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Regional climate model data used within the SWURVE project 2: addressing uncertainty in regional climate model data for five European case study areas

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Abstract

To aid assessments of the impact of climate change on water related activities in the case study regions (CSRs) of the EC-funded project SWURVE, estimates of uncertainty in climate model data need to be developed. This paper compares two methods for estimating uncertainty in annual surface temperature and precipitation for the period 2070–2099. Both combine probability distribution functions for global temperature increase and for scaling variables (i.e. the change in regional temperature/precipitation per degree of global annual average temperature change) to produce a probability distribution for regional temperature and precipitation. The methods differ in terms of the distribution used for the respective probability distribution function. For scaling variables, the first method assumes a uniform distribution, whilst the second method assumes a normal distribution. For the probability distribution function of global annual average temperature change, the first method uses a uniform distribution and the second uses a log-normal approximation to a distribution derived from Wigley and Raper, 2001. Although the methods give somewhat different ranges of change, they agree on how temperature and precipitation in each of the CSRs are likely to change relative to each other. For annual surface temperature, both methods predict increases in all CSRs, although somewhat less so for NW England (5^{th} and 95^{th} percentiles vary between 1.1–1.9 °C to 3.8–5.7 °C) and about 1.7–3.1 °C to 5.3–8.6 °C for the others. For precipitation, most probability distributions (except for NW England) show predominantly decreasing precipitation, particularly so for the Iberian CSR (5^{th} and 95^{th} percentiles vary from –29.3 to –44 % to –9.6 to –4 %).

Keywords: uncertainty, regional climate model, temperature, rainfall, Europe

Introduction

As climate model projections are often used in climate change impact studies that may influence policy decisions within different socio-economic sectors, it is important to have some understanding of the uncertainties involved with climate model data (Webster *et al*., 2003). This is particularly true within the framework of the EU-funded project SWURVE, which is focused on the impacts of climate change on specific water management activities (Kilsby, 2007).

Uncertainties linked with climate projections stem from several different sources, e.g. uncertainty in estimates of emission scenarios, scientific uncertainty (due to inadequacies of the models) and uncertainty due to natural variability. The first category relates to the storylines upon which the rates of emission scenarios are based, i.e. descriptions of what a future world may look like in terms of population growth, economic development and technological change (see, for example, Nakicenovic, 2000, and Webster *et al*., 2002). The second group of uncertainties is due to the climate models, i.e. uncertainty in the present understanding of climate processes and how they are represented in global atmospheric and global coupled Atmosphere-Ocean General Circulation Models (AGCMs and AOGCMs) (Allen and Ingram, 2002; Collins and Allen, 2002; Jenkins and Lowe, 2003). Because individual modelling groups have used different formulations and often simplifications when representing physical processes, individual Global Circulation Models (GCMs) will have different strengths and weaknesses that lead to inter-model differences (Covey *et al*., 2003; Grotch and MacCracken, 1991; Lambert and Boer, 2001; Räisänen, 1997, 2001, 2002). Furthermore, when a GCM is combined with a regional climate model (RCM), systematic errors may be added as the climate of the RCM is affected by model resolution, numerical scheme and physical parameterisations and by the forcing boundary conditions (Rummukainen *et al*., 2001). These errors are difficult to quantify and few publications, (Moberg and Jones, 2004), are available on the subject. The uncertainty introduced by the RCM is, however, generally considered to be substantially smaller than that inherited by the driving GCM (Jenkins and Lowe, 2003). The last category of uncertainties, due to natural variability, represents the year-to-year and decade-to-decade variability due to the chaotic nature of the climate system. It also includes the impact on climate of changes in the output of the sun or changes in stratospheric aerosols due to volcanic activity (Jenkins and Lowe, 2003).

There are broadly two different ways in which to address uncertainty when working with forecast or predicted data. These are: scenario analysis (outcomes are given for a range of probable scenarios, e.g. the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) described in Nakicenovic and Swart (2000)) and uncertainty analysis (the outcomes are associated with specific probabilities, e.g. Jones (2000a,b); Wigley and Raper (2001); Forest *et al*. (2002) and Tebaldi *et al*. (2004, 2005). Whilst the scenario analyses explore a range of different views of the world with no attached likelihood, the uncertainty analyses quantify the likelihood for a particular variable to fall within a specified range.

In SWURVE, an uncertainty approach was chosen to estimate probability distributions associated with regional surface (1.5 m) temperature and precipitation for the future perturbed period 2070–2099. These two variables were used as input data for hydrological studies in five European case study regions (CSRs) (Kilsby *et al*., 2007). The choice of methodology was motivated by the wish to use a probabilistic approach for climate change impact assessments performed within the CSRs.

In this paper, two methods to estimate uncertainty for the two regional variables are described and compared. Both methods estimate the probability distribution for change in the regional variables by combining a probability density function for global temperature change (1961–1990 to 2070–2099), with a probability density function of the scaling variables (i.e. the change in regional temperature/ precipitation per degree of global temperature change) for the same period. The first approach follows the methodology outlined by Jones (2000a,b) (Method I). It uses a uniform shape for both probability density functions to represent the view that, because the probability density functions of the uncertainties are not known, a uniform distribution limited by an upper and lower limit is probably the most appropriate. The second method, developed by Hingray *et al*., (2007) (Method II) assumed the distribution of the scaling variable to be normal instead of uniform. Its variance is estimated by applying an ANalysis Of VAriance (ANOVA) to scaling variables calculated from a suite of 19 GCM-RCM experiments. A log-normal approximation to a distribution derived from Wigley and Raper (2001) is used for global temperature change. Examples using both methods are shown for each of the five SWURVE case study regions (CSRs) (Kilsby *et al*., 2007).

Climate model data

To estimate the uncertainty in the scaling variables for regional temperature and precipitation changes, a suite of RCM experiments (Table 1), forced by different GCMs (Table 2) is used. The RCM data were made available through the EC project PRUDENCE (Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects, Christensen *et al*., 2002). The individual RCMs have different integration domains and resolutions; however, within the PRUDENCE project, 30-year average seasonal grids were produced for the control (1961–1990) and future (2070–2099) simulations on a common European grid (0.5° latitude by 0.5° longitude) for each RCM. With one exception (ECHAM4/OPYC, Table 2) the GCMs used to provide the boundary conditions to the PRUDENCE RCMs were not coupled Atmosphere-Ocean GCMs but high resolution Atmospheric GCMs.

