

# GCM-based regional temperature and precipitation change estimates for Europe under four SRES scenarios applying a super-ensemble pattern-scaling method

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**Abstract** Seasonal GCM-based temperature and precipitation projections for the end of the 21st century are presented for five European regions; projections are compared with corresponding estimates given by the PRUDENCE RCMs. For most of the six global GCMs studied, only responses to the SRES A2 and B2 forcing scenarios are available. To formulate projections for the A1FI and B1 forcing scenarios, a super-ensemble pattern-scaling technique has been developed. This method uses linear regression to represent the relationship between the local GCM-simulated response and the global mean temperature change simulated by a simple climate model. The method has several advantages: e.g., the noise caused by internal variability is reduced, and the information provided by GCM runs performed with various forcing scenarios is utilized effectively. The super-ensemble method proved especially useful when only one A2 and one B2 simulation is available for an individual GCM. Next, 95% probability intervals were constructed for regional temperature and precipitation change, separately for the four forcing scenarios, by fitting a normal distribution to the set of projections calculated by the GCMs. For the high-end of the A1FI uncertainty interval, temperature increases close to 10°C could be expected in the southern European summer and northern European winter. Conversely, the low-end warming estimates for the B1 scenario are  $\sim 1^\circ\text{C}$ . The uncertainty intervals of precipitation change are quite broad, but the mean estimate is one of a marked increase in the north in winter and a drastic reduction in the south in summer. In the RCM simulations driven by a single global model, the spread of the temperature and precipitation projections tends to be smaller than that in the GCM simulations, but it is possible to reduce this disparity by employing several driving models for all RCMs. In the present suite of simulations, the difference between the mean GCM and RCM projections is fairly small, regardless of the number of driving models applied.

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## 1 Introduction

Owing to an increase in the concentrations of greenhouse gases, the global mean temperature is projected to rise by several degrees by the end of the 21st century (IPCC 2001). The objective of the PRUDENCE project is to assess how this global change manifests itself in the climate of Europe (Christensen et al. 2007). The PRUDENCE regional climate model (RCM) simulations use boundary conditions taken from only one or two global climate models (GCMs). This strongly constrains the RCM responses; Déqué et al. (2007) report that differences between the simulations arising from the driving GCM are generally larger than those due to the internal structures of RCMs. Moreover, most of the RCM projections are calculated merely for the SRES A2 forcing scenario of the IPCC (2001).

Accordingly, to put the RCM simulations into a wider perspective, near-surface (2 m) air temperature and precipitation projections based on experiments performed with six coupled atmosphere-ocean GCMs are analyzed in this paper. These GCMs represent climate sensitivities and patterns of change that are much more variable than those in the smaller set of GCMs employed to drive the RCM simulations. Projections are composed separately for four SRES forcing scenarios (A1FI, A2, B2 and B1). For each scenario, we calculate both the mean estimates and the 95% probability intervals of the GCM- and RCM-based regional temperature/precipitation change. Projections are presented for the 30-year time span 2070–2099 (for RCMs 2071–2100), relative to the baseline period 1961–1990.

In most cases, computationally-demanding GCMs have only been employed for simulating responses to the A2 and B2 scenarios. Responses to the remaining scenarios are then derived applying a new version of pattern-scaling developed during this study. The method and its applicability are discussed in Section 3. Generally, pattern-scaling methods can be applied to such climate parameters for which the local response is linearly proportional to the global mean temperature change. As will be shown, local temperature and precipitation changes fulfil this condition fairly well. For some other parameters, such as the number of frost days, the relationship is strongly nonlinear, and a more sophisticated approach is required.

Probability intervals for regional projections, as well as a comparison with simulations performed with the RCMs participating in the PRUDENCE project, are presented in Section 4. The probability intervals are available as numerical values from the authors on request.

## 2 Climate models and regional subdivision

The main characteristics of the GCMs and the runs performed are summarized in Table 1. More detailed information and references to model documentation are given in chapter 8 of IPCC (2001). As a measure of how sensitively the models react to radiative forcing on the time-scale discussed in this study, Table 1 gives the global mean temperature response to the A2 forcing scenario for each model.

The responses to the A2 and B2 forcing scenarios had been simulated for all models in Table 1. The low-forcing B1 response was available for HadCM3 and CSIRO Mk2, while the high-forcing A1FI response was only available for HadCM3. Furthermore, HadCM3 was the only model for which ensemble runs were available.

The RCM analyzed in this study are HIRHAM, HadRM3P, CHRM, CLM, REMO, RCAO, PROMES, RACMO and Arpège; information about the RCMs is

**Table 1** Coupled GCMs analyzed in the present work

Model	Country	TRUNC	GRID	L	ADJ	$\Delta T_{glob}$	SCENS
CGCM2	Canada	T32	$3.8 \times 3.8^\circ$	10	Yes	3.5°C	A2, B2
CSIRO Mk2	Australia	R21	$3.2 \times 5.6^\circ$	9	Yes	3.4°C	A2, B1, B2
ECHAM4/OPYC3	Germany	T42	$2.8 \times 2.8^\circ$	19	Yes	3.3°C	A2, B2
GFDL R30	U.S.A.	R30	$2.2 \times 3.8^\circ$	14	Yes	3.1°C	A2, B2
HadCM3	United Kingdom	-	$2.5 \times 3.8^\circ$	19	No	3.2°C	A1FI, A2 (3), B1, B2 (2)
NCAR DOE PCM	U.S.A.	T42	$2.8 \times 2.8^\circ$	18	No	2.4°C	A2, B2

Column 1 gives the model acronym and column 2 the country where the model was developed. For horizontal resolution, the truncation in spherical harmonics space (TRUNC) and the approximate grid distance in grid-point space (GRID) are given (HadCM3 is a grid-point model). L denotes the number of model levels. The next column tells whether flux adjustment is employed.  $\Delta T_{glob}$  is the global mean temperature increase from 1961–1990 to 2070–2099 as a response to the A2 forcing. SCENS shows the SRES simulations performed with each model; if parallel runs are available, the number of the ensemble members is given in parentheses.

given in other papers of this special issue, e.g., Déqué et al. (2007). Most RCMs contain an atmospheric component only,<sup>1</sup> the sea surface data and atmospheric lateral boundary values being derived from a global GCM. Experiments with HadCM3<sup>2</sup> as a driving model have been conducted with all the RCMs, but there are only two models (HIRHAM and RCAO) for which ECHAM4/OPYC3-forced runs are available. Arpège/OPA as a driving model has been employed by one RCM only.

