with a sample of the behavioural sets of parameters and initial conditions in order to capture *some* of the hydrologic model parameter uncertainty in the resulting projections of flow. We sampled randomly in the behavioural space and selected 100 representative parameter sets which we assume to be representative of the behavioural space (although this remains an assumption which the reader should bear in mind).

The climate model output was then used to drive the catchment model, to produce a simulation of flow for the period 1950–2080. This was repeated for each parameter set and initial conditions.

RESEARCH QUESTION 1: ANALYSIS OF MODEL PERFORMANCE, SENSITIVITY AND UNCERTAINTY

In this section, a comparison is made of simulation results driven by observed precipitation against the naturalized observed flow for the period 10 April 1990 to 14 July 1996.

CATCHMOD model performance

Behavioural parameter sets were selected based on the performance for the entire observed time series as so little data were available, although it should be noted that the winter of 1991–1992 was relatively dry. For this study, the best fit combined NS value (see Section on CATCHMOD Simulations) has a value of 0·8, which indicates that overall the model can perform very well (Table II). In Table III, we evaluate the implications of our 0·6 behavioural threshold. The statistics of the NS efficiency and other performance measures have been calculated based on the observed flow record. Measures are calculated here by first taking NS and NS-log *both* over particular thresholds of 0·4, 0·5, 0·6 and 0·7 and then subsequently calculating the combined measure; this tests the robustness of the threshold. It can be seen that there are no results for NS and NS-log both being over 0·7. The choice of 0·6 as a behavioural threshold is therefore not unreasonable in this case: the percentage of outliers (beyond 0·5 and 0·95 limits) should be $\sim$0·1, and for our results the value is 0·14.

Table II. 'Best fits' according to Nash–Sutcliffe efficiency and corresponding other performance measures result from these parameter sets; calculations based on the entire record of observed flows

Performance measures	Monte Carlo simulations
Nash–Sutcliffe combined	0·80
RMSE	8·54
MAE	4·78

Sensitivity analysis of model parameters and initial conditions

We then performed a sensitivity analysis on the model parameters and the initial conditions, to see their effects on model performance. There is very little structure evident in the parameter sensitivity, even with a shaping factor ($N = 30$) applied to increase the weighting given to the better fits. Only the linear storage constant (Cr) has a strong influence on model performance, with the direct percolation (DP) parameter showing some sensitivity (Figure 5). This finding supports the EA's user experience that the Cr parameter is the most sensitive (according to author Byrne). Further analysis revealed seasonality in these parameters, e.g. direct percolation has a significant influence when simulating low flows (Figure 6).

Higher order effects affecting model performance were also analysed (not shown here but see Jeffers, 2008) and found some interaction between slope and the potential drying constant; which makes sense physically as they both control the way actual evapotranspiration is calculated. The potential drying constant also appears to interact with direct percolation to some degree. The initial conditions do not appear to have a strong influence on model behaviour.

Analysis of predictive uncertainty

The observed flows are, on the whole, found to fall within the prediction limits although some low flows and high flow peaks were not captured. In Figure 7, an example of the water year 1992–1993 is shown. It can be seen that for this year both winter high flows and summer/early autumn low flows are within the prediction bounds, although flows in March are somewhat underpredicted. Low flows are consistently found to be slightly underpredicted in the results (spring and/or summer), and this is most likely due to model structural problems as noted above, although may possibly be due to the method of naturalizing abstractions from the river record.

Likelihood-weighted predicted flow distributions are shown in Figure 8 for six example timesteps, illustrating that the model predictions are not normally distributed. Predictions are often skewed towards lower flows and occasionally double-peaks develop which can persist

Table III. Statistics of the Nash–Sutcliffe (NS) efficiency and other performance measures, based on the observed flow record. Measures are calculated here for combinations of NS and NS-log *both* over particular thresholds of 0·4, 0·5, 0·6 and 0·7 in order to illustrate the implications of selecting a behavioural threshold for the combined measure of 0·6. Columns with NS and NS-log both being over 0·7 produce no results

Performance measures				
Nash–Sutcliffe (NS)	>0·4	>0·5	>0·6	>0·7
Nash–Sutcliffe–log (NS–log)	>0·4	>0·5	>0·6	>0.7
Combined Nash–Sutcliffe—Nash Sutcliffe log (mean)	0·56	0·62	0·64	—
Combined Nash (min)	0·4402	0·6026	0·6109	—
RMSE (mean)	13·3171	12·3874	11·4902	—
MAE (mean)	6·6455	6·1841	5·7658	—
Outliers (%)	0·06	0·14	0·35	—