Using the seasonal PRUDENCE grids, annual averages of surface temperature and precipitation for the control and future simulations were calculated using only those grid boxes that covered each specific CSR: NW England, Rhine basin, the Iberian region, Jura lakes basin (Switzerland) and Mauvoisin dam (Switzerland). The extent of each CSR in the PRUDENCE regular grid is shown in Fig. 1.

The GCMs (and hence the RCMs) were forced using emissions scenarios from the IPCC SRES A2 and the B2 scenario (Nakicenovic and Swart, 2000). The two scenarios follow different storylines with respect to technological and economic growth in the world. The A2 storyline describes a heterogeneous world with strengthening of regional cultural identities, high population growth but with less concern for rapid economic development (Nakicenovic, 2000). The B2 storyline also describes a heterogeneous world, but emphasises local solutions to economic, social and environmental sustainability. It describes a less rapid but more diverse technological change compared to A2

Table 1. The modelling groups within the PRUDENCE project (Christensen *et al*., 2002) and the corresponding RCM.

Acronym	*Institution*	*RCM*	*Scenario*	*Reference*
CNRM	Centre National de Recherches Météorologiques, Toulouse, France	ARPEGE	A2 and B2	Gibelin and Déqué (2003)
DMI	Danish Meteorological Institute, Copenhagen, Denmark	HIRHAM	A2 and B2	Christensen *et al.* (2001)
ETHZ	Institute for Atmospheric and Climate Science, Zurich, Switzerland	CHRM	A2	Vidale *et al*. (2003)
GKSS	Institute for Coastal Research, Geesthacht, Germany	CLM	A2	Doms and Schättler (1999)
HC	Hadley Centre for Climate Prediction and Research, United Kingdom	HadRM3H	A2 and B2	Hulme *et al*. (2002)
ICTP	International Centre for Theoretical Physics, Trieste, Italy	RegCM	A2	Giorgi *et al*. (1993ab)
MPI	Max-Planck-Institut für Meteorologie, Hamburg, Germany	REMO	A2	Jacob (2001)
SMHI	Swedish Meteorological and Hydrological Institute, Norrköping, Sweden	RCAO(E)	A2 and B2	Räisänen *et al*. (2003)
UCM	Universidad Complutense de Madrid, Toledo, Spain	PROMES	A2 and B2	Arribas *et al*. (2003)

Table 2. Global average warming [°C] for the two SRES scenarios A2 and B2 obtained with the GCMs used in the PRUDENCE project (Christensen *et al*., 2002)

G*CM*	*Reference*	*ΔT-A2*	*ΔT-B2*
HadAM3H	Pope *et al*. (2000)	3.09	2.28
HadCM3	Gordon *et al*. (2000)	3.25	2.39
ARPEGE/OPA-SST	Gibelin and Déqué (2003)	3.02	2.35
ARPEGE/HadCM3-SST	Gibelin and Déqué (2003)	3.07	2.30
ECHAM4/OPYC3	Roeckner *et al*. (1999)	3.56	2.76

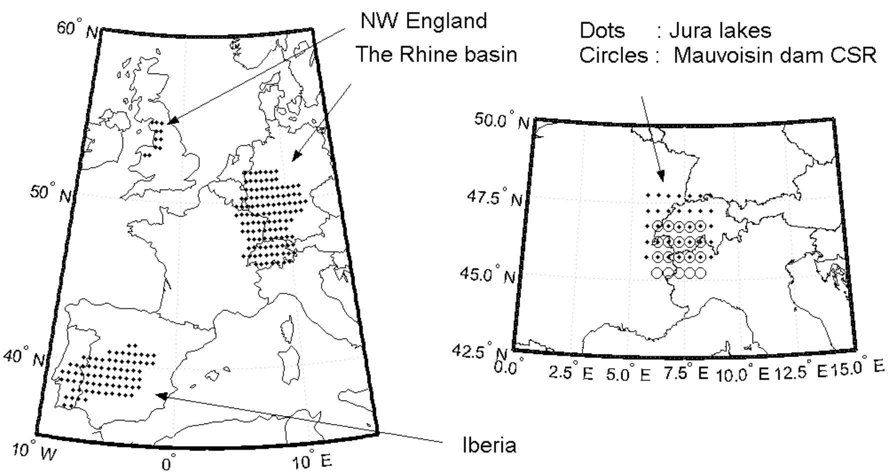

Fig. 1. *Positions of selected regional grids in the regular PRUDENCE grid (0.5° longitude by 0.5° latitude).*

storyline (Nakicenovic, 2000). In terms of emissions, an A2 world experiences larger emissions of greenhouse gases compared to B2, hence greater global temperature increase is associated with A2 than the B2 world. It should be noted that not all models were run for both scenarios. In the cases where only one integration experiment was completed, this generally used the A2 scenario.

The lower and upper limits of the uniform probability distribution function of global temperature change used in Method I were given by the range of annual global mean temperatures from the GCM experiments used to drive the PRUDENCE RCM experiments (Table 2). For comparison, a second uniform distribution was given by the projected IPCC range (IPCC, 2001). The first range includes five GCM experiments based on the A2 and B2 scenarios and is calculated from the difference between the future (2070–2099) and the control simulation (1961–1990) (2.28 to 3.56°C). The second range is derived from 35 SRES scenarios, based on the increase in global annual mean temperature from 1990 to 2100 as predicted from a number of GCMs (1.4 to 5.8°C). The latter range does not take into consideration the uncertainties in the modelling of radiative forcing (IPCC, 2001). The two ranges of future global temperature change are not directly comparable as the range obtained from IPCC experiments gives the increase from 1990 to 2100 rather than the difference between the future (2070–2099) and the control (1961–1990) period. Hence, the range given by the IPCC is larger, not only due to the inclusion of more scenarios and more GCMs but also due to the way in which the range was computed. For Method II, the probability distribution function of the 1990 to 2070–2100 global temperature change is given by a log-normal approximation to the Wigler and Raper (2001) distribution, which considers uncertainties in emissions, the climate sensitivity, the carbon cycle, ocean mixing and aerosol forcing (Hingray *et al*., 2007).

Assessing uncertainty of regional changes

To derive probability distributions for the change in regional annual surface (1.5 m) temperature [°C] and precipitation [%] between the control (1961–1990) and the future (2070–2099) simulation period a probability distribution function of global annual average temperature increase was combined with a PDF of change in regional temperature/precipitation per degree of global temperature increase (Jones, 2000a,b). The combination of the two probability distribution functions gives a total estimate of the uncertainties associated with climate simulations.