An effective method to condense the model-derived information is to represent it as spatial averages over a number of discrete regions. The subdivision into five regions employed in this study is illustrated in Fig. 1. Henceforth, most of the results to be presented are area-weighted spatial means over the grid boxes inside the given region.

In addition to externally-forced changes, there occurs in the climate system unforced internal variability on various timescales. The statistical properties of that variability were inferred from a 1,000-year HadCM3 simulation, in which the composition of the atmosphere and other external forcing agents were kept constant. Standard deviations of the temperature and precipitation were calculated from the simulated of 30-year temporal averages of regional means.

### 3 The super-ensemble pattern scaling method

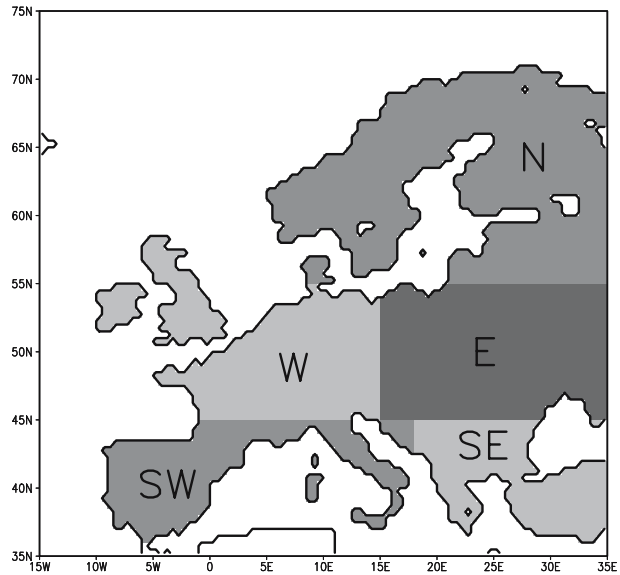
#### 3.1 Principle of the method

Pattern-scaling techniques have been widely used to create climate change projections for scenarios or time spans not simulated by GCMs. Various versions of scaling

<sup>1</sup>In two RCMs there is a submodel for the Baltic Sea.

<sup>2</sup>In fact, the boundary conditions are not taken directly from the HadCM3 runs, but an atmospheric model HadAM3 is used as a 'bridge' between the HadCM3 and the RCMs.

**Fig. 1** The five regions employed in reporting subcontinental scale changes of temperature and precipitation; *N*, *W*, *E*, *SW*, and *SE* represent the regions of northern, western, eastern, south-western and south-eastern Europe, respectively



techniques have been presented by Mitchell et al. (1999), New and Hulme (2000), Huntingford and Cox (2000), Mitchell (2003), Ruosteenoja et al. (2003) and Hingray et al. (2007), for instance. In the RCM experiments employed in this work, however, only two discrete 30-year periods have been simulated. In order to apply the same scaling technique to both the GCM and RCM responses, an amended version of the time-slice method has been developed. The geographical pattern of the temperature, precipitation or other response is assumed to be independent of the forcing, the amplitude of this fixed pattern being proportional to the global mean temperature change.

The traditional simple time-slice method calculates the scaled response employing an individual GCM response, e.g.:

$$\Delta T_{A1FI,s} = \frac{\langle \Delta T_{A1FI} \rangle}{\langle \Delta T_{A2} \rangle} \Delta T_{A2,g} \quad (1)$$

where the subindex *g* refers to the GCM-simulated and *s* to the scaled temperature change for an individual grid-point or region.  $\langle \Delta T \rangle$  denotes the global mean temperature change that is calculated using the simple energy balance climate model MAGICC<sup>3</sup> (IPCC 2001, Appendix 9.1). Such a computationally simple model can readily be used to calculate global mean temperature change for all forcing scenarios of interest.

The GCM-simulated climate response includes, besides the actual climate change signal, random noise caused by internal variability. This noise is transmitted into the scaled response. The problem is common to all scaling methods.

One way to reduce the influence of the noise is to carry out the scaling in Eq. 1 using an ensemble mean instead of an individual GCM response. The effective