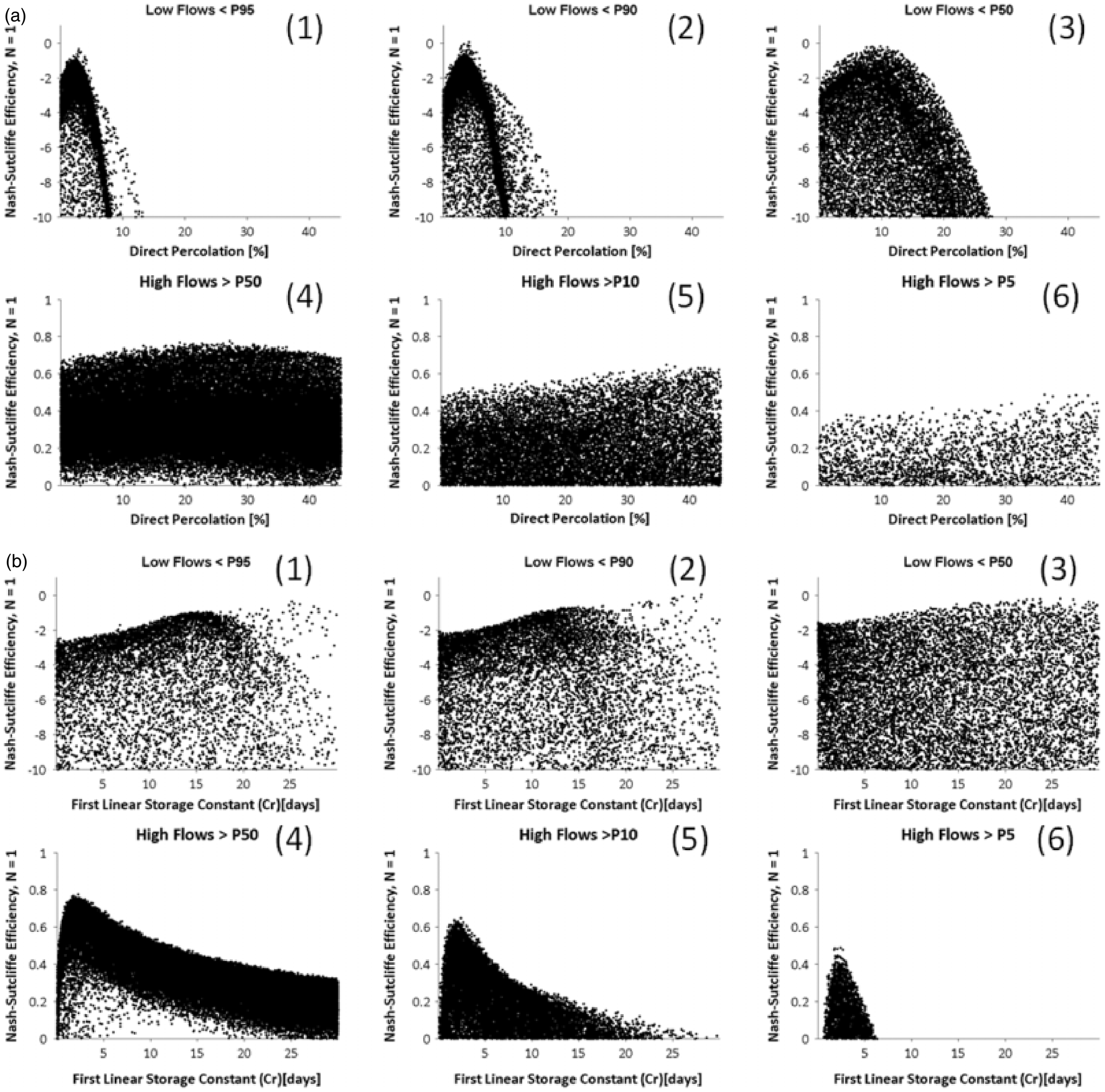

Figure 5. Dotty plots for *direct percolation* (top) and *first linear storage constant* (bottom) based on low flow and high flow subsets of simulated flows, illustrating the relationships between parameters and model performance when observed flow is (1) <Q95; (2) <Q90; (3) <Q50; (4) >Q50; (5) >Q10; (6) >Q5