The suggested methodology assumes that a linear relationship exists between change in regional temperature/precipitation and change in global temperature, which allows for the creation of a scaling variable, giving the change in regional temperature/precipitation per degree global temperature change. Although a perfect linear relationship between regional variables and global temperature is unlikely to exist, Huntingford and Cox (2000) and Mitchell (2003) confirmed that many changes associated with mean surface climatology projected by climate models may be scaled by changes in global mean temperature. Scaling variables were also used in the UK climate impacts programme (Hulme et al., 2002) to derive climatologies for years between the 1990s and the 2070s, when global but not regional simulations were available. There may however be cause for concern if, within a case study area, different emission scenarios, e.g. A2 and B2, exhibit differently signed scaling ratios; however, this is not the case in any of the regions used here.

Assuming that the annual regional change in temperature or precipitation is zero for zero global-mean temperature increase, the scaling variables (δT [dimensionless] and δP [$°C^{-1}$] for regional temperature and precipitation respectively) were estimated using the following expressions:

$$\delta T = \Delta T_{reg.} \big/ \Delta T_{glob.} \tag{1}$$

where $\Delta T_{reg.} = T_{reg.fut.} - T_{reg.contr.}$
and

$$\delta P = \frac{\left(\left(P_{reg.fut.} \big/ P_{reg.contr.}\right) - 1\right)}{\Delta T_{glob.}} \tag{2}$$

where ΔT_{glob} is the global average temperature increase expressed in °C, and $T_{reg.contr}$, $T_{reg.fut}$, $P_{reg.contr}$, $P_{reg.fut}$, are the regional annual average temperature and precipitation for control and future simulation periods. Scaling variables were computed for all 19 GCM-RCM experiments (Table 1 and 2) for each of the five SWURVE CSRs (see range in scaling ratios for each CSR in Table 3).

The scaling variables were used in two different ways to estimate probability distributions for regional temperature and precipitation. The methods have varying degrees of complexity and make different assumptions with respect to the shape of the probability distribution functions that

Table 3. The range of the regional variable (annual mean surface temperature and seasonal mean daily precipitation total) per degree of global temperature change for each case study.

Case study region	*Local variable per degree of global temperature increase*			
	Temperature $[\Delta T_{reg}/\Delta T_{glob}]$		*Precipitation* $[\%P_{reg}/\Delta T_{glob}]$	
	Ann low	*Ann high*	*Ann low*	*Ann high*
NW England	0.7	1.2	-1.4	5
Rhine basin	1.0	1.7	-3.1	0.7
Iberia	1.2	1.7	-9.7	-3.1
Jura lake	1.0	1.8	-5.5	-0.1
Mauvoisin	1.0	1.8	-5.7	0.4

describe: (1) the global temperature change and 2) the scaling variables for regional temperature and precipitation changes. Descriptions of the methods are provided here, with examples of the probability distributions for the regional variables for each of the European CSRs.

METHOD I

In Jones (2000a,b) two uniform distributions (for global annual average temperature change and for the scaling variables) are combined to give a peaked distribution. The uniform distribution is used to represent the view that current knowledge does not allow the creation of accurate estimates of the uncertainties surrounding regional and global climate data. Because the distributions of the uncertainties are unknown, a uniform distribution, limited by upper and lower bounds, is probably appropriate.

To estimate the probability distributions for annual regional surface temperature, 50 000 values were sampled randomly (assuming a uniform distribution) within the minimum and maximum values of absolute change in regional temperature per degree of global annual average temperature change for each case study area (see limit values in Table 3). These were then multiplied with 50 000 values sampled randomly (assuming a uniform distribution) within the two global ranges to produce probability distributions for the change in annual regional temperature. The same procedure was repeated for precipitation but this time percent change was used as the unit for the regional variable rather than the absolute difference, as used for the regional temperature.

METHOD II

Here, the distribution of each scaling variable is assumed to be normal. The selection of distribution was based on the spread of the residuals from the mean value of the 19 GCM-RCM combinations. This procedure relies on the assumptions that all available GCM-RCM experiments are equally skilful and that increased confidence can be given to scaling values that tend to be similar. To find the variance parameter for the normal distribution, an unbalanced Analysis of Variance was applied to the 19 scaling values derived from the PRUDENCE dataset. Each scaling variable is assumed to have the following expression:

$$y_{ij} = \mu + a_i + b_j + e_{ij} \quad \begin{cases} i = 1,2,\ldots,A \\ j = 1,2,\ldots,B \end{cases} \tag{3}$$

with A the number of 'emission-scenario GCM' configurations (A=6 in the present study), B the number of RCMs in the PRUDENCE ensemble (B=10), μ an unknown constant, a_i a deviation related to the particular "emission-scenario GCM" configuration, b_j a deviation associated with the RCM, and e_{ij} a noise term that accounts for the natural variability of a 30-year mean. The three random variables on the right-hand side of Eqn. (3) are assumed to have zero mean and variances σ_a^2, σ_b^2 and σ_e^2, respectively. Assuming that these variables are independent, the variance σ_y^2 of y is given by:

$$\sigma_y^2 = \sigma_a^2 + \sigma_b^2 + \sigma_e^2 \tag{4}$$

Equation (3) represents a two-way crossed classification (Searle, 1977). A specific ANOVA framework was developed by Hingray *et al*. (2007) to account for the dependence of σ_e^2 to the global temperature change ΔT and the correlation between the e_{ij}. This correlation results from the strong correlation between annual temperatures (resp. annual precipitation) from two different RCMs driven by the same GCM boundaries. The mean scaling ratio m, the variance components and the correlations between the e_{ij} are estimated as described in Appendix A and Appendix B of Hingray *et al*. (2007).

The mean value (μ), and a pooled estimate of the total variance (σ_y^2) of the scaling variables are given for each CSR in Table 4. A mean scaling value for regional temperature greater than 1 indicates that regional annual average temperature change is expected to be greater than

Table 4. Mean scaling variable (μ) and total variance (σ_y^2) for annual regional surface temperature and precipitation for the SWURVE CSRs.

