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Methodologies of pattern scaling across the full range of RT2A GCM ensemble members

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Introduction

Pattern scaling techniques have been widely used to provide climate change projections for time periods and emission scenarios that have not been simulated by GCMs. The assumption underlying these methods is that the local response of a climate variable is linearly related to the global mean temperature change, with the geographical pattern of change independent of the forcing. Thus the anomaly in variable V, for a particular grid-box (i), month or season (j), year or period (y), and forcing scenario (x) is given by:

$$\Delta V_{xijy} = \Delta T_{xy} \,.\, V'_{ij} \tag{1}$$

where ΔT is the global mean temperature anomaly and V' is a fixed response pattern. As detailed below, this condition is largely satisfied for temperature and to a lesser degree precipitation (Mitchell *et al.*, 1999, and Mitchell, 2003).

A number of different methods are described in the literature for obtaining the response pattern, V'. Traditionally, where simulations are only available for two discrete time periods for a given forcing scenario, a simple time-slice approach has been used (e.g. Christensen *et al.*, 2001). In this case the response pattern is given by the mean spatial field of anomalies for a particular period (p), scaled by the global mean temperature change. An alternative approach, used by Mitchell *et al.* (1999) and Huntingford and Cox (2000) is to use a linear least squares regression on a sequence of periods. This has the advantage of making use of the full time series of data and also gives higher weight to periods of higher global mean temperature change, when the signal-to-noise ratio is higher. Mitchell (2003) finds that, in general, more robust response patterns are obtained when using the least squares method. Ruosteenoja *et al.* (2006) developed a super-ensemble pattern scaling method using responses from several realisations of a GCM run from different initial conditions rather than just one. This has the advantage of reducing noise induced by GCM internal variability.

A number of studies have assessed the applicability of pattern scaling techniques for estimating local changes in mean temperature and precipitation for untried scenarios and time periods. In general, linear scaling by the global mean temperature change is found to perform well for local temperature (Mitchell *et al.*, 1999, Mitchell, 2003). Deviations from linearity are found to be less than 25% of the total regional change for temperature in Giorgi (2005) and typically smaller than differences between ensemble runs arising from internal variability (Mitchell *et al.*, 1999, Ruosteenoja *et al.,* 2006). Giorgi (2005) found that the *non-linear* fraction• of the climate change

• The non-linear fraction of the signal, in the context of pattern scaling techniques, is usually defined as the fraction of the signal which does not scale linearly with global mean temperature (see e.g. Giorgi, 2005).

signal tended to decrease with increasing magnitude of the signal, suggesting that the scaling assumption will hold increasingly well as the climate change signal becomes more pronounced. Slight non-linearities arise as a result of the dependence of regional climate change on the rate of change as well as the magnitude of the scalar, and also on the extent to which the climate has stabilised (Mitchell, 2003). Also, linear scaling techniques may not be valid near sea ice and snow margins (IPCC, 2001).

In the case of precipitation, Mitchell *et al.*, (1999) find that internal variability dominates the local climate change signal when using decadal means. Giorgi (2005) also finds significant interdecadal variability for seasonal precipitation that is not reflected in the global temperature change time series and varies considerably between regions. Thus pattern scaling techniques are not valid for precipitation on the decadal timescale. However, on using longer averaging periods of 30 years, Mitchell (2003) was able to obtain robust response patterns, suggesting the technique may be valid for precipitation on multi-decadal timescales. This then raises the issue of how to incorporate information on interdecadal variability when trying to construct transient behaviour (Giorgi, 2005).

The accuracy of pattern scaling is found to deteriorate on extrapolating to higher forcing scenarios, with errors being much greater when scaling from low to high scenarios than when scaling from high to low scenarios (Huntingford and Cox, 2000, Mitchell, 2003). However, equally important to the direction of the scaling is the distance between the forcing scenarios sampled during calibration of the response pattern and the target scenario (Mitchell, 2003, Ruosteenoja *et al.,* 2006). This perhaps indicates that for scenarios associated with similar forcings, e.g. A1B and A2, the direction of scaling may not be crucial.

