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Comparaison de différentes sources d'incertitude dans une étude d'impact du changement climatique en Grande Bretagne

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Abstract. The paper assesses the range of changes from a comprehensive set of scenarios describing uncertainties due to climate modelling and climate projections for the 2080s. The study focuses on the mean annual flow ANN and the low flow regime indicator Q95. The changes are represented by confidence bands including 90% of the future simulations and are compared with estimated variations in ANN and Q95 due to natural climatic variability. The climatic projections include uncertainty in future emissions of greenhouse gases, in modelling global climate and in downscaling methodologies, while the natural variability is assessed through data resampling. Results are analysed to assess which of the considered uncertainties is largest for one British test catchment, and to provide guidance for incorporating uncertainty in future impact studies.

Résumé. L'article analyse les changements dus à un ensemble de scenarii décrivant les incertitudes relatives à la modélisation climatique pour la période 2080. L'étude se concentre sur le débit moyen annuel ANN et l'indicateur d'étiage Q95. Ces changements sont représentés par une bande de confiance comprenant 90% des simulations futures et sont comparés aux variations de ANN et Q95 dues à la variabilité climatique. Les incertitudes sur les projections climatiques tiennent compte des incertitudes sur les futures émissions de gaz à effet de serre, sur les modèles climatique globaux et sur les méthodes de désagrégation, et la variabilté naturelle est estimée par re-échantillonnage. Les résultats sont analysés pour évaluer lesquelles des incertitudes considérées sont les plus importantes pour un basin versant test en Grande Bretagne, et pour fournir des guides sur la prise en compte de l'incertitude dans des études de changement climatique.

Key words: Water resource; Climate change impact; hydrological modelling; uncertainty

Mots clefs: Resource en eau; impacts du changement climatique; modélisation hydrologique; incertitude

INTRODUCTION

There is increasing concern about the impact of climate change on water resources, and potential implications for water resource management. According to the IPCC, future GCMs projections indicate that temperature and precipitation patterns are likely to change in Britain, with summer runoff, water availability and soil moisture likely to decrease in southern Europe, and both variables (temperature and precipitation) likely to increase everywhere in Europe (Intergovernmental Panel on Climate Change, 2001). Global Climate Models (GCMs) provide us at present with the most reliable and robust methods for assessing the response of the climate system to changes in forcing. These GCMs are based upon the fundamental laws of physics and on assumptions on the content of greenhouse gases (in terms of CO2 equivalent) in the atmosphere, such as the IPCC-SRES scenarios (based on assumptions on societal development). However, it is recognised that different climate models provide different projections. For example, Prudhomme et al. (2003) found that GCMs uncertainty was larger than emission uncertainty in the impact on the flood regime in Britain, and recommended to consider different GCMs when undertaking any impact study on the hydrological regime.

GCMs are subject to a number of limitations, in particular the limited spatial detail of the relatively coarse grid of a GCM and consequently the inadequacy to model appropriately the short-time scale variability. Techniques to downscale the results of the GCM integrations to the appropriate scale for climate change impact assessments in hydrology have been developed to overcome the limitations of coarse scales, such as:

- Complex models, such as dynamical downscaling, use atmospheric general circulation model (AGCMs) outputs as limiting conditions for high-resolution regional climate models (RCMs) and provide daily climate outputs at a 50x50km grid over Britain;
- Statistical downscaling techniques are simpler and computationally less expensive than dynamical models and can be repeatedly re-run to generate large ensembles of daily precipitation series at the point/catchment scale for uncertainty assessment;
- Simple models, such as the delta method, use monthly factors (average changes for each GCMs grid) to perturb observed series to produce changed series (e.g. Prudhomme et al., 2003).

METHODOLOGY

Climate change uncertainty

Two main sources of uncertainty in climate change modelling have been considered.