	Regional temperature change per degree global temperature increase				
	NW England	*Rhine*	*Iberia*	*Jura lakes*	*Mauvoisin*
μ [dimensionless]	0.89	1.239	1.351	1.308	1.331
σ_y^2 [dimensionless]	0.041	0.061	0.041	0.061	0.055
	Regional precipitation change per degree global temperature increase				
	NW England	*Rhine*	*Iberia*	*Jura lakes*	*Mauvoisin*
μ [°C^{-1}]	0.0109	-0.0135	-0.0671	-0.0229	-0.0257
σ_y^2 [°C^{-2}]	0.00034	0.00023	0.00063	0.00034	0.00039

the global annual average temperature increase (all regions except NW England in Table 4). For precipitation, negative mean scaling ratios indicate decreasing regional precipitation with increasing global annual average temperatures (all regions except NW England in Table 4). The variance of the scaling relationships indicates the spread of results amongst the RCM experiments. The variance is particularly large for precipitation; thus, although the mean scaling ratio is often negative, positive scaling ratios are also possible.

For each SWURVE CSR, the probability distribution function of regional change is obtained via 50 000 Monte Carlo simulations from the log-normal approximation of the global mean warming distribution derived from Wigley and Raper (2001) and the probability distribution for the scaling ratio.

Uncertainty estimates for regional variables

Probability distributions were constructed for the future change in annual regional surface (1.5 m) temperature [°C] and annual precipitation [%] for each of the five CSRs (Figs. 2–4). In total, three sets of probability distributions were produced: two sets were produced using Method I and one set using Method II. The two Method I approaches are henceforth referred to as Method Ia (global temperature increase in the range from Table 2: 2.28 to 3.56 °C) and Ib (global temperature increase in the range from IPCC (2001): 1.4 to 5.8 °C) to differentiate between their respective results.

Graphs illustrating the probability distribution for regional annual temperature and precipitation are displayed as occurrences in 5% increments of the total range (Figs. 2–

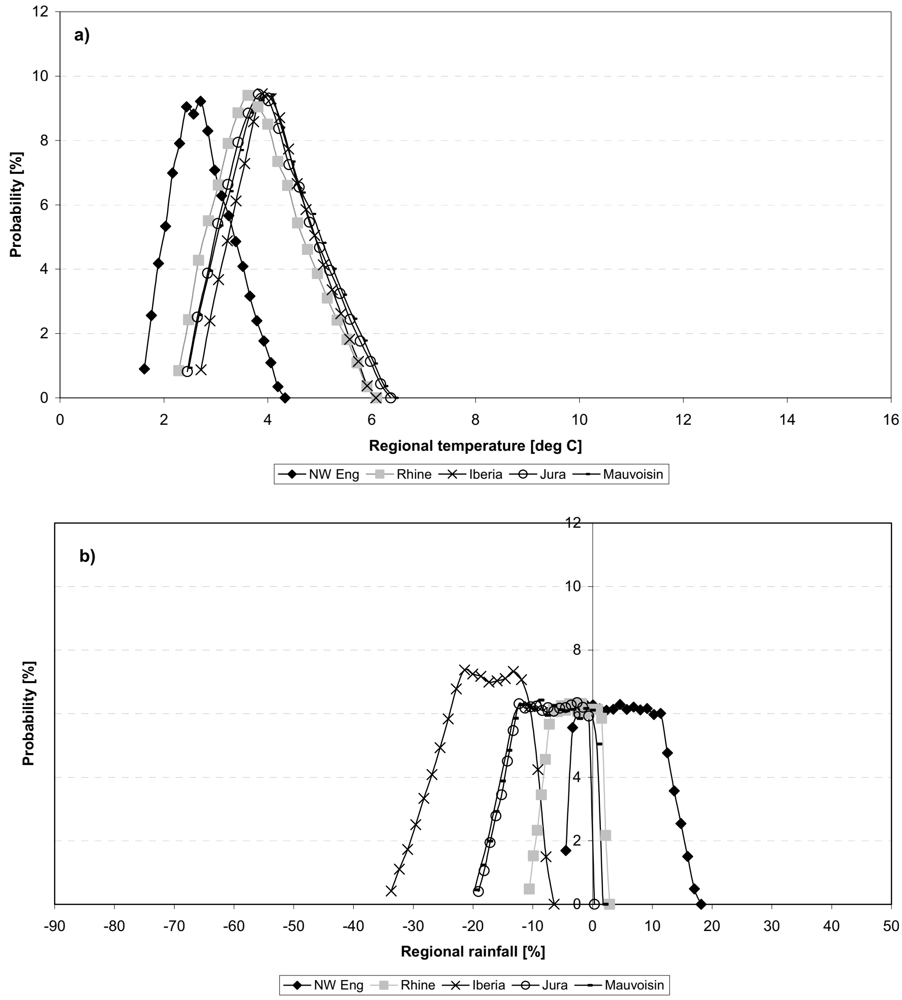

Fig. 2. *Probability distributions for (a) annual regional temperature and (b) precipitation in the SWURVE case study areas. The plots show the probability of occurrence in 5% increments (see percentiles in Table 5). The markers show the mid-value of the increment and the line is a visual aid indicating the trend. The ranges of the respective regional components are found in Table 3 and the range of global temperature increase is 2.28 to 3.56 °C (Table 2).*