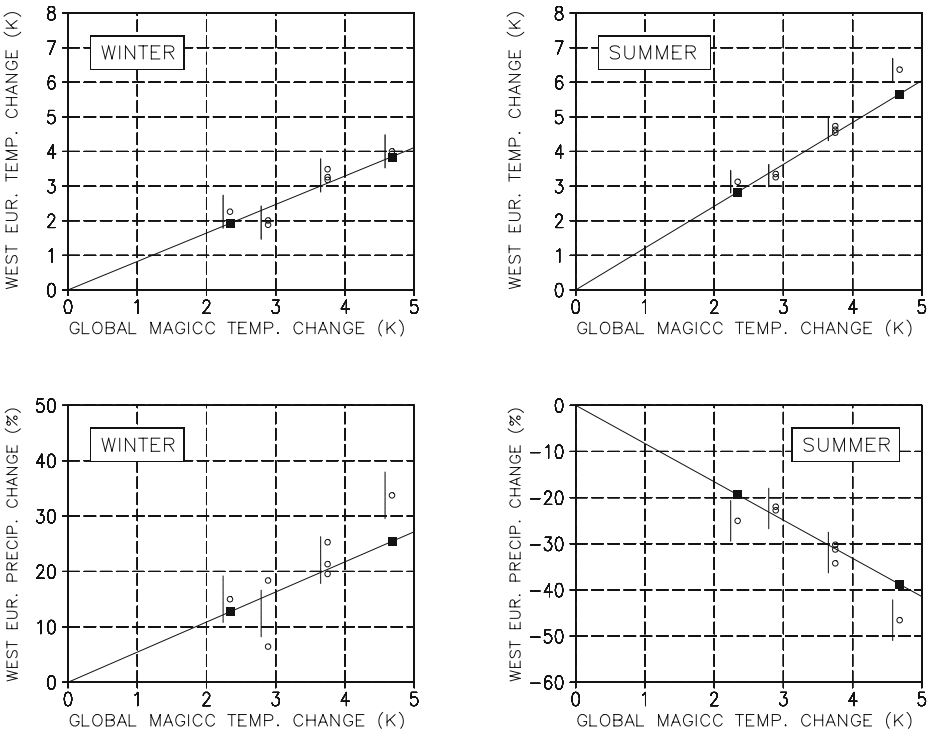
<sup>3</sup>Model for the Assessment of Greenhouse-gas Induced Climate Change.

ensemble size can be further increased by calculating the scaled response from a least-square regression line fitted to a set consisting of GCM responses to several SRES scenarios:

$$\Delta T_{A1FI,s} = a_T(\Delta T_{A1FI}); \quad a_T = \frac{\sum_{i=1}^n \langle \Delta T_i \rangle \Delta T_{i,g}}{\sum_{i=1}^n \langle \Delta T_i \rangle^2} \quad (2)$$

$n$  being the number of the simulations considered, i.e., the size of the super-ensemble. Scaled responses to the B1 scenario are calculated analogously. The principle of the method is illustrated in Fig. 2. Since  $\langle \Delta T \rangle = 0$  represents a zero climate change, the least-square regression line is constrained to pass through the origin. The regression fit can also be employed to scale the precipitation change  $\Delta P$ :

$$\Delta P_{A1FI,s} = a_P(\Delta T_{A1FI}); \quad a_P = \frac{\sum_{i=1}^n \langle \Delta T_i \rangle \Delta P_{i,g}}{\sum_{i=1}^n \langle \Delta T_i \rangle^2} \quad (3)$$



**Fig. 2** An example of super-ensemble scaling. Temperature (*upper panels*) and precipitation (*lower panels*) change (2070–2099) – (1961–1991) for western Europe (region ‘W’ in Fig. 1) in winter (DJF) and summer (JJA) in various HadCM3 simulations (open circles) are given as a function of the MAGICC-simulated global annual mean temperature change. Scenarios examined are B1 ( $\langle \Delta T \rangle = 2.34^\circ\text{C}$ ; 1 ensemble member), B2 ( $2.89^\circ\text{C}$ ; 2 members), A2 ( $3.75^\circ\text{C}$ ; 3 members) and A1FI ( $4.68^\circ\text{C}$ ; 1 member). Each panel includes a regression line calculated from the three A2 and two B2 responses; the resulting scaled A1FI and B1 responses are denoted by closed squares. The vertical bar on the left side of the points, centred on the ensemble mean, depicts the  $\pm$  standard deviation of the differences between two arbitrarily-chosen 30-year averages, derived from the standard deviations of temperature and precipitation variability in a millennial HadCM3 control run

One can readily notice that simple time-slice scaling (1) is obtained as a special case (with  $n = 1$ ) of the super-ensemble method. Analogously, if all the simulations from which  $a_T$  or  $a_P$  is calculated belong to an ensemble consisting of responses to the same forcing scenario, Eqs. 2 and 3 reduce to a conventional scaling from an ensemble mean.

The idea of modelling the relationship between the local and global climate response by linear regression has been employed independently by Hingray et al. (2007). Unlike the present study, they do not give projections separately for individual forcing scenarios.

The MAGICC-emulated time series of global annual mean temperature changes for four coupled GCMs (CSIRO Mk2, ECHAM4, HadCM3 and NCAR PCM) were supplied to us by Dr. Sarah Raper. For the CGCM2 and GFDL, we used the average four-GCM emulated values of  $\langle \Delta T \rangle$  in determining the scaling coefficients.

From the MAGICC-emulated time series of  $\langle \Delta T \rangle$  for the A1FI, A2, B1 and B2 scenarios, we calculated the temperature response for 2070–2099, relative to 1961–1990. These global-mean temperature change estimates were employed to calculate the scaled responses of regional temperature (2) and precipitation (3), separately for each season.

### 3.2 Applicability of the super-ensemble scaling

The performance of various versions of the scaling technique is analyzed for HadCM3, i.e., for the only GCM for which simulations with all four scenarios are available. In applying pattern-scaling, there are two fundamental sources of uncertainty:

- Nonlinearity error: the local responses of temperature, precipitation and other meteorological variables may not be inherently linear functions of the global mean temperature change
- Noise due to internal variability

Errors due to random noise always occur in scaled responses. This type of error can be reduced by increasing the ensemble or super-ensemble size in Eqs. 1, 2 and 3. The super-ensemble scaling method is intended to keep in check just this type of error.

On the other hand, the nonlinearity error affects the quality of the scaled response most seriously if the scaling is based on a ‘distant’ simulation, i.e., on a simulation in which  $\langle \Delta T \rangle$  is much larger or smaller than in the target scenario to be scaled. In super-ensemble scaling the regression coefficient ( $a_T$  or  $a_P$ ) is generally determined by responses to several forcing scenarios, some of which are usually not very close to the target scenario. Accordingly, in the super-ensemble method the nonlinearity error tends to be larger than in the simple method (1), in which the closest existing simulation is typically utilized.