The above studies assessing the accuracy of pattern scaling methods have examined the applicability of the technique to climate variables at the GCM scale. Based on these GCM-scale verification studies, a number of studies have gone on to apply the techniques on the RCM grid scale using global mean temperature change as the scalar (e.g. Christensen *et al.*, 2001). Although as acknowledged in Giorgi (2005), there is likely to be increased non-linearity at the regional scale. In this report, the applicability of pattern scaling methods to provide climate projections at the RCM-scale for a full range of GCM ensemble members is investigated. This raises the possibility of using anomalies (in temperature and also possibly precipitation) at the GCM scale as the scalar rather than global mean temperature change. A 'local scaling' method for downscaling precipitation from GCM to 50km scales was developed by Widmann *et al.* (2003). In this method the local precipitation on the high resolution grid is obtained by multiplying the corresponding (in time and space) GCM large-scale precipitation by a spatially varying but time-invariant factor. Thus the large-scale precipitation replaces global mean temperature in equation (1) above. The physical basis for this local scaling is that regional patterns of precipitation are produced predominantly by the interaction between large-scale systems and the stationary topography. The method was found to perform well in predicting monthly mean regional precipitation over the USA state of Washington, except in the rain shadow of the mountains.

The above studies all examine the accuracy of pattern scaling techniques for predicting regional climate change in time-mean variables, however there has been little work to date exploring whether measures of variability are amenable to pattern scaling or to what extent these techniques can be extended to climate extremes. A study by Frei *et al.* (2005) examining projections of future change in extreme precipitation from six European RCMs, found that for winter the change in extreme precipitation is similar to that obtained simply by scaling present day extremes by the change in the mean. These results suggest that scaling techniques may be equally successful for extreme quantiles as for mean precipitation in this season. For summer there appears to be a tail-specific factor that is superimposed onto the change in the mean, which suggests that simple pattern scaling may not work in general for all seasons. Other known processes which invalidate the linearity are those involving thresholds, like snow and sea-ice melting (Mitchell *et al.* 1999). Good *et al.* (2006) argue that linear pattern scaling techniques may not be appropriate for climate extremes. They find that a quadratic fit between drought and heat wave indices, aggregated onto a GCM grid, and the local GCM-scale annual mean of daily maximum temperature performs better than a linear fit. It is noted that the choice of a quadratic fit in this study was argued on the grounds of simplicity. This approach could be used for those variables or indices for which simple linear scaling is found not to be applicable and could be extended to a different family of curves to obtain an improved fit. However, adding complexity above a simple linear scaling should be justified on physical grounds.

A fundamental problem underlying the analysis of changes in climate extremes is the issue of non-stationarity. Typically a sample size greater than 30 is needed to get robust statistics, thus more than 30 years of data are needed to calculate seasonal climate extremes at the 99th percentile level, whilst 10 years of data would be sufficient for calculating 95th percentiles. In order to calculate an extreme index stationary needs to be assumed over the aggregating period. However, for long time periods this assumption may not be valid particularly in the case of temperature extremes, with the dependence of an extreme index on a temporally varying scalar explicitly stating this non-stationarity. Thus, when selecting periods over which to aggregate data, there is a trade off between getting sufficient data for robust statistics of climate extremes and introducing errors from non-stationarity. In the case of temperature, the assumption of stationarity is likely to be valid for 10-year periods (Mitchell *et al.*, 1999), but 30-year periods have been used to increase the signal-to-noise ratio (Mitchell, 2003). For precipitation, the assumption of stationarity may be valid over longer timescales, with good results obtained using 30-year periods (Mitchell, 2003).

In this report we examine methodologies of pattern scaling, appropriate for providing climate projections at the RCM-scale across the full range of RT2A ensemble members for a given GCM. It is emphasised that pattern scaling techniques cannot be used to estimate regional changes for a different driving GCM but only for variants of a given GCM with differing initial conditions or forcing scenarios (Mitchell, 2003). Methods for scaling mean and variance and also extremes are examined, focussing on temperature and precipitation.

Scaling of Gaussian distributed variables.

This section presents a method for scaling the mean and variance of regional climate data to provide regional projections consistent with GCM variants for which no corresponding RCM simulation exists.