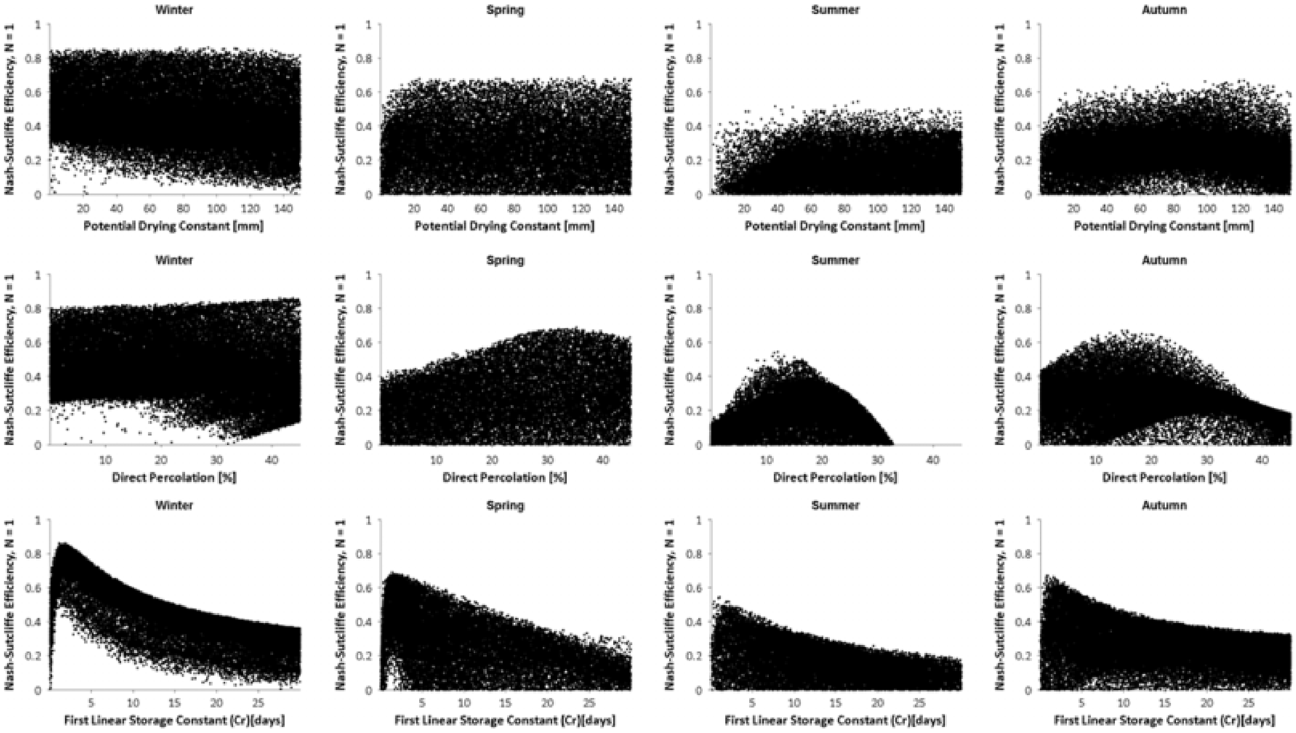

Figure 6. Dotty plots for *potential drying constant* (top), *direct percolation* (middle) and *first linear storage constant* (bottom) based on seasonal subsets of simulated flows, illustrating the relationships between parameters and model performance in winter (DJF); spring (MAM); summer (JJA) and autumn (SON)

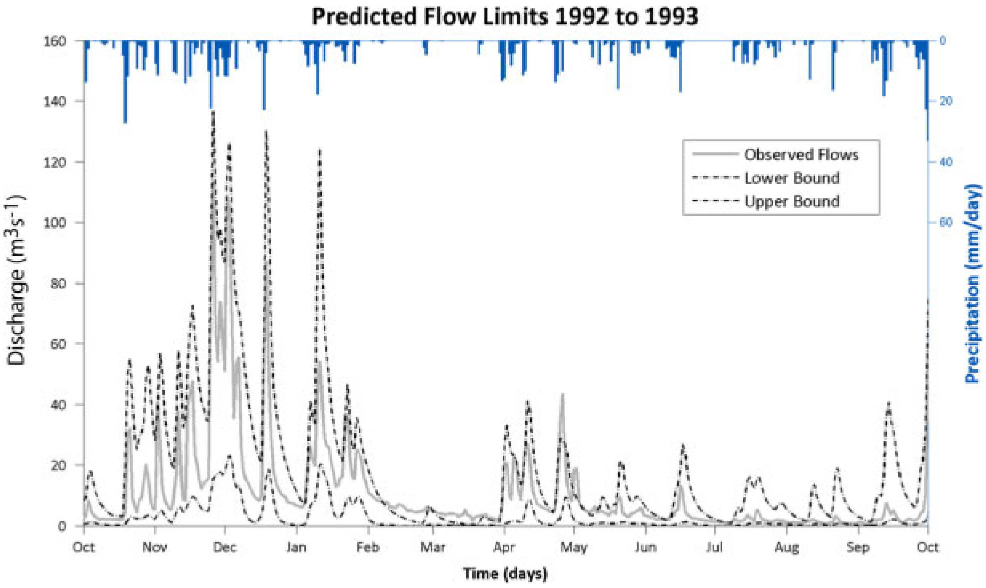

Figure 7. Predicted flow limits for water year (1992–1993) taken as an illustrative example of the whole time series. Upper and lower uncertainty bounds contain 90% of the total behavioural likelihood

over several days, sometimes resulting in bi-modal flow distributions (e.g. 25 November 1992).

The double-peaks in the likelihood-weighted predicted flow distributions indicate there may be two different modes of model behaviour which can produce good fits (according to the methodology used here). This idea was explored further by looking in detail at the model outputs and intermediate states of the 'best fit' models in *below observed* and *above observed* subsets. Figure 9 illustrates the controlling influence of direct percolation on predictions of flow *below* observed flow and the controlling influence of the first linear storage constant on predictions of flow *above* observed flow. It can be inferred from this that interactions between these two parameters have a role in producing the double-peaks in the flow distributions. At the end of November 1992, when the double-peak manifested itself in the likelihood-weighted predicted flow distributions, the two models were predicting different patterns of soil moisture deficit. Relatively high deficits were predicted by the 'best fit' model in the