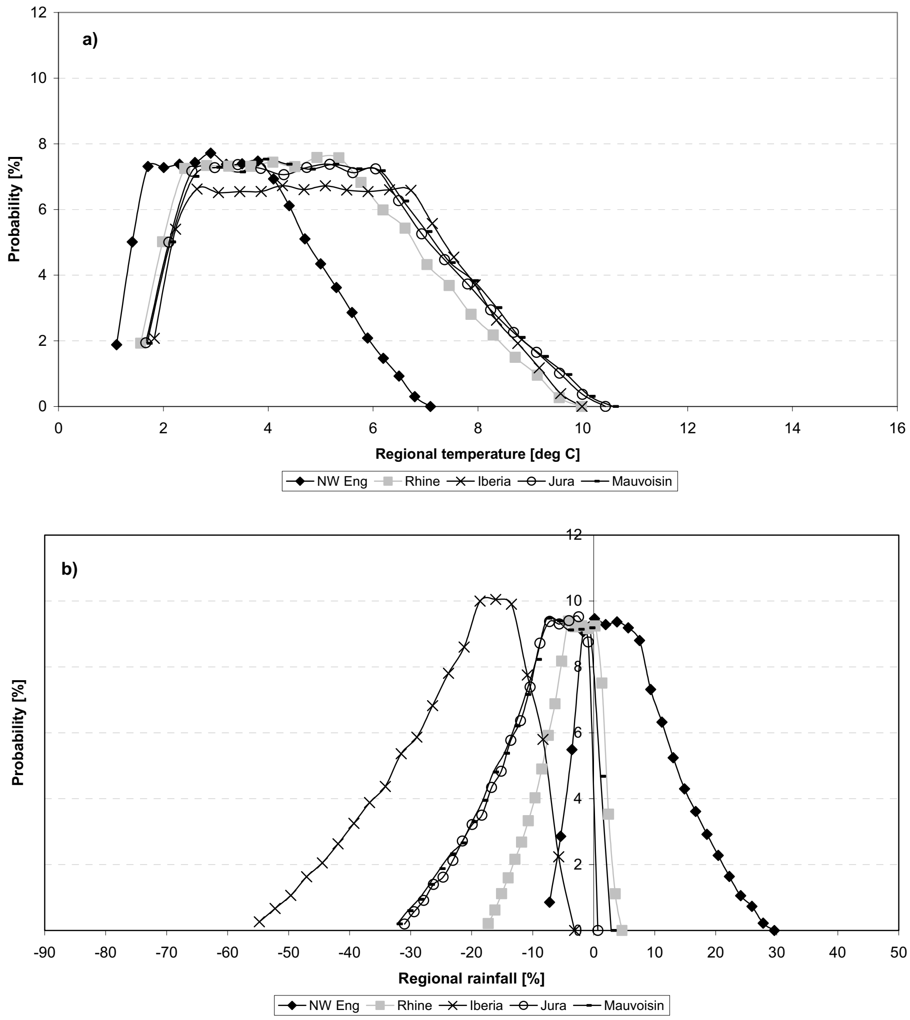

Fig. 3. *Probability distributions for (a) annual regional temperature and (b) precipitation in the SWURVE case study areas. The plots show the probability of occurrence in 5% increments (see percentiles in Table 5). The markers show the mid-value of the increment and the line is a visual aid indicating the trend. The ranges of the respective regional components are found in Table 3 and the range of global temperature increase is 1.4 to 5.8°C (IPCC, 2001).*

4). The 1st, 5th, 50th, 95th and 99th percentiles for each probability distribution are given in Table 5.

REGIONAL TEMPERATURE

The projected changes for annual regional temperature are similar for all CSRs except for NW England (Figs. 2a, 3a and 4a). The generally lower and narrower range of the NW England probability distribution is evident when comparing the 5th and 95th percentiles of the three methods. For this region, for Method Ia, Method Ib and Method II, the percentiles are, respectively: 1.9 and 3.8°C / 1.5 and 5.7°C / 1.1 and 4.2°C; for the rest of the CSRs the same percentiles are approximately 2.9 and 5.5°C/ 2.2 and 8.4°C/ 1.8 and 6°C (Table 5). Whilst the distributions using Method Ia and Method II peak about 2.5°C/2°C for NW England and about 4°C/ 3.5°C for the rest of the CSRs, the distributions using Method Ib have a flattened top between 1.5 to 4°C for NW England and about 2 to 6.5°C for the rest of the CSRs. The flattening of the temperature distributions is a direct result of combining a large uniform range (the global range) with a smaller uniform range (the regional range).

In short, in all CSRs, regional temperature is expected to rise, but less so for NW England. The uncertainty, given by the probability distributions, is similar for all CSRs with only NW England showing a somewhat smaller range in projected change. The mean and variance of the scaling ratios (Table 4) suggests that the RCMs are in overall agreement concerning the future change in regional annual temperatures.

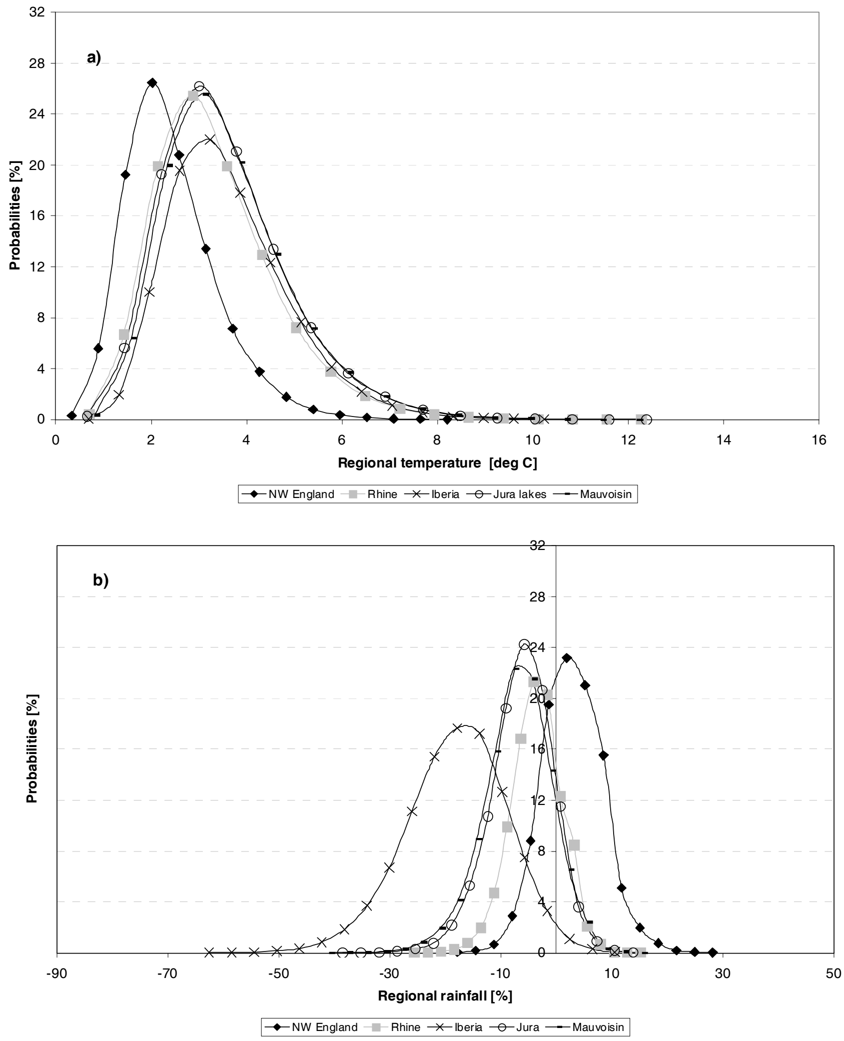

Fig. 4. *Probability distributions given by Method II for (a) regional temperature and (b) regional precipitation in the SWURVE case study areas. The plots show the probability of occurrence in 5% increments (see percentiles in Table 5). The markers show the mid-value of the increment and the line is a visual aid indicating the trend. Increments associated with less than 0.01 probability of occurrence are removed from the plot. PDFs were obtained from 50 000 Monte-Carlo simulations where the scaling ratio was randomly selected from its normal PDF and where the global temperature increase was randomly selected from the Wigley and Raper PDF (Wigley and Raper, 2001). The mean scaling ratio and its variance are found for each regional variable in Table 4.*