Direct scaling of mean and variance

A procedure developed by D. Rowell (unpublished) within the PRUDENCE project to generate regional climate change projections assumed that the time-varying mean and standard deviation of RCM data, which constitutes the anthropogenic component, is linearly related to the smoothed global mean surface air temperature from the driving GCM. The smoothing applies a low-pass filter, with amplitude cut-off at 20 years. Thus, expressing the local variables from the RCM as x_{ijm} and the smoothed global temperature from the GCM as T_{ijm}, where i is the year, j is the forcing scenario, and m is the month, the anthropogenically forced component (F) of each RCM monthly mean is:

$$x^F_{ijm} = a_{0m} + a_{1m}T_{ijm} \tag{2}$$

where the a's are linear regression coefficients determined separately for each month. The geographical location of the RCM data is not indexed as all calculations are independent of this. The linear regression coefficients can be determined using a time-slice approach whereby simulated values of x_{ijm} and T_{ijm} are averaged over control and future time periods, for a given month and scenario, producing two data points for the linear fit. In the case where a full transient RCM run has been performed, following Mitchell (2003), a better approach would be to perform a linear least squares regression on a sequence of periods. Where available the mean of an ensemble of parallel runs should be used (Ruosteenoja *et al.,* 2006).

The anomaly from the anthropogenic component is given by:

$$x'_{ijm} = x_{ijm} - x^F_{ijm} \tag{3}$$

A similar procedure is used to estimate the anthropogenically forced component of the standard deviation of x'_{ijm}:

$$\sigma^{xF}_{ijm} = b_{0m} + b_{1m}T_{ijm} \tag{4}$$

The linear regression coefficients, b_{0m} and b_{1m}, again can be obtained using either a time-slice or a least squares approach. In the latter case, the standard deviation of x' in each of a sequence of periods would be regressed against mean T, with the regression performed separately for each month and for a given scenario.

A standardised RCM time series from which the majority of the anthropogenic signal has been removed is then given by:

$$x''_{im} = x'_{ijm} / \sigma^{xF}_{ijm} \tag{5}$$

This standardised time series can then be used to reconstruct RCM data for missing periods between two time slice runs or for runs with different initial conditions or forcing scenarios, for which only GCM data are available. Thus for some 'new' scenario k, the local anthropogenically forced mean and variance are estimated from the global temperature time series using equations (2) and (4) above with $j = k$. These are then used to rescale the standardised time series x''_{im} to provide the RCM time series x_{ikm}, as required.

The above procedure can be applied directly in the case of local temperature. However, in the case of precipitation the temporal distribution of precipitation is first transformed to one which is more Gaussian by taking its logarithm prior to all calculations. This transformation improves the linearity between the local precipitation variable and global mean temperature.

This method, which relies on the assumption of an approximately linear relationship between local climate changes in the RCM and global mean climate changes in the driving GCM, is supported by the studies of Mitchell *et al.* (1999), Huntingford and Cox (2000), and Mitchell (2003), amongst others. However, unlike previous studies this methodology applies the assumption of a linear relationship to the standard deviation of RCM data as well as to the mean. In addition, this procedure retains the non-anthropogenically forced component of variability as a standardised time series.

The validity of this method for providing local data at the GCM scale in the intervening period between two time slice runs was tested for both temperature and precipitation (Dave Rowell, personal communication, 2006). Data from a full transient GCM run was used as the 'truth' and compared with that obtained by scaling the mean and variance by the global mean temperature, using future and control periods to train the relationships. It is found that the global fraction of grid points which show significant non-linearity in the relationship between global mean temperature and the local mean (standard deviation) is 17-22% (11-17%) for temperature and 11-18% (24-29%) for precipitation. In the case of scaling the local mean, the greater fraction of significantly non-linear grid points for temperature compared to precipitation may simply reflect the greater noise in the precipitation fields. Over Europe, the fraction of locally significant non-linearities is similar to that found globally. Thus these results suggest that the methodology is likely to perform reasonably in predicting changes in the mean and variance at the GCM scale. This provides some support for the validity of the method at the RCM scale, although greater non-linearity is expected at smaller scales.

Scaling of extremes

In this section the applicability of pattern scaling methodologies for providing regional projections of changes in climate extremes is examined. In particular two possible approaches are considered:

1. Local scaling of daily variability, assuming a linear relationship between large-scale GCM and local RCM variables on the daily timescale with subsequent calculation of changes in the mean, variance, skewness or any other index of the daily distribution
2. Direct scaling of extremes, in which linear relationships are assumed between extreme indices and large-scale temperature (or precipitation).