An example illustrating the degree of linearity of the regional temperature and precipitation responses as a function of  $\langle \Delta T \rangle$  is given in Fig. 2. The responses do not exactly lie on the linear regression line, but for temperature the deviations from linearity are generally of the same order of magnitude as the variations due to internal variability. For regional precipitation changes, in this example the deviations from linearity are larger than for temperature changes.

Another conclusion to be drawn from Fig. 2 is that, due to the small size of the ensembles, the spread among the ensemble members does not generally give a representative picture of the internal variability.

For a quantitative evaluation of the various scaling methods, the scaled seasonal temperature and precipitation responses to the A1FI and B1 scenarios were first calculated at each grid point using the super-ensemble method (Eqs. 2 and 3). As a measure of the quality of the scaled responses, we calculated area mean rms differences between the scaled and the corresponding directly GCM-simulated temperature/precipitation reference fields, either over the entire globe, over global land areas or over European land areas west of 35°E. The annual means of these rms differences are reported in Table 2.

In a situation with no ensemble runs (i.e., only one A2 and one B2 simulation available), the super-ensemble method appears in all cases to work better than the simple method (1); compare rows (1) and (3) and rows (5) and (7) in Table 2.

**Table 2** Annual means of rms differences between the scaled and HadCM3-simulated seasonal (a) 2 m air temperature and (b) precipitation responses

(a) Scaling of temperature response (unit: °C)

SCEN	Scaling From	N	EUROPE	Land Areas	Global
(1) A1FI	Individual A2	1	0.557	0.571	0.497
(2) A1FI	A2 ensemble mean	3	0.402	0.423	0.384
(3) A1FI	Regression 1xA2+1xB2	2	0.531	0.502	0.450
(4) A1FI	Regression 3xA2+2xB2	5	0.420	0.402	0.378
(5) B1	Individual B2	1	0.654	0.468	0.352
(6) B1	B2 ensemble mean	2	0.617	0.425	0.318
(7) B1	Regression 1xA2+1xB2	2	0.539	0.400	0.321
(8) B1	Regression 3xA2+2xB2	5	0.510	0.377	0.305

(b) Scaling of precipitation response (unit: mm/d)

SCEN	Scaling From	N	EUROPE	Land Areas	Global
(1) A1FI	Individual A2	1	0.242	0.327	0.537
(2) A1FI	A2 ensemble mean	3	0.174	0.258	0.383
(3) A1FI	Regression 1xA2+1xB2	2	0.229	0.316	0.487
(4) A1FI	Regression 3xA2+2xB2	5	0.181	0.269	0.391
(5) B1	Individual B2	1	0.230	0.216	0.392
(6) B1	B2 ensemble mean	2	0.206	0.185	0.344
(7) B1	Regression 1xA2+1xB2	2	0.190	0.204	0.357
(8) B1	Regression 3xA2+2xB2	5	0.177	0.194	0.334

Values are presented separately for European land areas west of 35°E, global land areas and for the entire globe. 'SCEN' denotes the SRES scenario for which the evaluations are calculated, 'SCALING FROM' the scaling method; N states the number of GCM simulations employed in calculating the scaled response. (1) is the mean of the three rms values that are obtained by comparing the patterns scaled from the three individual A2 responses with the GCM-simulated A1FI field. Analogously, (5) is the mean of two rms values. (3) and (7) are both means of six rms differences, each corresponding to a super-ensemble scaling from a pair consisting of one individual A2 and one B2 ensemble member. (4) and (8) refer to super-ensemble scaling from a set of two B2 and three A2 ensemble members.

When parallel runs are available, scaling from the ensemble mean always improves the result when compared to scaling from an individual simulation (rows (1) vs (2), (5) vs (6)). Furthermore, the super-ensemble method utilizing three A2 and two B2 responses beats scaling from the simple ensemble mean in predicting the B1 temperature response (rows (6) vs (8)). By contrast, in predicting the A1FI temperature response and the scaling of precipitation in general, the super-ensemble method and scaling from the ensemble mean could not be ranked.

The A2 and B2 scenario runs are available for all the GCMs, and in this paper the projections to be presented for these scenarios will be based on the direct GCM data. For the A1FI and B1 scenarios, on the other hand, simulations are available for one or two models only, and these projections are mainly formulated employing responses scaled with the super-ensemble method. Scaled responses are calculated separately for each individual GCM.

For the RCMs, A2 is the only scenario for which there is a run for all models. Other projections have to be based mainly (B2) or exclusively (A1FI, B1) on scaled responses.

#### 4 95% probability intervals for regional projections

Since we have analyzed six GCMs only, modelled climate change projections applied as such do not give a statistically representative picture of regional climate change. Instead, we have fitted the normal (Gaussian) distribution to the set of model projections.

The validity of the normal distribution approximation can be evaluated by means of quantile plots (Vining 1998, p. 117–120). Due to the small number of GCMs, projections for all five regions are incorporated into the same diagram. In order to make the responses for different regions comparable, all GCM projections are standardized:

$$\Delta T_{i,j,k}^{st} = (\Delta T_{i,j,k} - \overline{\Delta T_{j,k}}) / s_{j,k}^{\Delta T}; \quad \Delta P_{i,j,k}^{st} = (\Delta P_{i,j,k} - \overline{\Delta P_{j,k}}) / s_{j,k}^{\Delta P} \quad (4)$$

where the subindices  $i, j$  and  $k$  refer to the six GCMs, five regions and four seasons, respectively. The overbar stands for a mean over the six models,  $s$  for the standard deviation.

In fact, in calculating the means and standard deviations employed in Eq. 4, each of the three members of the HadCM3 ensemble is given a weight of 2/3, the remaining model projections being unity-weighted. Thus, HadCM3 runs have a double total weight compared to the other GCMs. Enhanced weighting is given to that model because parallel runs can simulate a part of the internal variability.