REGIONAL PRECIPITATION

The graphs of probability distributions for annual change in regional precipitation show larger differences amongst the CSRs compared to the distributions for the regional temperature (Figs. 2b, 3b and 4b). The relative order of change amongst the CSRs is, however, similar across all methods. The two Swiss areas show almost the same distributions; with Method Ia and Ib, the distributions indicate mainly decreased precipitation (5th and 95th percentiles for Ia/Ib are, on average: –16.3/–24% and –0.4/ 0.5%, Table 5) whilst Method II suggests a somewhat more positively skewed distribution (the 5th and 95th percentiles are, on average: –17% and 2%, Table 5). The distribution for the Rhine basin is narrower than that for the Swiss CSRs (probably because it is a much larger region) (the 5th and 95th percentiles for Method Ia/Ib/II are: –8.8/–12.7/–11% and 1.5/1.8/3%, Table 5), indicating a smaller reduction in future rainfall. The NW England differs from the rest in being the only distribution with a likely positive increase, particularly so for Method Ia and Ib (the 5th and 95th percentiles for Method Ia/Ib/II are: –3.2/–3.9/–6% and 14/ 20.2/12%, Table 5). The largest decrease in annual rainfall is evident in the probability distributions for Iberia (the 5th and 95th percentiles for Method Ia/Ib/II are: –29.3/–44/ –34% and –9.6/–8.4/–4%, Table 5).

Hence, most regions, except for NW England, predict a

Table 5. Probability distributions (1st, 5th, 50th, 95th and 99th percentile) for change in annual regional temperature and precipitation in the SWURVE case study areas between control (1961-1990) and future (2070-2099) simulations. Probability distributions are calculated using Method I (a: range of global temperature increase provided by the GCMs in Table 2, b: range of global temperature increase provided by IPCC (2001)), and Method II. The distributions are based on 50 000 randomly sampled values.

Case study region	*Temperature [°C]*					*Precipitation [%]*				
	P1	*P5*	*P50*	*P95*	*P99*	*P1*	*P5*	*P50*	*P95*	*P99*
METHOD IA										
NW England	1.7	1.9	2.7	3.8	4.0	-4.1	-3.2	5.0	14.0	16.0
Rhine	2.4	2.7	3.8	5.3	5.7	-10.0	-8.8	-3.4	1.5	2.1
Iberia	2.8	3.1	4.1	5.4	5.7	-32.2	-29.3	-18.5	-9.6	-8.2
Jura lakes	2.6	2.8	4.0	5.5	6.0	-18.0	-16.1	-8.0	-1.0	-0.4
Mauvoisin	2.6	2.9	4.1	5.6	6.0	-18.6	-16.5	-7.8	0.2	0.8
METHOD IB										
NW England	1.2	1.5	3.3	5.7	6.4	-6.2	-3.9	5.4	20.2	24.9
Rhine	1.6	2.1	4.7	8.1	9.0	-15.4	-12.7	-3.7	1.8	3.0
Iberia	1.9	2.3	5.1	8.3	9.1	-50.8	-44.0	-21.2	-8.4	-6.1
Jura lakes	1.8	2.2	4.9	8.5	9.5	-28.3	-23.7	-8.7	-1.1	-0.4
Mauvoisin	1.8	2.2	5.0	8.6	9.6	-29.1	-24.3	-8.4	0.2	1.1
METHOD II										
NW England	0.8	1.1	2.3	4.2	5.4	-9	-6	3	12	17
Rhine	1.2	1.7	3.2	5.8	7.4	-15	-11	-4	3	6
Iberia	1.5	1.9	3.4	6	7.4	-42	-34	-18	-4	2
Jura lakes	1.3	1.8	3.3	6.1	7.6	-22	-16	-6	2	6
Mauvoisin	1.4	1.8	3.4	6.1	7.7	-24	-18	-7	2	6

general decrease in regional precipitation. The width of the probability distribution suggests that uncertainty is largest for Iberia (particularly at the negative end of the distribution), followed by the two Swiss CSRs and NW England, with the narrowest distribution being that for the Rhine basin (the largest region). The relatively large differences in range between the probability distributions indicate less relative agreement between models with respect to change in regional precipitation compared to change in regional temperature.

Discussion and conclusions

Two methods were applied to five CSRs to estimate uncertainty associated with RCM data (annual average surface temperature and precipitation) in the SWURVE CSRs. The methods are similar in the sense that they combine a probability distribution function for change in the regional variable per degree of global temperature change with a probability distribution function for global temperature increase to derive a probability distribution of the regional variable. The combination of probability distribution functions produces a probability distribution that incorporates (i) uncertainty due to spread in global temperature increase amongst different GCMs, (ii) uncertainty due to different RCM parameterisations and (iii) uncertainty in future emissions. Method II additionally accounts for a random natural variability component. Communal assumptions on which both methods rely are (1) the existence of a linear relationship between global temperature increase and regional changes in temperature and precipitation and (2) that global warming and scaling variables can be described by two independent random variables. These are strong assumptions and more GCM-RCM experiments are required to investigate their validity. Although the methods share these basic assumptions, there are also some fundamental differences between them.

While Method I assumes uniformly distributed probability distribution functions, Method II combines a normal (for the scaling variable) with a log normal (for the global temperature change) distribution to produce probability distributions for the regional variables. The choice of distribution reflects two different views of the GCM and RCM data. While a shaped distribution assumes that some outcomes are more likely than others, the uniform distribution states that each outcome has the same likelihood. In Jones (2000 a,b), the choice of a uniform distribution followed recommendations by the Climate Impact Group of CSIRO Atmospheric Research (Jones, 2000a). To avoid central tendencies (which looks too much like a prediction) and because of a lack of knowledge of the probability distribution function of uncertainties, CSIRO recommends the use of an upper and lower limit of regional projections in impact studies. Similar recommendations are given by Nakicenovic (2000) who suggests that the broad range of alternatives presented by future scenarios cannot be represented by a single or even by a set of scenarios.