GCMs and emission scenarios uncertainty. Three GCMs were considered: HadCM3 from the Hadley Centre for Climate Prediction and Research (Met.Office, UK); CCGCM2, from the Canadian Centre for Climate Modelling and Analysis (CCCMA; Canada) and CSIRO-Mk2 from the Commonwealth Science and Industrial Research Organisation (CSIRO, Australia). These were chosen because daily outputs of range of climate variables were available through the LINK project IPCC-DDC (http://ipcc-ddc.cru.uea.ac.uk/). For the emission uncertainty, two SRES scenarios were considered, A2 and B2, that encompass most of the range of the SRES scenarios. Results from A2 and B2 runs are considered together when assessing uncertainty in GCMs and downscaling techniques, and separately when assessing emission scenarios uncertainty.

Uncertainty in downscaling methodologies. Three downscaling techniques have been considered: (1) dynamical downscaling, with daily outputs from the Hadley Centre's regional model, HadRM3H at a 25x25-km grid-scale, driven indirectly from the HadCM3 simulation under the A2 scenario. (2) Statistical downscaling, with the Statistical DownScaling Model (SDSM), described as a hybrid between regression-based and stochastic weather generation techniques (Wilby et al., 2002). It uses empirical regression equations between large-scale atmospheric conditions and the observed daily local weather conditions, combined with a stochastic element to improve the reproduction of daily variability not suitably captured by the large-scale variables. In this study, 20 separate runs were made for each of the GCM and emission scenario combinations (Osborn et al., 2005). The final regression equation models were chosen after various combinations of predictors were tested and the model verified on an independent period. (3) A simple 'delta' (or proportional) approach that creates scenarios in perturbing observed baseline series according to average monthly factors of change (e.g. a +10% factor for January leads to a new series where all observed daily records for January are increased by 10% to produce a new future series; see Prudhomme et al., 2003). This is the most commonly used technique in climate change impact studies. The factors used are the four 'UKCIP02 scenarios' (i.e. monthly factors of change), specifically developed for impact studies in Britain by the UK Climate Impact Project (Hulme et al., 2002) from HadRM3 runs with four SRES emissions scenarios.

A schematic of the different uncertainty sources considered and the corresponding scenarios is provided in Fig. 1 (for the future time horizon 2080s).

PE scenarios. These were derived using the delta method, with factors of change calculated using the Penman Monteith equations (Allen et al., 1994) for PE estimates from the relevant climate variables from all the combinations of GCMs, RCMs and emissions scenarios.

Uncertainty due to natural climate variability

Natural variability. Oceanic climate such as observed in the British Isles is extremely variable, and the inter-annual climatic variability is significant. Yet, this natural climate variability (hereafter natural variability) is generally ignored in climate impact studies. A simple methodology of block resampling with replacement has been used to define and incorporate natural climate variability. The resampling procedure randomly selects 3-month blocks from the original series (respecting the annual sequences) to create a new series the same length as the original. A three month resampling was preferred to a 1-month resampling so that the medium-term seasonal structure of the rainfall is maintained, as this is particularly important for the recharge process. For this study, 99 new series were produced using that method, thus providing a set of 100 scenarios including the observed series.

Climate variability. Natural variability, as defined with resampling of short records of observed series, does not incorporate any extreme event that is not included in the observations nor any change in the inter-seasonal variability (due to the 3-month resampling procedure, the original 3-months sequences are maintained in all resamples). One way of more extensively capturing the climate variability is via the modelling of the climate. The random element built in SDSM introduces some variability in each of the simulated series and hence has been used to derive 20 daily precipitation series for each GCM representative of the baseline time horizon (1961-1990). A further 5 block-resamplings of each of the 20 series was done to finally produce 100 scenarios (same scenario group size as used to assess the natural variability).

Only precipitation series were derived with SDSM. For current climate, observed PE series were used for simulations of current conditions except for dynamical downscaling (modelled).

Calculation of changes and uncertainty

Reference indicator and calculation of changes. The reference indicators are calculated from the daily flow series simulated with the observed rainfall and PE (and NOT from the flow records). This is to eliminate the bias due to hydrological model errors. For each simulated flow series, an indicator is calculated and the difference with the reference indicator expressed as percentage of that reference value. For example, for a reference value of 20 and a scenario value of 22, the change is 10%.