In the quantile plots of Fig. 3, the points are mostly concentrated close to the  $x = y$  line. In all, the projections of the various GCMs thus appear to follow the normal distribution fairly well. Utilizing the Gaussian approximation, we can construct 95% probability intervals for the temperature and precipitation change for each season and region:

$$I_{i,j,k}^{\Delta T} = \overline{\Delta T_{j,k}} \pm 1.96s_{j,k}^{\Delta T}; \quad I_{i,j,k}^{\Delta P} = \overline{\Delta P_{j,k}} \pm 1.96s_{j,k}^{\Delta P} \quad (5)$$

Since the projections for the A1FI and B1 scenarios are mainly based on scaled responses, we assessed what kind of uncertainty for the probability intervals arises

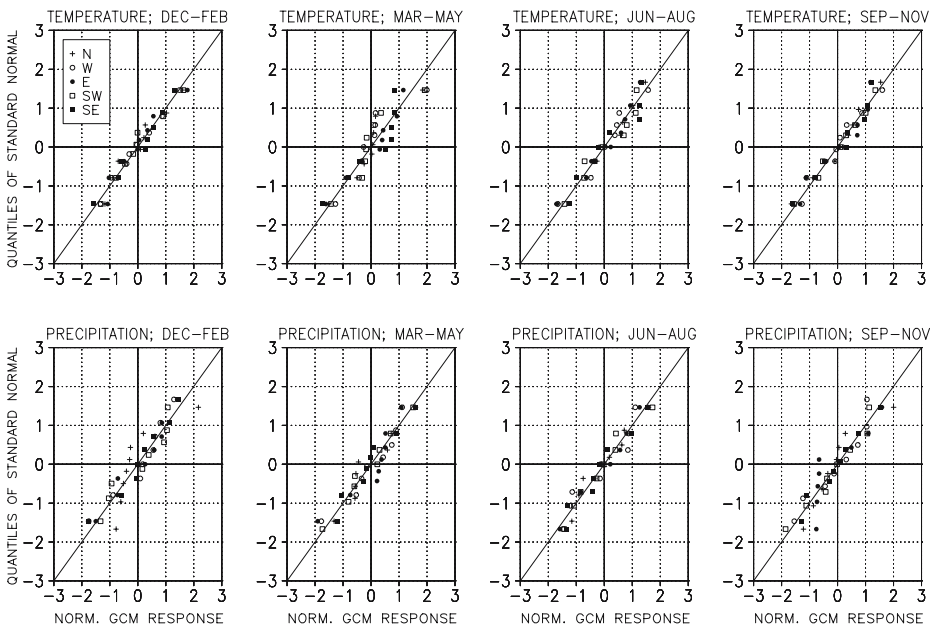


from the application of pattern scaling. For that purpose, scaled and GCM-derived probability intervals for the B2 temperature and precipitation changes were compared. The B2 scenario is chosen for inspection since the original and scaled A2 responses are by definition close to one another; in calculating the regression coefficients, the contribution of the large-amplitude A2 responses is larger than that of the weak B2 responses (see Eqs. 2 and 3). The scaled and directly GCM-simulated median changes appeared to be very close to one another. The widths of both probability intervals are generally nearly the same in summer, but in winter scaling tends to underestimate the intervals, especially for precipitation in southern Europe. Note that the super-ensemble scaling reduces the contribution of internal variability, which partly explains the smaller spread in the scaled projections.

To conclude this section, the differences between the scaled and the original model-derived projections seem to be small enough for the scaled responses to be used as reasonable approximations for missing GCM projections.

### 4.1 Probability intervals for GCM projections

In this study probability intervals are determined separately for all four scenarios. As in the previous subsection, the summed weight of the HadCM3 ensemble runs is 2, while the weight of other models is 1. For the B1 and A1F1 scenarios no multiple runs have been performed. In order to reduce the influence of the noise, we have therefore created an artificial 2-member HadCM3 ensemble for these scenarios. This ensemble



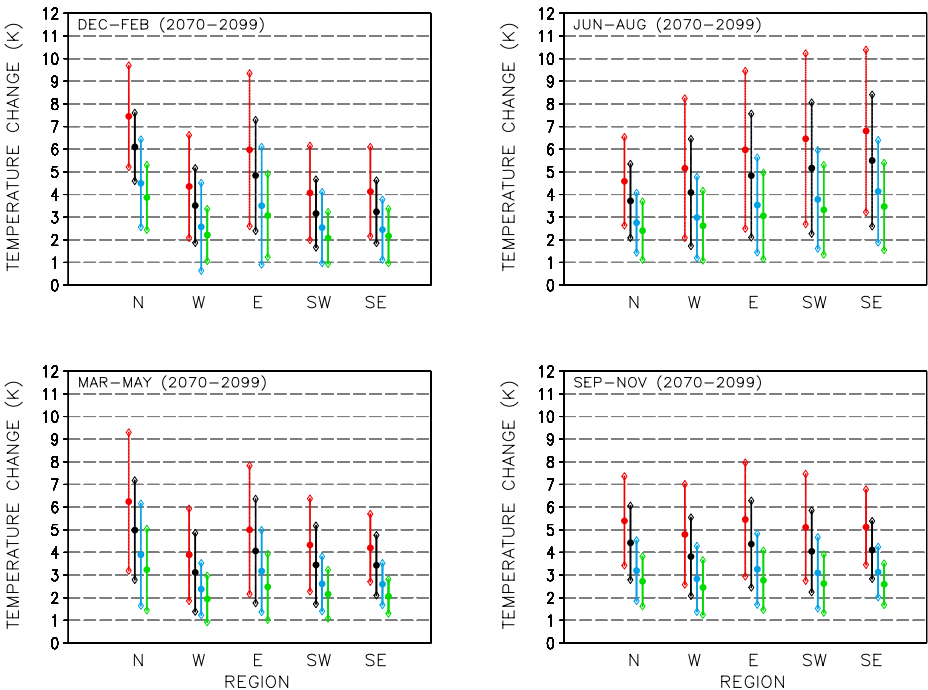
**Fig. 3** Quantile plots for seasonal temperature (*upper panels*) and precipitation (*lower panels*) responses to the A2 forcing. The *x*-axis represents the standardized GCM-simulated temperature/precipitation responses rearranged in ascending order. The corresponding quantile values inferred from the standard normal distribution are given by the *y*-axis. Each diagram includes data from six GCMs. All the five regions are depicted in the diagrams, see legend

consists of two estimates, one being the direct GCM response, the other being scaled from the set of three A2 and two B2 runs. (In fact, the probability intervals obtained with this procedure and with the inclusion of one double-weighted direct HadCM3 A1FI or B1 response were very similar.)