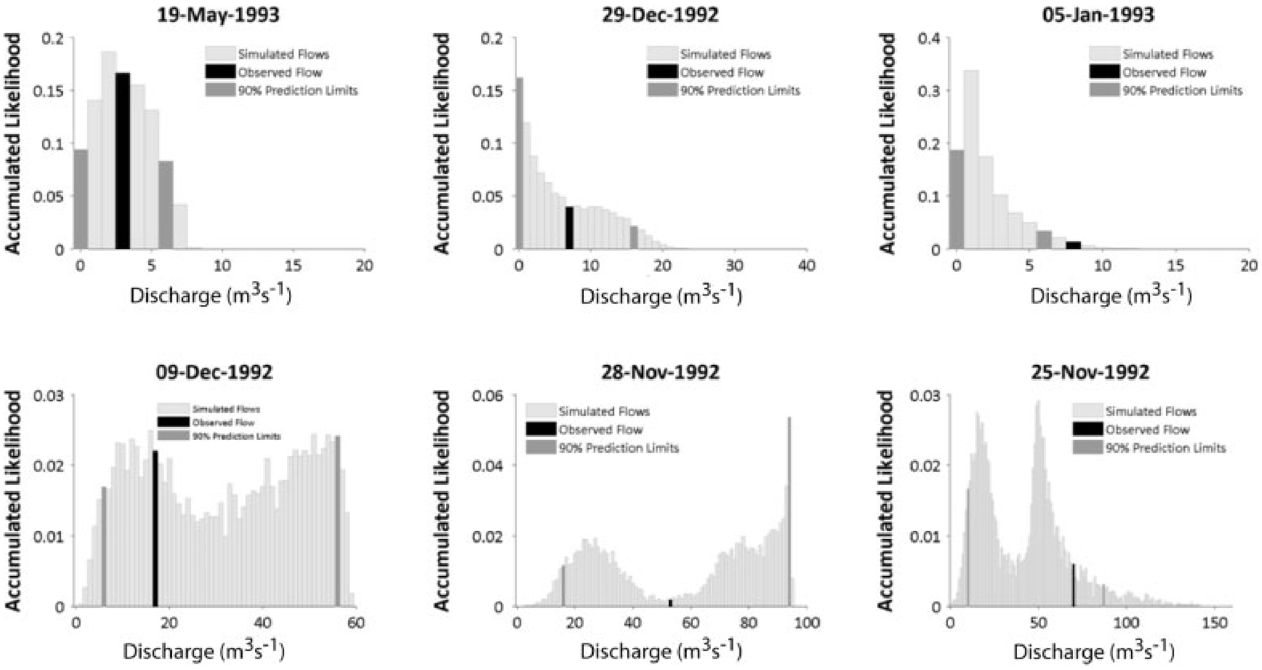

Figure 8. Likelihood-weighted predicted flow distributions for the single zone version of CATCHMOD, for six example timesteps. Observed flow (black) and predicted flow limits (dark grey) are also indicated. The panels are ordered to illustrate the variations in the type of distribution (skew through to double-peaks)