Uncertainty. For one indicator type and a given source of uncertainty, the uncertainty is represented by the range comprising 90% of the simulated indicators (or 90% Confidence Interval CI). Ranking all the 100 indicators in ascending order, CI is defined by the 5th and the 95th values (corresponding to the 5th and 95th percentiles). The 25th and 75th percentiles are also derived, showing the range comprising half of the simulations around the median. These percentiles are graphically shown by a box-plot diagram, with the whiskers representing the 5th (lower) and 95th (upper) percentiles, and the black boxes the 25th (lower limit) and 75th (upper limit) percentiles (e.g. Fig. 2). For example, let's consider the results from the SDSM downscaling method with the outputs from the Hadley Centre Model HadCM3 run for the 2080s time horizon with the A2 SRES emission scenario. The 100 precipitation series (the 20 SDSM series, each resampled 5 times) and the same future PE series are used in the hydrological model to produce 100 daily flow series. The indicators are calculated for each of the 100 simulated flow series, and ranked to provide the 5th, 25th, 75th and 95th percentiles values of the Confidence Interval.

CASE STUDY

Catchment

The catchment selected is the Thrushel at Tinday, a rural catchment with grazing and low grade agriculture located in South West of Britain in Cornwall (Marsh and Lees, 2003). It has an area of 113 km^2 and an average altitude of 175 m. The mean annual rainfall is

1195 mm; the Base Flow Index, a measure of permeability of the catchment, is 0.42, indicating that around 42% of the river flow is from stored sources. The catchment was selected from a pool of good hydrometric quality, natural, gauged catchments from the National River Flow Archive held at CEH-Wallingford using the classification system of Gustard et al. (1992).

Data used

Daily time series of catchment average precipitation for the study period 1969-97 was derived using the Meteorological Office daily rainfall library and a modified version of the Triangular Planes interpolation methodology of Jones (1983). Time series of potential evaporation (PE) was estimated for each catchment from the Meteorological Office of Rainfall and Evaporation Calculation System (MORECS) II potential evaporation estimates available at a 40 km grid resolution.

Hydrological model

The hydrological model used is based on the Probability Distributed Model theory (Moore, 1985) that represents the soil storage capacity as a probability distribution and has two second-order linear routing reservoirs simulating quick and slow flows. The model includes an interception storage term and a soil-moisture related drainage term and has five free parameters for calibration. The parameters of the equations are calibrated so that the river flow time series simulated by the model provide a good match with the observed river flow records of the same period as the input data (bias and errors minimized). Evaluation is done on a separate period than the calibration. Uncertainties due to hydrological modelling are not discussed in this paper.

RESULTS

Two indicators of river flow are analysed: the annual mean flow (ANN) and the flow exceeded or equalled 95% of the time (Q95). For practicality, the results are named after the GCM and the downscaling technique used to derive the input series. Results are shown as box-plot graphs (Fig. 2 and Fig. 3).

Current climate uncertainty

For the current climate, the variation (in % change compared to the reference value) of ANN is smaller than that of Q95 (Fig.2 and Fig.3, baseline scenarios). Because of the small absolute value of Q95 (Q95 in this catchment is about 10% of ANN), large percentage variations in Q95 can be associated to a small absolute change. This larger uncertainty size for Q95 is in no way reflecting a poor modelling performance of the low flows.

Uncertainty due to 'climate variability' (as defined by running a range of scenarios derived by SDSM simulations and resampling techniques under current conditions) is smaller than the natural variability (as defined by running resamples of observed series) for ANN with the CI size varying from 8.7% (CCGCM) to 10.4% (CSIRO). This may be because the stochastic element integrated within SDSM does not produce extreme scenarios. Conversely, the climate variability is larger than natural variability for Q95 (from 36.7% (CSIRO) to 43% CCGCM)). For all GCMs ANN is underestimated and Q95 overestimated. Those results highlight the difficulty that GCMs encounter in modelling the climate (and in particular precipitation). The potential bias in reproducing current climate should always be borne in mind when analysing any projected changes in climate change impact studies.