Probability intervals for temperature change are given in absolute terms, while precipitation changes are here expressed in percentages to facilitate application of the results to impact studies. In transforming the precipitation changes into percentages ( $100\% \times \Delta P/P$ ), the denominator  $P$  is the baseline-period precipitation averaged over the six GCMs, the weights being as stated above.

The probability intervals for temperature change, separately for each season, region and scenario, are depicted in Fig. 4. The intervals are quite broad, reflecting the large scatter among the various model projections. For example, the extreme estimates for regional springtime responses to the A1FI forcing range from  $\sim 2^\circ\text{C}$  to more than  $9^\circ\text{C}$ . Another striking feature is that the probability intervals representing different forcing scenarios overlap strongly.

The 95% probability intervals for precipitation change are presented in Fig. 5. Note that in the A1FI and A2 scenarios the southern Europe summertime precipitation manifests a very large decrease at the lower end of the probability interval. Since  $-100\%$  is a categorical limit for the decrease, the normal distribution is inappropriate



**Fig. 4** 95% probability intervals of seasonal temperature change (*vertical bars*) from 1961–1990 to 2070–2099 for five regions, derived from (SRES)-forced simulation performed with six GCMs. Intervals are given separately for the A1FI (*red*), A2 (*black*), B2 (*blue*) and B1 (*green*) scenarios. The *dot* at the centre of the bar denotes the median of the interval

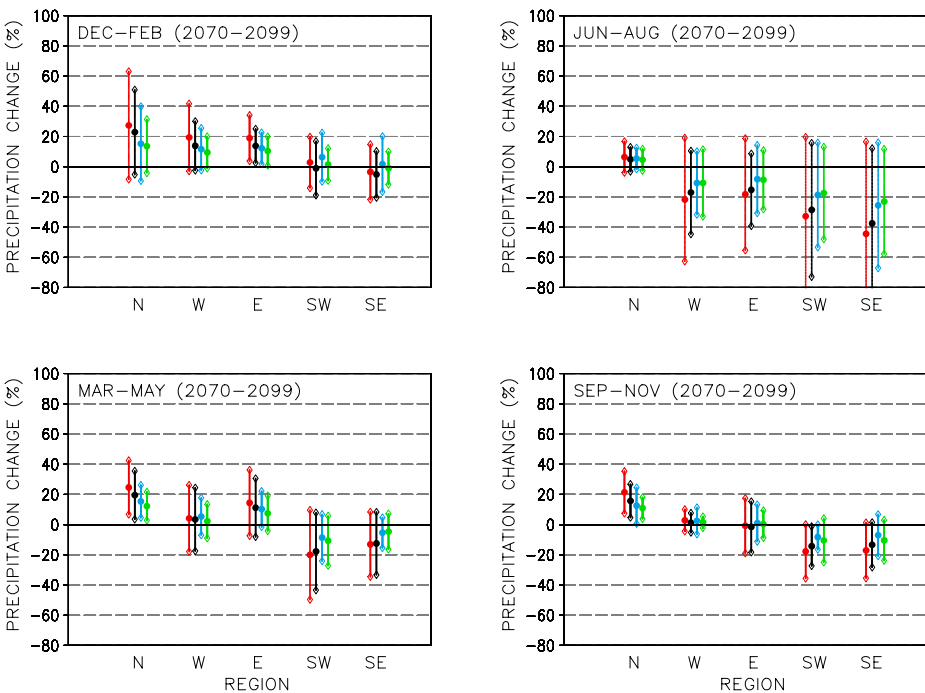
for describing such strong decreases. Hence, in Fig. 5 the probability intervals have been truncated at  $-80\%$ .

With the exception of eastern Europe in winter and northern Europe in the intermediate seasons, the 95% probability intervals of precipitation change intersect the zero line. Consequently, in most cases even the sign of the future precipitation change cannot be established.

In simulating the wintertime precipitation change in northern Europe, there is one model (ECHAM4) that yields a very large relative increase (more than 50%) in precipitation compared to the other GCMs. When fitting a normal distribution to that data set, such a distinctly different data value tends to spuriously widen the probability interval at both ends. In the absence of that model, the width of the interval would be reduced by more than half, and the lower end of the interval would also be positive. Thus, the Gaussian distribution is not an ideal tool for studying such a special case.