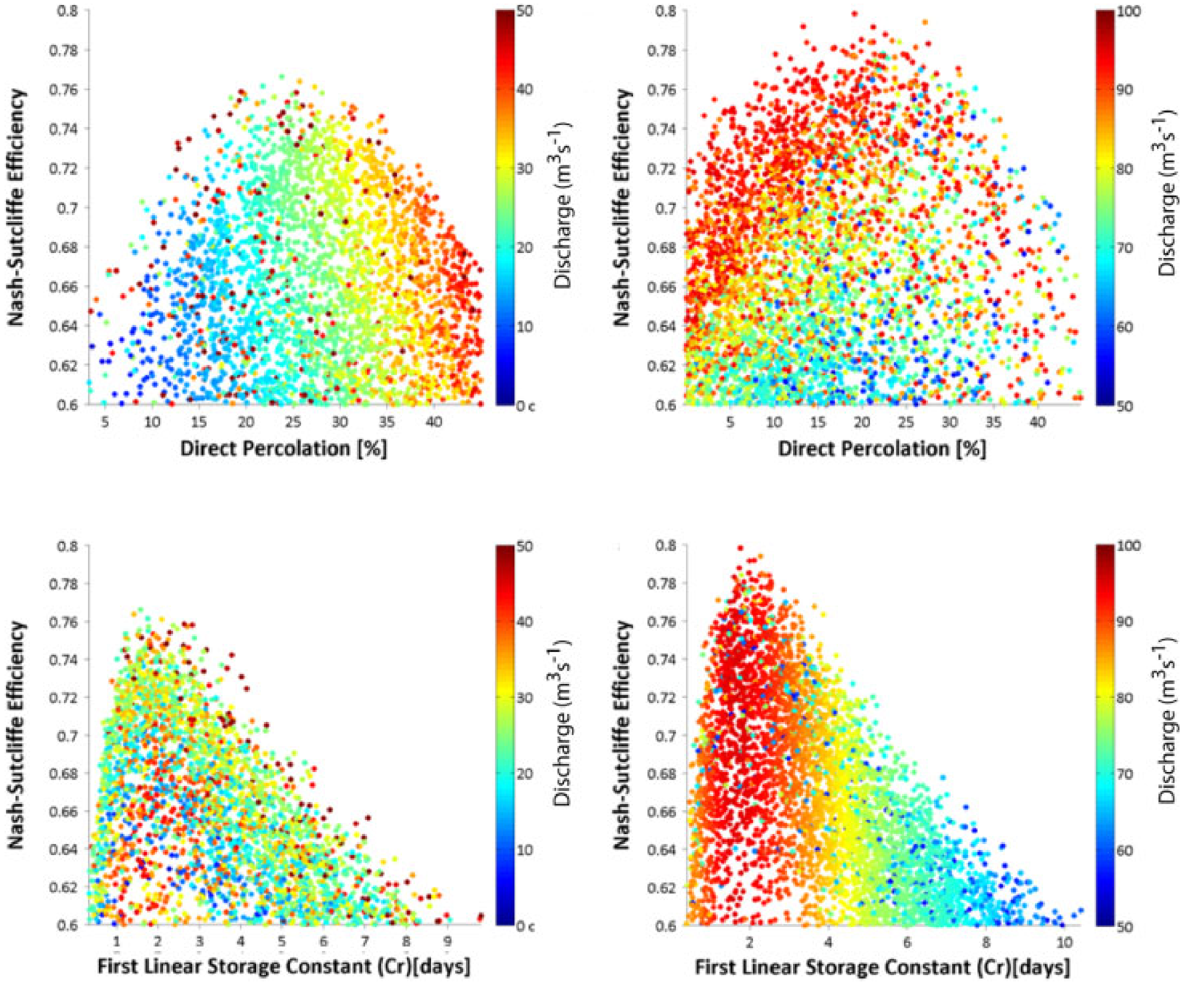

Figure 9. Three-dimensional scatter plots illustrating the influence of *direct percolation* and the *first linear storage constant* on model performance and predictions of flow (colour axes) for 28 November 1992, for two separate subsets of the behavioural models based on a single-zone version of CATCHMOD. Left: behavioural models predicting flows *less than* observed flow on 28 November 1992. Right: behavioural models predicting flows *greater than* observed flow on 28 November 1992

below observed subset, and this indicates that more of the water going into the system (precipitation) is being used to reduce the soil moisture deficits, which in turn means there is less water available to produce effective rainfall; this leads directly to lower predictions of flow. To test whether this behaviour controls the double-peak pattern observed, soil moisture deficit predictions were analysed for the ten 'best fit' models in each subset (not shown here for brevity). A comparison between the two subsets showed a clear and consistent difference in the models' predictions of soil moisture deficit. The models in the *below observed* subset all predicted higher soil moisture deficits than the models in the *above observed* subset.

Summary of model performance results

The preceding analysis demonstrated that the Cr parameter has a strong influence on model performance, with the DP parameter showing some sensitivity. Other parameters are important with regard to modelling particular aspects of catchment behaviour, e.g. lower (higher) values for direct percolation produced better simulations of (higher) flows.

In general, the model performed well with observations falling within the prediction bounds for both winter high flows and summer/late autumn low flows. Likelihood-weighted predicted flow distributions showed that model predictions are not normally distributed and often exhibit multiple peaks. DP controlled predictions of flow *below* observed flow and the Cr controlled predictions of flow *above* observed flow; thus interactions between these two parameters controlled the resulting flow distributions.

RESEARCH QUESTION 2: ANALYSIS OF PROJECTIONS OF RIVER FLOW UNDER FUTURE CLIMATE

Projections of river flow under future climate based on the early release UKCP09 projections have been routed through CATCHMOD in order to analyse climate impact on river flow. We used 100 randomly sampled behavioural parameter/initial condition sets found in the preceding uncertainty analysis to produce flow for the period 1960–2080. For this analysis, we make the assumption that these sets represent both modes of model behaviour (see Section on Analysis of Predictive Uncertainity) and remain valid for future climate scenarios. Two sources of uncertainty were explicitly explored in the production of these projections of river flow under future climate: climate model uncertainty and hydrologic model parameter uncertainty.

In Figure 10, box plots illustrate the full range of river flow projections for the control and three future time slices and the observations (10 April 1990 to 14 July 1996). The similarities in the discharge distribution over the year between the observed flow (10 April 1990 to 14 July 1996) and the RCM predictions can be seen. The two datasets are not directly comparable because the observed data were averaged over a much shorter period, and the climate data will reflect some bias in the RCM (but see earlier discussion on bias). Winter flows have a high absolute uncertainty with whiskers covering the full range of possible flows, with possibilities of some very high flows. Medium and summer low flows also displayed significant uncertainty in results. However, there is a clear climate change impact signal evident in these results with a persistent lowering of mean daily river flows for all months and for all time slices. This