Results from HadRM3 outputs show significant bias, with overestimation of ANN (ranging from 42 to 61%) and large uncertainty for Q95 (62.3%). The difference in the sign of the 'errors' between statistical and dynamical downscaling of the Hadley Centre model is partly explained by the bias correction that is introduced within the SDSM calibration procedure. This bias correction is absent from the HadRM3 precipitation outputs that were directly used as input of the hydrological model.

Future climate uncertainty

Uncertainty (i.e. size of 90% CI) associated with SDSM-derived scenarios increases for all three GCMs for 2080s future projections compared to current climate projections (ANN) or remains the same (Q95). All scenarios show a decrease in ANN, with changes in the median between current and future projections ranging between 3.9% (CSIRO) to 14.4% (CCGCM) (Fig. 2). Compared to the reference indicators, the decreases in ANN appear much greater, up to a 37.2% median decrease for CCGCM (Fig. 2). This is because all GCMs underestimate ANN during current conditions and that underestimation is propagated to future projections. Uncertainty due to each downscaling methodology (SDSM-HadCM3 or HadRM3) is of similar magnitude for ANN (around 15%), but they are very large discrepancies in terms of the sign of the changes of the projections by the different methods: HadRM3 scenarios show an increase of ANN in 2080s when compared to natural variability (+50.4% for the median of simulations), but these changes are insignificant when comparing current and future projections of

HadRM3 (current median simulation has a +52.3% bias compared to the reference value. the annual pattern of HadRM3 projections, however, shows considerable variation (not shown) between the two time horizons); SDSM-HadCM3 projects a decrease between 6.2 and 11.7%. The overall uncertainty in ANN due to downscaling is therefore extremely large for that catchment.

Q95 is also projected to decrease by the 2080s (Fig. 3) by all GCMs and downscaling methods, but the magnitude of that decrease greatly differs from one GCM to another, with HadCM3 projecting the largest reduction (median of changes by both A2 and B2 scenarios of -56.2%) and CSIRO the smallest (-16.5%). Unlike for ANN, the downscaling methods using the Hadley Centre GCM show consistent results in terms of sign of change and magnitudes, with a reduction of Q95 ranging from -39 to -70% (SDSM-HadCM3), -53 to -67% for HadRM3, and -47 to -71 for UKCIP02 (factors).

The uncertainty due to the emission scenarios (range between A2 and B2 for each GCM) is smaller than that of GCMs or downscaling methodology for ANN: uncertainty due to emission is about half of that of GCMs for both ANN and Q95, and smaller than that due to downscaling methods for ANN and about the same size for Q95. This is reflected by the UKCIP02 range not capturing the full range of uncertainty of climate change impact due to other sources than emission.

CONCLUSION

The results obtained are specific for this catchment: they are only examples of how the uncertainty in hydrological modelling and climate change impact study can be assessed. They are in no way an assessment of the quality of any of the modelling techniques considered. However, they depict features inherent to climate change modelling that should be considered when undertaking a climate change impact study:

- Different flow indicators can show different changes. Assessment studies should specify the indicator analysed and results should not be generalised further;
- Natural variability comprises some uncertainty. It is important to compare potential climate change impact and its uncertainty to uncertainty due to natural variability ;
- GCMs (downscaled with sophisticated or simple techniques) do not always accurately reproduce current climate (see the modelling of the current climate). Their ability to do so should be borne in mind when assessing climate change impact;
- For future projections, GCMs carry the largest uncertainty: it would be misleading to only undertake an impact study solely from outputs from one single GCM ;
- Downscaling uncertainty can be significant: statistical methods compensate for modelling errors in the current climate, but the assumptions they are based upon may not remain true in the future; dynamical models cater for changes in the atmospheric processes producing precipitation, but retaining potential bias in the model;
- Uncertainty in the emission scenarios is the smallest of the GCM-associated uncertainties. Instead of undertaking impact studies with several scenarios from different emission assumptions but the same GCM (e.g. UKCIP02 scenarios), it would be preferable to use different GCM outputs under the same emission assumption, to carry more of the uncertainty surrounding future climate projections.