In Method II, however, non-uniform distributions were used to estimate the probability distribution for the regional variables. Unlike Method I, the underlying assumption for Method II is that the likelihood of outcomes can be derived from the relative agreement between outcomes of available climate experiments; hence, it is possible to estimate a non-uniform probability distribution function for regional change per degree of global temperature increase from RCM and GCM data. This approach is in accord with that of Giorgi and Mearns (2002), who suggest that, using available GCM data, it is possible to assess the reliability of the projected regional climate. Giorgi and Mearns (2002) used two reliability criteria: the performance of the model in representing present-day climate and the convergence of the simulated changes across models. This view is based on the assumption that increased confidence in simulated regional climate changes is justified if the models are in agreement, particularly if it is maintained under different forcing scenarios (Giorgi *et al*., 2001).

It is not possible to say whether one method is more correct than the other; Method I is more conservative and is sometimes difficult to assess when the distributions exhibit a flat top. It is, however, less influenced by central tendencies amongst the models as it treats all outcomes within the uniform range as equally plausible. Method II, on the other hand, produces probability distributions with clear indications of ranges with increased likelihoods. Although the distributions of Method II may be easier to implement in impact studies, it is highly conditioned on the shape and parameters of the distribution used to describe the scaling variables derived from the available GCM-RCM experiments.

It should be noted that the probability distributions developed here are based on a relatively small number of GCMs; this is likely to cause an underestimation of the uncertainty, as the driving model is generally assumed to contribute the largest portion of the uncertainty (Jenkins and Lowe, 2003). Furthermore, only the two SRES scenarios representing the medium to high and the medium to low scenarios were available. This suggests that uncertainty could be larger if experiments with other more extreme (but equally plausible) scenarios had been available. Finally, even if a broad range of scenarios were used, the uncertainty would probably still be underestimated because GCMs are generally designed as 'best guess' representations of the system, giving a clustering of model results towards the centre of the range of physically plausible behaviour (Allen and Ingram, 2002). Hence, the spread of response in climate models is not a direct measure of uncertainty in climate forecasts (Allen and Ingram, 2002). Nevertheless, even if the probability distributions of regional change in temperature and precipitation are likely to be conservative, they provide some guidance on the spread in response that may be expected from a future climate. While both methods agree on how temperature and precipitation in the CSRs are likely to change in a future climate, they differ slightly in terms of the magnitude of the projected change, where somewhat larger differences amongst the methods are shown for precipitation rather than temperature (Table 5).

For temperature, all methods predict increases for all CSRs, although these are somewhat less for NW England. The smallest ranges between the 5th and the 95th percentile are given by Method Ia, which reflects the smaller range of the probability distribution function of global temperature increase compared to the other two approaches. Overall, larger regional temperature changes are predicted using Method Ib rather than Method II, because of the use of uniform distributions. As lesser weight is given to RCM-GCM combinations that project extreme regional changes in Method II rather than in Method I, differences between the methods are greater at higher percentiles.

For precipitation, the probability distributions range from negative to positive percent change, indicating that regional increases or decreases are possible in all CSRs. However, because most distributions (except NW England) show predominantly negative percent changes, decreases are more likely than increases, particularly for Iberia with a median value of –18.5% (Method Ia),–21.2% (Method Ib) and –18% (Method II) (Table 5).

For all methods, the probability distributions indicate that the range of uncertainty with respect to annual regional temperature is smallest for the NW England CSR (the other CSRs have similar ranges). For annual regional precipitation the variation is greater but the smallest range is the Rhine basin (the largest region) followed by the two Swiss CSRs, NW England and Iberia.

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References

Allen, M.R. and Ingram, W.J., 2002. Constraints on future changes in climate and the hydrologic cycle, *Nature*, **419**, 224–232.

Arribas, A., Gallardo, C., Gaertner, M.A. and Castro, M., 2003. Sensitivity of the Iberian Peninsula climate to a land degradation. *Clim. Dynam*., **20**, 477–489.

Christensen, J.H., Räisänen, J., Iversen, T., Bjørge, D., Christensen, O.B. and Rummukainen, M., 2001. A synthesis of regional climate change simulations - a Scandinavian perspective. *Geophys. Res. Lett*., **28**, 1003–1006.

Christensen, J.H., Carter, T.R. and Giorgi, F., 2002. PRUDENCE employs new methods to assess European climate change. *EOS*, AGU, **83**, 147.

Collins, M. and Allen, M.R., 2002. Assessing the relative roles of initial and boundary conditions in interannual to decadal Climate predictability. *J. Climate*, **15**, 3104–3109.

Covey, C., AchutaRao, K.M., Cubasch, U., Jones, P., Lambert, S.J., Mann, M.E., Phillips, T.J. and Taylor, K.E., 2003. An overview of results from the Coupled Model Intercomparison Project, *Global Planet. Change*, **37**, 103–133.

Doms, G. and Schättler, U., 1999. *The Nonhydrostatic Limited-Area Model LM (Lokal-Modell) of DWD, Part I: Scientific Documentation*. Deutscher Wetterdienst, Geschäftsbereich Forschung und Entwicklung.

Forest, C.E., Stone, P.H., Sokolov, A.P., Allen, M.R. and Webster, M.D., 2002. Quantifying uncertainties in climate system properties with the use of recent climate observations. *Science*, **295**, 113–117.

Gibelin, A.L. and Déqué, M., 2003. Anthropogenic climate change over the Mediterranean region simulated by a global variable resolution model. *Clim. Dynam.*, **20**, 327–339.

Giorgi, F., and Mearns, L., 2002. Calculation of average, uncertainty range and reliability ensemble averaging (REA) method. *J. Climate*, **15**, 1141–1158.

Giorgi, F., Marinucci, M.R. and Bates, G.T., 1993a. Development of a second generation regional climate model (REGCM2). Part I: Boundary layer and radiative transfer processes. *Mon. Weather Rev.*, **121**, 2794–2813.

Giorgi, F., Marinucci, M.R., Bates, G.T. and DeCanio, G., 1993b. Development of a second generation regional climate model (REGCM2). Part II: Cumulus cloud and assimilation of lateral boundary conditions. *Mon. Weather Rev*., **121**, 2814–2832.