#### 4.2 Comparison to RCM results

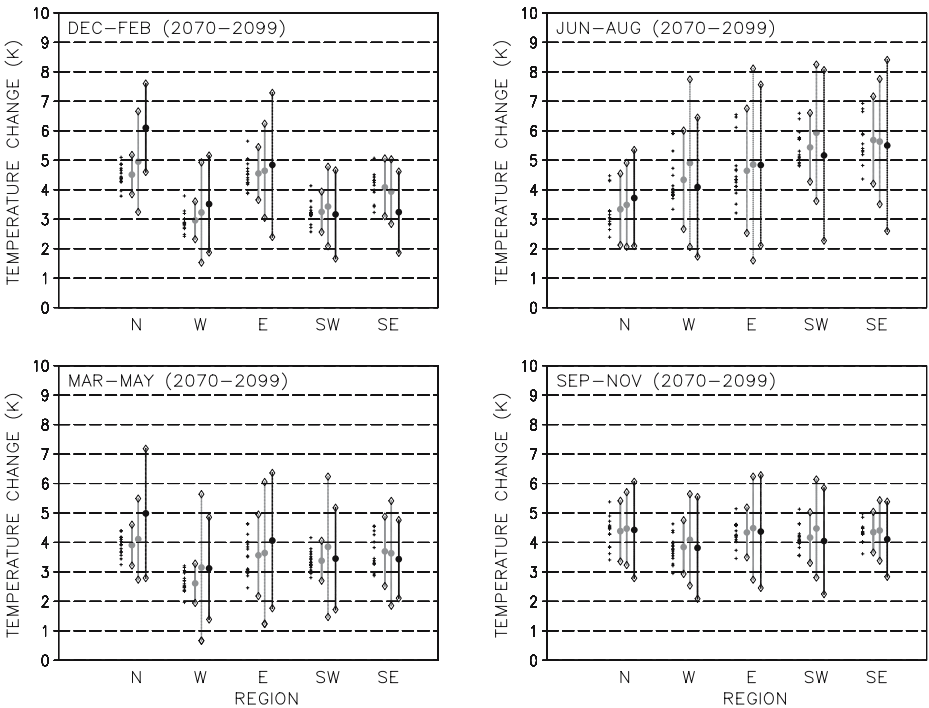
To study how much RCM- and GCM-based climate change projections differ from one another, we chiefly discuss the A2 projections, since this is the only forcing scenario simulated by all RCMs. Two estimates for the 95% probability intervals of RCM-simulated climate change are presented. The first one is merely based on HadCM3/HadAM3-driven simulations that are available for all RCMs. The other



**Fig. 5** Seasonal GCM-derived 95% probability intervals of percentage precipitation change. For denotations, see Fig. 4. In the diagrams changes  $< -80\%$  are excluded

estimate utilizes RCM simulations driven by all three global models (Arpège/OPA, ECHAM4, HadCM3). Since the number of ECHAM4- and Arpège/OPA-driven simulations is too small (two/one) to yield any statistical distribution by itself, we have completed the matrix of experiments by creating a synthetic extended set containing simulations with all RCMs for all the three driving models. The standard deviation of the ECHAM4- and Arpège/OPA-driven RCM projections is assumed to be the same as in the HadCM3-driven RCM experiments. The average of these projections is approximated by adding to the mean of the HadCM3-driven responses the difference of the responses calculated with the same RCM applying the two driving models. This procedure is rather crude, since there are only one (Arpège/OPA – HadCM3) or two (ECHAM4 – HadCM3) such analogous pairs of RCM runs. Finally, the extended sets of (real and surrogate) RCM runs driven by the three models are combined to give an estimate for the full probability interval.

The comparison for temperature change is presented in Fig. 6. For the three RCMs (HIRHAM, HadRM3P, Arpège) with parallel runs, all individual runs have been incorporated in the analysis with equal weight. In calculating the RCM probability intervals, the CHRMs, PROMES and RACMO models are excluded, since the computational domain of these three models does not cover all the five regions.



**Fig. 6** Comparison of the seasonal RCM- and GCM-derived temperature responses to the A2 forcing for the five regions defined in Fig. 1. The plus signs denote projections of individual HadCM3-driven RCM runs. The grey bar on the left of each triad denotes the 95% probability interval derived from the HadCM3-driven RCM runs; the middle grey bar gives an estimate for the interval that would be obtained if simulations with all RCMs had been available for all the three driving global models (see text). The black bar on the right of the triad stands for the GCM-based probability intervals

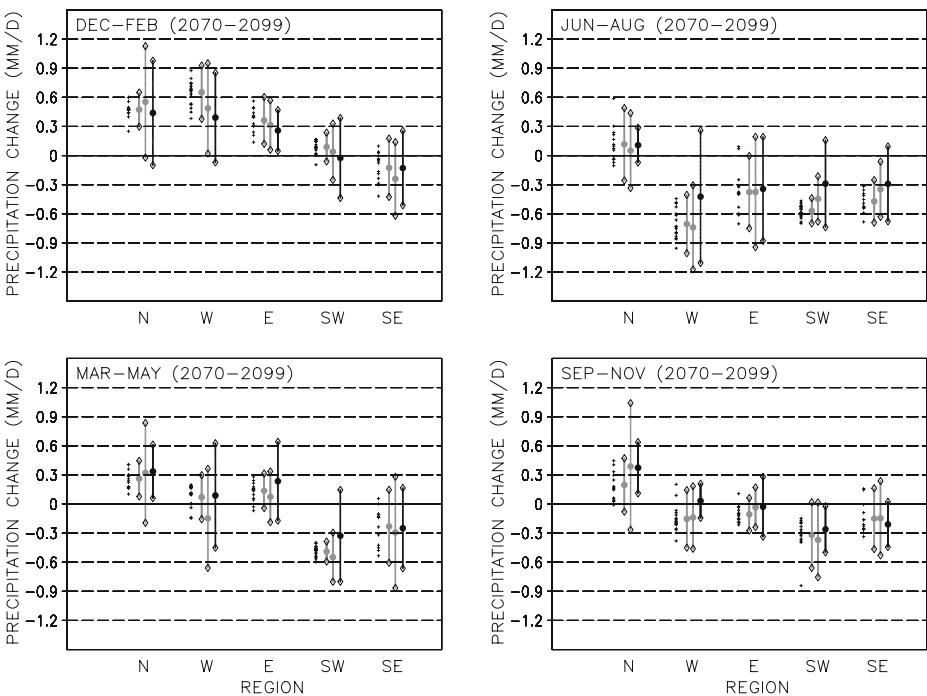
The individual RCM projections, by contrast, are depicted for all RCMs that cover the region concerned.