In this study, the hydrological model parameters were assumed to remain valid under changing climatic conditions, and the same sets used both for current and future simulations. However, there is concern that this assumption may not be true under drier, hotter conditions where the soil moisture deficit may be aggravated and hence hydrological processes modified. This was not tackled by the study, firstly because of the absence of available records long enough to show different periods with significantly different climate characteristics for two parameter sets to be calibrated; secondly because the analysis focused on comparing GCMs uncertainty with natural variability under current conditions, and how GCM uncertainty is projected to vary in the future, all the rest being equal.

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Captions

Fig. 1. Schematic diagram of graph of the suite of scenarios considered in the study to define each uncertainty

Fig. 2. Uncertainty in mean annual flow ANN for baseline climate due to hydrological modelling (3 boxes in right-hand side), climate variability and downscaling (baseline-marked scenarios), and for future projections 2080s due to GCMs (all 2080s scenarios), downscaling (HadCM3, HadRM3 and UKCIP02 scenarios) and emission scenarios (legend with A2 and B2 scenarios). Box plots show (from bottom to top) the 5th (lower whisker), 25th (lower limit of black box), 75th (higher limit of black box) and 95th (higher whiskers) percentiles. The black box contains 50% of the simulations around the median.

Fig. 3. Uncertainty in Q95 for baseline climate due to hydrological modelling (3 boxes in right-hand side), climate variability and downscaling (baseline-marked scenarios), and for future projections 2080s due to GCMs (all 2080s scenarios), downscaling (HadCM3, HadRM3 and UKCIP02 scenarios) and emission scenarios (legend with A2 and B2 scenarios). Box plots as in Fig. 2

Fig. 1

Downscaling Methods/ GCM	Dynamical	SDSM						Factor			
	HadRM3	HadCM3		CCGCM2		CSIRO-Mk2		HadRM3			
SRES Emission scenarios	A2	A2	B2	A2	B2	A2	B2	A1	A2	B1	B2
No. runs	1	20	20	20	20	20	20	1	1	1	1
No. resampling	100	5 (x20)	5 (x20)	5 (x20)	5 (x20)	5 (x20)	5 (x20)	1	1	1	1
Total no. scenario	100	100	100	100	100	100	100	1	1	1	1