Giorgi, F., Whetton, P.H., Jones, R.G., Christensen, J.H., Mearns, L., Hewitson, B., von Storch, H., Fransixo, R. and Jack, C., 2001. Emerging patterns of simulated regional climatic changes for the 21st century due to anthropogenic forcings. *Geophys. Res. Lett*., **28**, 3317–3320.

Gordon, C., Cooper, C., Senior, C.A, Banks, H.T., Gregory, J.M., Johns, T.C., Mitchell, J.F.B. and Wood, R.A., 2000. The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Clim. Dynam*., **16**, 147–168.

Grotch, S.L. and MacCracken, M.C., 1991. The use of general circulation models to predict regional climate change. *J. Climate*, **4**, 286–303.

Hingray, B., Mezghani, A. and Buishand, A., 2007. Development of probability distributions for regional climate change from uncertain global mean warming and an uncertain scaling relationship. *Hydrol. Earth Syst. Sci*. **11**, 1097–1114.

Hulme, M., Jenkins, G.J., Lu, X., Turnpenny, J.R., Mitchell, T.D., Jones, R.G., Lowe, J., Murphy, J.M., Hassell, D., Boorman, P., McDonald, R. and Hill, S., 2002. *Climate change scenarios for the United Kingdom: the UKCIP02 scientific report*. Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK, 120pp.

Huntingford, C. and Cox, P.M., 2000. An analogue model to derive additional climate change scenarios from existing GCM simulations. *Clim. Dynam*., **16**, 575–586.

Huntingford, C., Jones, R.G., Prudhomme, C., Lamb, R., Gash, J.H.C. and Jones, D.A., 2003. Regional climate-model predictions of extreme rainfall for a changing climate. *Quart. J. Roy. Meteorol. Soc*., **129**, 1607–1621.

IPCC, 2001. *Climate change 2001: the scientific basis. Summary for policymakers and technical summary of the working group 1.* Intergovernmental Panel on Climate Change 2001, 98pp.

Jacob, D., 2001. A note to the simulation of the annual and inter-annual variability of the water budget over the Baltic Sea drainage basin. *Meteorol. Atmos. Phys*., **77**, 61–73.

Jenkins, G. and Lowe, J. 2003. *Handling uncertainties in the UKCIP02 scenarios of climate change.* Hadley Centre Technical note 44, UK Met Office.

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

Jones, R.N., 2000b. Managing uncertainty in climate change projections - issues for impact assessments. *Climatic Change*, **45**, 403–419.

Kilsby, C., 2007. Sustainable water: uncertainty risk and vulnerability in Europe. *Hydrol. Earth Syst. Sci*., **11**, 1065–1068.

Lambert, S.J. and Boer, G.J., 2001. CMIP1 evaluation and intercomparison of coupled climate models. *Clim. Dynam*., **17**, 83–106.

Mitchell, T.D., 2003. Pattern scaling. *Climatic Change*, **60**, 217–242.

Moberg, A. and Jones, P.D., 2004. Regional climate model simulations of daily maximum and minimum near-surface temperatures across Europe compared with observed station data 1961–1990. *Clim. Dynam*., **23**, 695–715.

Nakicenovic, N., 2000. Greenhouse gas emissions scenarios. *Technol. Forecast. Soc. Change,* **65**, 149–166.

Nakicenovic, N. and Swart, R. (Eds.), 2000. *Special report on emissions scenarios.* Cambridge University Press, Cambridge.

Pope, V.D., Gallani, M.L., Rowntree, P.R. and Stratton, R.A., 2000. The impact of new physical parameterizations in the Hadley Centre climate model: HadAM3*, Clim. Dynam.*, **16**, 123–146.

Roeckner, E., Bengtsson, L., Feichter, J., Lelieveld, J. and Rodhe, H., 1999. Transient climate change simulations with a coupled atmosphere-ocean GCM including the tropospheric sulphur cycle. *J. Climate*, **12**, 3004–3032.

Rummukainen, M., Räisänen, J., Bringfelt, B., Ullerstig, A., Omstedt, A., Willen U., Hansson, U., and Jones C., 2001. A regional climate model for northern Europe: model description and results from the downscaling of two GCM control simulations. *Clim. Dynam.*, **17**, 339–359.

Räisänen, J., 1997. Objective comparison of patterns of CO_2 induced climate change in coupled GCM experiments. *Clim. Dynam.*, **13**, 197–211.

Räisänen, J., 2001. CO_2-induced climate change in CMIP2 experiments: Quantification of agreement and role of internal variability. *J. Climate*, **14**, 2088–2104.

Räisänen, J., 2002. CO_2-induced changes in interannual temperature and precipitation variability in 19 CMIP2 experiments. *J. Climate*, **15**, 2395–2411.

Räisänen, J., Hansson, U., Ullerstig, A., Döscher, R., Graham, L.P., Jones, C., Meier, M., Samuelsson, P. and Willén, U., 2003. GCM driven simulations of recent and future climate with the Rossby Centre coupled atmosphere – Baltic Sea regional climate model RCAM. *SMHI Reports Meteorology Climatology*, *101*.

Searle, S.R., 1997. *Linear Models*. Wiley, New York, USA.

Tebaldi, C., Mearns, L.O., Nychka, D. and Smith, R.L., 2004. Regional probabilities of precipitation change: A Bayesian analysis of multimodel simulations. *Geophys. Res. Lett.*, **31**, Art. No. L24213.

Tebaldi, C., Smith, R.L., Nychka, D. and Mearns, L.O., 2005. Quantifying uncertainty in projections of regional climate change: a Bayesian approach to the analysis of multimodel ensembles. *J. Climate*, **18**, 1524–1540.

Vidale, P.L., Lüthi, D., Frei, C., Seneviratne, S. and Schär, C., 2003. Predictability and uncertainty in a regional climate model. *J. Geophys. Res*., **108 (D18)**, 4586, doi: 10.1029/2002JD002810.

Webster, M.D., Babiker, M., Mayer, M., Reilly, J.M., Harnisch, J., Hynman, R., Sarofim, M.C. and Wang, C., 2002. Uncertainty in emissions projections for climate models. *Atmos. Environ*., **36**, 3659–3670.

Webster, M., Forest, C., Reilly, J., Babiker, M., Kicklichter, D., Mayer, M., Prinn, R., Sarofim, M., Sokolov, A., Stone, P. and Wang, C., 2003. Uncertainty analysis of climate change and policy response. *Climatic Change*, **61**, 295–320.

Wigley, T.M.L. and Raper, S.C.B., 2001. Interpretation of high projections for global-mean warming. *Science*, **293**, 451–454.