The mean estimates of temperature change inferred from the GCM and RCM experiments analyzed are mostly fairly close to one another. RCM-simulated warming tends to be smaller than that of the GCMs in northern Europe in winter and spring, the opposite being true in the southeast in winter.

Except for summer, scatter among the HadCM3-driven RCM temperature projections is generally much smaller than among the GCM projections. The single GCM applied as a boundary condition strongly constrains the climate response, especially from autumn to spring when climate is mainly determined by large-scale weather phenomena. The probability intervals calculated from the extended set of RCM simulations, including simulations with all RCMs for each of the three driving models, by contrast, are of the same order of magnitude as the GCM probability intervals.

For precipitation change (Fig. 7), the spread among the HadCM3-driven RCM runs is in most cases smaller than that among the GCM simulations. The probability intervals inferred from the expanded RCM set are not systematically broader or narrower than those given by the GCMs.

Projected temperature responses were compared with the internal variability of temperature in a millennial HadCM3 control simulation. The standard deviation of internal variability was multiplied by  $\sqrt{2}$  to give an expectation for the difference



**Fig. 7** Comparison of RCM- and GCM-derived 95% probability intervals of regional precipitation change. For denotations, see Fig. 6

between two arbitrarily-chosen 30-year means. Both the RCM and GCM temperature responses appeared to be statistically significant. Moreover, the spread among the various GCM projections was larger than the measure of internal variability. This indicates that intermodel differences are caused by the dissimilarity of the model codes rather than by mere internal variability.

Applying the super-ensemble pattern-scaling method introduced in Section 3, RCM-based projections for scenarios other than A2 can be easily formulated. The RCM-based projections driven by a single model continue to have a smaller spread than the GCM projections. For instance, the A1FI-forced 95% probability interval of summertime temperature change for south-western Europe, derived from the HadCM3-driven RCMs, was 5.4–8.2°C, the corresponding GCM-derived range being 2.7–10.2°C.

## 5 Conclusions

This paper introduces a new version of the pattern-scaling method, which enables one to create climate parameter projections for those forcing scenarios for which GCM or RCM simulations are not available. In addition to surface air temperature and precipitation, the methodology is suited to all such variables for which local responses are linearly dependent on global mean temperature change. The method treats all available model runs as a super-ensemble, which may contain both simulations for several forcing scenarios and parallel runs for the same forcing. Projections for the missing scenarios are inferred from a regression line representing the relationship between the local or regional response of the meteorological parameter of interest and the global mean temperature change simulated by a simple energy balance model.

In our evaluation, the super-ensemble scaling method proved to improve on the conventional time-slice method in situations with no parallel simulations for individual scenarios available. If there are multiple simulations for each forcing scenario, differences in the performance were small. Due to the smallness of the ensemble sizes, however, these conclusions should be considered somewhat tentative.

In principle, the super-ensemble pattern-scaling method has several advantages. First, the method utilizes all the available information in calculating the scaled response, especially when responses to more than one forcing scenario have been calculated by a sophisticated GCM or RCM. Second, the method reduces the impact of random noise. This is particularly advantageous if, in some of the GCM simulations, internal variability happens to be at opposite extremes during the control and target periods. Third, several more simple versions of the time-slice scaling method (e.g., Eq. 1) are obtained as special cases of the super-ensemble method. Note also that strong-amplitude responses (e.g., A2) have the largest weight in calculating the regression coefficients  $a_T$  and  $a_P$ , which further tends to reduce the noise.

We have formulated mean as well as upper and lower estimates of 2 m air temperature and precipitation change for five regions covering the bulk of continental Europe. Results are based on simulations performed with six global coupled atmosphere-ocean GCMs. SRES A2 and B2 simulations are available for all models, while the A1F1 and B1 projections for most of the GCMs are based on the super-ensemble scaling. The 95% probability intervals for the regional temperature/precipitation change have been constructed by approximating the changes simulated by the various models by a normal distribution.

The upper GCM-based estimates of warming for the A1F1 scenario mostly range from 6 to about 10°C, while the lower estimates for the B1 scenario are generally close to 1°C. If the driest end of the A1FI probability interval happens to be true, precipitation in the southern Europe summer might be reduced by more than 80%.

GCM-derived climate change estimates were compared with projections based on RCM output. The RCM response is largely determined by the driving global GCM wherein the RCM is nested. If only one driving GCM is employed, the spread is generally much smaller in the RCM than in the GCM climate projections. This problem appears to be partly solved by utilizing three driving GCMs, but the conclusion remains uncertain due to the small number of RCM simulations actually performed with driving models other than HadCM3. RCMs are certainly a valuable tool for resolving spatial details of climate change, but one should be cautious in basing the actual climate change projections merely on the RCM data if the number of driving models is small.

In calculating the means and standard deviations of the regional GCM responses, HadCM3 was given, somewhat arbitrarily, a double weight. This was done because the number of runs performed with that model was large compared to the remaining models. Several more sophisticated ways to determine the weights are suggested in the literature. For example, Murphy et al. (2004) and Giorgi and Mearns (2003) have given enhanced weight to models showing a good performance in reproducing the present-day climate. In these studies, probability distributions obtained by employing equal and unequal weighting appeared to diverge to some extent, but the main conclusions remained unchanged.

As an example of an alternative approach, New and Hulme (2000) have constructed the probability distribution of projected regional climate change by performing a large number of Monte Carlo simulations with a simple energy balance model. The geographical patterns of the climate response were derived from seven global GCMs, with ensemble runs performed with HadCM2 given a summed weight greater than that of the remaining six GCMs together.

Pattern-scaling does not seem to be a very large source of error in constructing regional climate projections for extreme scenarios. It is possible that, for the A2 and B2 scenarios also, scaled projections may even be better than those inferred directly from model output; this depends on the ratio of the random noise error to the nonlinearity error.

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