Fig. 2

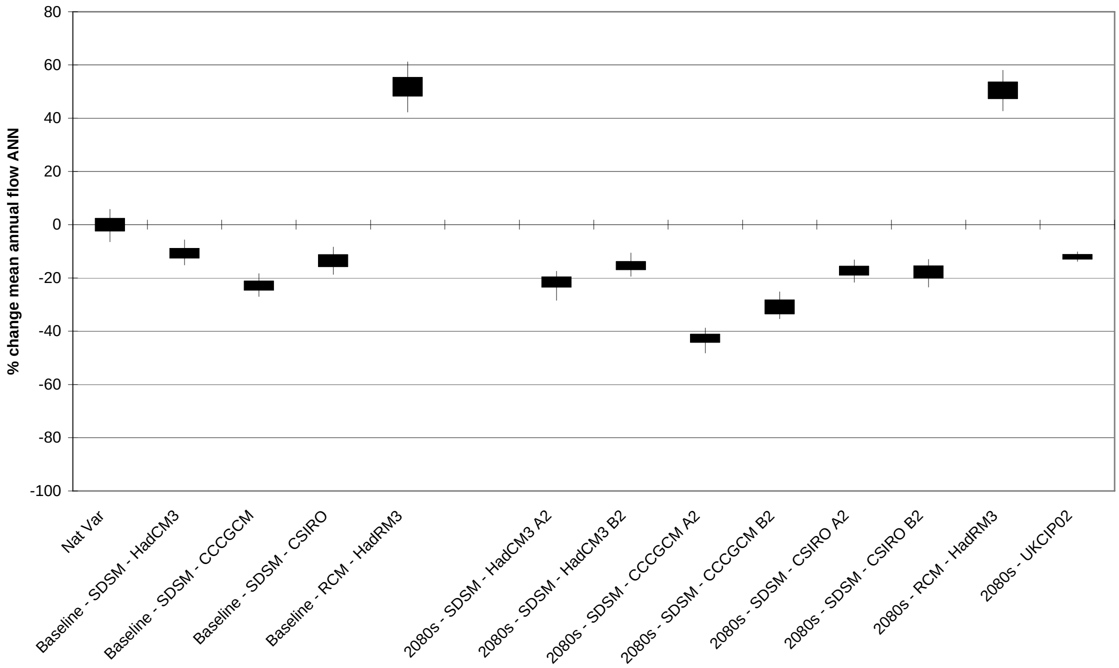
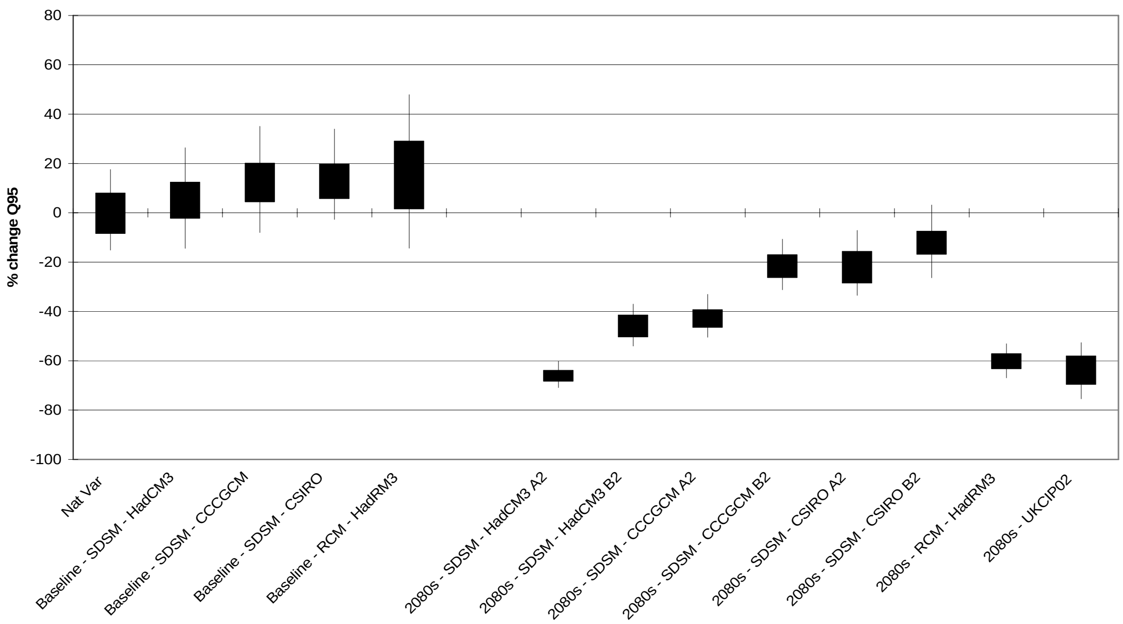

% change mean annual flow ANN
80
60
40
20
0
-20
-40
-60
-80
-100
Nat Var
Baseline - SDSM - HadCM3
Baseline - SDSM - CCCGCM
Baseline - SDSM - CSIRO
Baseline - RCM - HadRM3
2080s - SDSM - HadCM3 A2
2080s - SDSM - HadCM3 B2
2080s - SDSM - CCCGCM A2
2080s - SDSM - CCCGCM B2
2080s - SDSM - CSIRO A2
2080s - SDSM - CSIRO B2
2080s - RCM - HadRM3
2080s - UKCIP02

Fig. 3


% change Q95
80
60
40
20
0
-20
-40
-60
-80
-100
Nat Var
Baseline - SDSM - HadCM3
Baseline - SDSM - CCCGCM
Baseline - SDSM - CSIRO
Baseline - RCM - HadRM3
2080s - SDSM - HadCM3 A2
2080s - SDSM - HadCM3 B2
2080s - SDSM - CCCGCM A2
2080s - SDSM - CCCGCM B2
2080s - SDSM - CSIRO A2
2080s - SDSM - CSIRO B2
2080s - RCM - HadRM3
2080s - UKCIP02