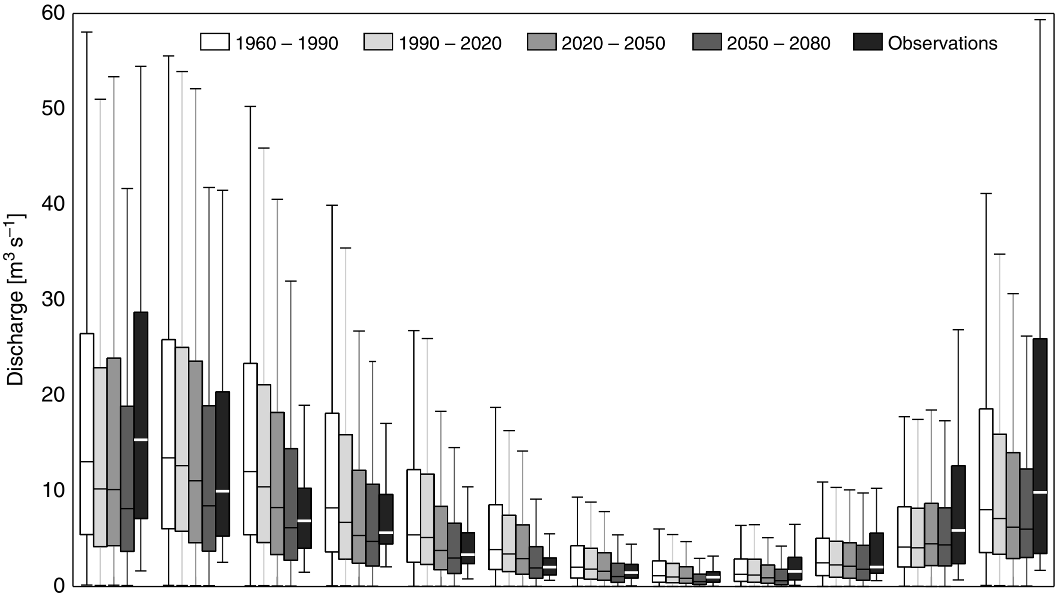

Figure 10. Climate projection time slices and observations for mean daily river discharge lumped per month of the year over all parameter sets. For the box and whiskers, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, i.e. the 1st and 99th percentiles

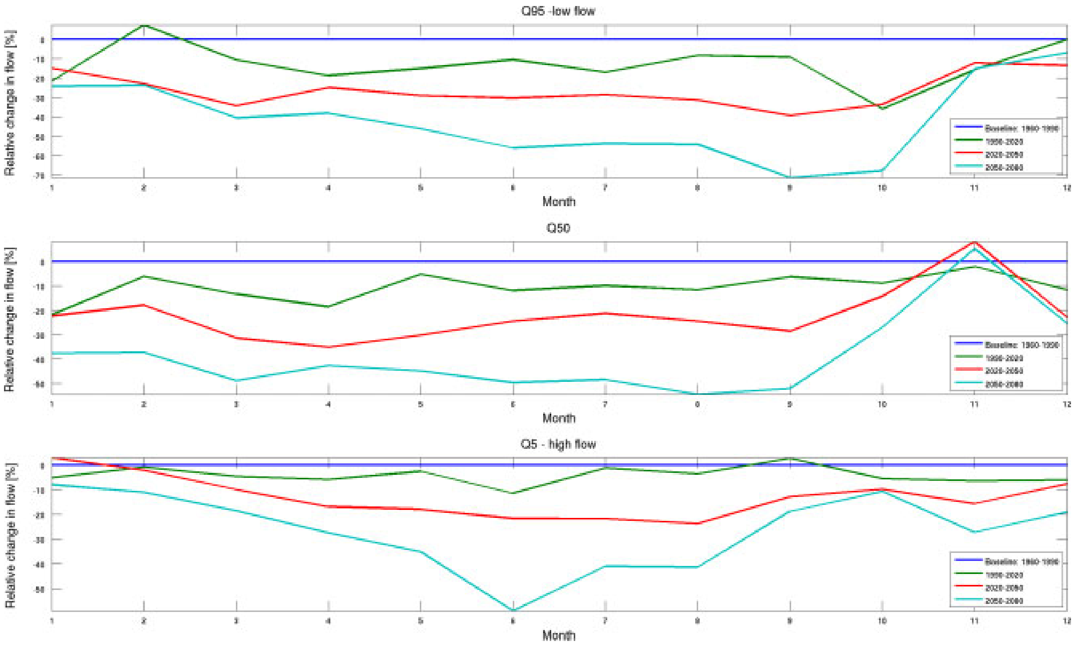

Figure 11. Relative change in mean daily river discharge for the future time slices for low flows: Q95 (top), medium flows: Q50 (middle) and high flows: Q5 (bottom). The change is calculated relative to the 1960–1990 baseline

is true for the entire range of flows and the uncertainty bounds reflected in the median (50th percentile), box (25th and 75th percentile) and whiskers (5th and 95th percentile). For example, for March (month 3) it can be seen that the 1960–1990 time-slice results have median, box and whisker results of 13, 6 : 26 and 0 : 55 $\mathrm{m}^3\ \mathrm{s}^{-1}$, respectively. These decrease over the future time slices and by 2050–2080 projected flows have median, box and whisker results of 7, 3 : 15 and 0 : 32 $\mathrm{m}^3\ \mathrm{s}^{-1}$, respectively. Thus results confirm that a projection of lower flows under future climate is valid even taking account of the uncertainties in this modelling chain exercise (bearing in mind that we have only analysed a subset of the full uncertainties, by only considering one GCM–RCM, one scenario, one hydrological model, etc.).

Figure 11 shows the projected relative change in low, medium and high flows throughout the year compared with the 1960–1990 baseline. Low flow is in this case calculated as the Q95 per month, i.e. the flow exceeded 95% of the time in each month separately, medium flow is the Q50 per month and highflow is the Q5 per month. This allowed us to visualize the change in flow behaviour on a month-by-month basis. The baseline is provided alongside the three future time-slice projections.

Low flows. For nearly all months (with the partial exception of February), flows were projected to be increasingly lower. Low flows were between 15 and 35% lower over the year in the 2020–2050 time slice. Low flow changes were particularly important in summer months when low absolute flows are evident, and indeed there was a relative lowering of flows of greater than 50% between the whole period of May to October in the 2050–2080 time slice, reaching 70 and 68% in September and October, respectively.

Medium flows. In general, the medium flows also showed similar trends: the projections for median flows decreased over the time slices except in late autumn, when the differences become smaller and in November a relative increase in flows was seen.

High flows. There is an overall trend of relative decrease in high flows, especially in summer months, e.g. in June this was projected to be a 60% decrease by the 2050–2080 time slice. Importantly for those months with higher discharges (December to April), the Q5 was projected to be increasingly lower. For January, the Q5 shows a general decrease in high flows. However, the Q5 over the 2020–2050 time slice suggests an increase of 3%, relative to the baseline but the Q5 for the 2050–2080 time slice again indicates a decrease in high flow of 9%. High flows were projected to decrease by up to 28% by the 2050–2080 time slice. Based on our earlier analysis it is not likely that this can be fully explained by the precipitation bias (underestimation) of flood generating rainfalls and could indeed be indicative of a reduction in high flows. However, this will need much more detailed analysis with a higher resolution modelling approach to fully understand.

Perhaps the most interesting seasonal feature is pattern observed for the November flows for the Q50 and Q95: a notably smaller decrease in relative flows or relative flow increases. For the Q5, the relative change is affected in a similar but more smoothed way, occurring earlier in the year and with the relative changes not so pronounced. This patterning can be partially attributed to the precipitation distributions in the future projections which are expected to generally increase in Winter, particularly in November, but the difference between the percentiles of flows suggests an unequal projected shift in the winter distribution of flows.

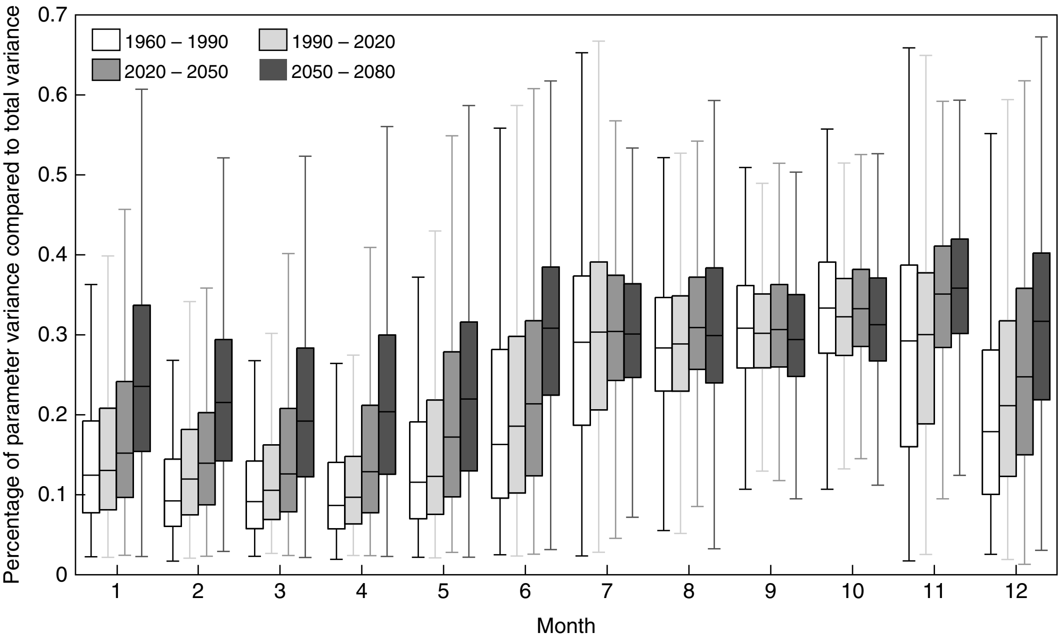

Figure 12. Importance of different uncertainty sources calculated as the percentage of parameter variance compared with the total variance

Figure 12 shows the importance of the model parameter uncertainty compared with all of the other sources of uncertainty (i.e. for our case the RCM input uncertainty). This 'importance' is calculated as the percentage of parameter variance compared with the total variance [which is similar to the computation of the Sobol index (Sobol, 1993)]. Higher values indicate an increase in importance of model parameter uncertainty, with values over 0·5 indicating that model parameter uncertainty is more important than other sources. This comparison of uncertainty sources shows that in late summer and early autumn, model parameter uncertainty becomes more important, with some whiskers even crossing the 0·5 threshold. This implies that the model parameter uncertainty becomes increasingly important in this study. For periods of low flow, model parameter uncertainty will be more important than RCM input uncertainty. This then becomes significant for projections of future flow when flows are generally predicted to be lower and thus model parameter uncertainty will become more dominant. It should be highlighted that the relationship between model uncertainty and climate uncertainty will be different if we were to attempt a multi-climate model, multi-scenario, multi-impact model approach, and may well be different in other studies that have a different combination of the above.

DISCUSSION

The previous analysis has provided evidence as to the functionality of CATCHMOD when producing river flow scenarios. Results have then been shown for future river flow projections based on UKCP09 climate model inputs. In the following, we discuss the main findings concerning the model, the future river flow projections, the consequences of this, limitations of the analysis and future recommendations.

Climate impact model performance and predictive uncertainty

The performance of our climate impact model, the CATCHMOD catchment hydrology model, has demonstrated that it is useful for the task in hand. Overall the likelihood-weighted flow distributions could capture the variation in observed low and medium flows. However, for this particular study results are sensitive to the Cr and the DP parameters. The DP parameter is seen to affect low flows and Cr is seen to affect high flows. This in turn affects the likelihood distributions.

DP controls the amount of water which bypasses the soil moisture store. Given that the soil water potential varies inversely with soil water content it makes sense that during periods of lower flows, when soils tend to be drier and soil water potentials relatively high, *less* water would bypass the soil moisture store than during periods of higher flows when soils tend to be wetter and soil water potentials relatively low. It is inferred from these results that soil water-retention characteristics have a significant influence on the Medway catchment's response to water input events. It may also be the case that during wetter periods high values for DP producing good model fits are indicative of preferential flow (such as macropore flow) having a significant role in the hydrology of the catchment. It may be that CATCHMOD could be improved by making DP a function of catchment wetness (although of course this would come at the price of further complexity in the model structure). This argument is supported by consideration of the predicted flow limits for 1992–1993 (Figure 7). These showed that during the period from July to September, when observed flows were relatively low and soil moisture deficits relatively high, rainfall events could produce spikes in predicted flow which were somewhat bigger than the spikes in observed flow. If DP was allowed to assume a lower value during this period then more water would be routed to the soil moisture store where it would reduce soil moisture deficits (making effective rainfall less) the spikes in flow following rainfall events would be smaller and predictions potentially improved. However, again we caution against making CATCHMOD more complicated. Future work should study the efficiency and structure of the CATCHMOD model in more detail to determine if it can be improved without compromising its relative parsimony and ease of use.

The results of this study illustrate how GLUE can be used to estimate predictive uncertainty in future climate projections of river flow. Uncertainty analysis is a very important activity if we are to intelligently analyse future climate projections (Pappenberger and Beven, 2006) and thus our river flow projections are very valuable as they provide explicit estimates of the uncertainty in projections and indeed the sources of such uncertainty (i.e. increasing importance of model parameter uncertainty). We can be confident that the random sampling strategy provided sufficient coverage of parameter space to fully explore hydrologic model equifinality. This led to the discovery of two distinct modes of behaviour in the single-zone hydrologic model which, within the context of this analysis, were found at certain timesteps to provide equally probable predictions of catchment behaviour.

River flow projections (with uncertainty)

Results clearly show a trend of projected future flows decreasing in nearly all cases with a projected shift in the seasonal distribution of flows, with summer flows experiencing a greater relative change. For example, we found low flows (Q95) to be between 15 and 35% lower over the year in the 2020–2050 time slice. We found summer flows to have very significantly lowered, $<50\%$ reduction for the 2050–2080 time slice, reaching a $\sim70\%$ reduction in some months. These relative changes in flows are greater than those found for the Medway by Norton and Byrne (2004).

However, even more importantly we provide evidence that this climate impact signal remains valid even taking into account the uncertainty and that model parameter uncertainty becomes more important with lower flows and thus will become more important for future flow prediction (as flows are predicted to be lower in the future). Wilby and Harris (2006) highlight the dangers in climate impact assessments that rely on a single climate model (driven by a single future scenario) and/or impact model. For example, the output from coupled GCM–RCM have in earlier studies shown to be dominated by the GCM (Graham *et al.*, 2007). We therefore note that our results remain indicative as this is a single GCM, single scenario study, and thus the total climate impact uncertainty remains constrained by this. We would expect climate impact uncertainty to be much larger for a multi-climate model and multi-scenario ensemble. The general applicability of the results presented in this study could be determined in future research by (i) using several hydrological models with various structures to produce improved projections of river flow under future climate and (ii) producing projections of river flow under future climate based on more than one climate model and emissions scenario, to assess the relative influence of climate model uncertainty and uncertainty about the future. We would also like to encourage comparison of this study with future work on the Medway, e.g. future studies from the ENSEMBLES project (van der Linden and Mitchell, 2009) and further studies using UKCP09 projections with and without the use of bias correction techniques.

Although our results are significant for water resources planners in the Medway catchment and beyond, a fuller set of results can be used together with other data to suggest policy direction. We note that planning in the South East is a complicated task and while the implications of climate change are an important consideration, there is a wide spectrum of other issues that planners must consider including land use change, over-exploitation of current water resources, etc.

CONCLUSIONS

Climate change, as captured in the UKCP09 projections, will have a significant impact on river flow for the Medway catchment. Results from a set of ensemble catchment model runs of CATCHMOD using the A1B scenario show that these impacts are a lowering of flows for all time slices, particularly severe in summer months. Uncertainty bounds are wide, but even taking these into account a clear lowering of flows is seen in results. Although remaining indicative, as this is a single GCM, single scenario, single impact model study, this has important implications for water resources. It was also found that sensitivity of model parameters can play an important role in such climate impact modelling, with two parameters in particular here influencing likelihood distributions and uncertainty in model parameters beginning to dominate the climate change signal for lower flows. For our study, this becomes particularly important for future projections where all flows are lower and so the climate change impact model uncertainty becomes increasingly important. These findings could be very significant for other climate impact studies. Future comparison with other studies of the Medway and elsewhere using other climate impact models and other GCMS are encouraged to determine the generality of our results and in order to help inform water resources policy.

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