Local scaling of daily variability

The Statistical DownScaling Model (SDSM) of Wilby *et al.* (2002) can be used to develop statistical relationships between local variables from a RCM and large-scale variables from the driving GCM. SDSM essentially performs a multiple linear regression to calibrate the relationship between a regional predictand and large-scale predictors. This relationship can then be used to downscale climate change scenarios when supplied with a time series of predictor values specified from GCM simulations.

The method has been applied to the PRUDENCE set of experiments performed with HadAM3P/HadRM3P (also used in the STARDEX and MICE EU projects), which includes three member ensembles for the present climate (1960-90) and A2 SRES scenario (2080-2100) and one B2 SRES experiment (also 2080-2100). The experimental design is discussed in Rowell (2005). It is worth noting that the horizontal resolutions are approximately 150km for HadAM3P and 50km for HadRM3P.

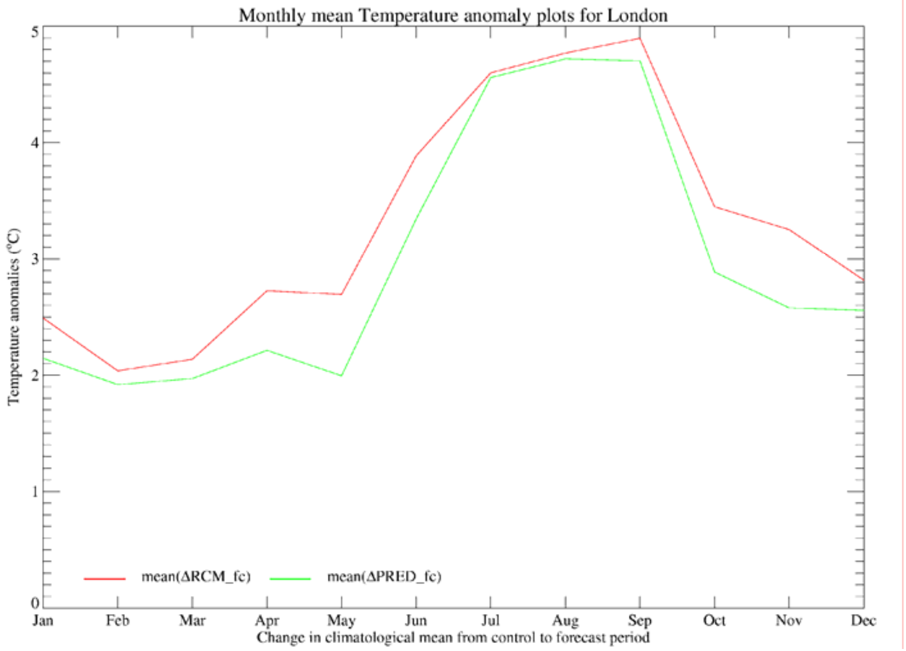

Figure 1: Change in multiyear mean surface air temperature for London grid point, for 2071-2100 relative to 1961-1990, for simulated RCM values (red curve) and values predicted by SDSM (green curve).

On applying SDSM to RCM surface temperature over the UK, it is found that large-scale temperature alone is able to explain about 70% of the variance of daily RCM temperature for the current climate, with the addition of further predictors found to give little improvement (Brown and Murphy, 2006). This suggests that local daily temperature is well predicted from large-scale temperature using a simple linear relationship. The ability of this model, trained on current climate relationships, to predict future changes in local temperature was tested using RCM simulated changes as ‘truth’. In general, it is found that SDSM performs reasonably in estimating changes in monthly mean RCM temperature for grid points across the UK, although it consistently underestimates the changes by a few tenths of a degree (Figure 1). The variance of daily temperatures is also systematically underestimated and generally by a larger amount (Figure 2a). Changes in the variance of the simulated daily temperature distributions were also generally well predicted, although SDSM tends to overestimate simulated increases in variance during July and August (Figure 2c). This is due to a reduced tendency to underestimate variance in these months for the future period (Figure 2b). This work suggests that the 'local scaling' of large-scale daily temperature anomalies can be used to predict changes in the mean of the local daily temperature distribution and, except for summer, its variance.

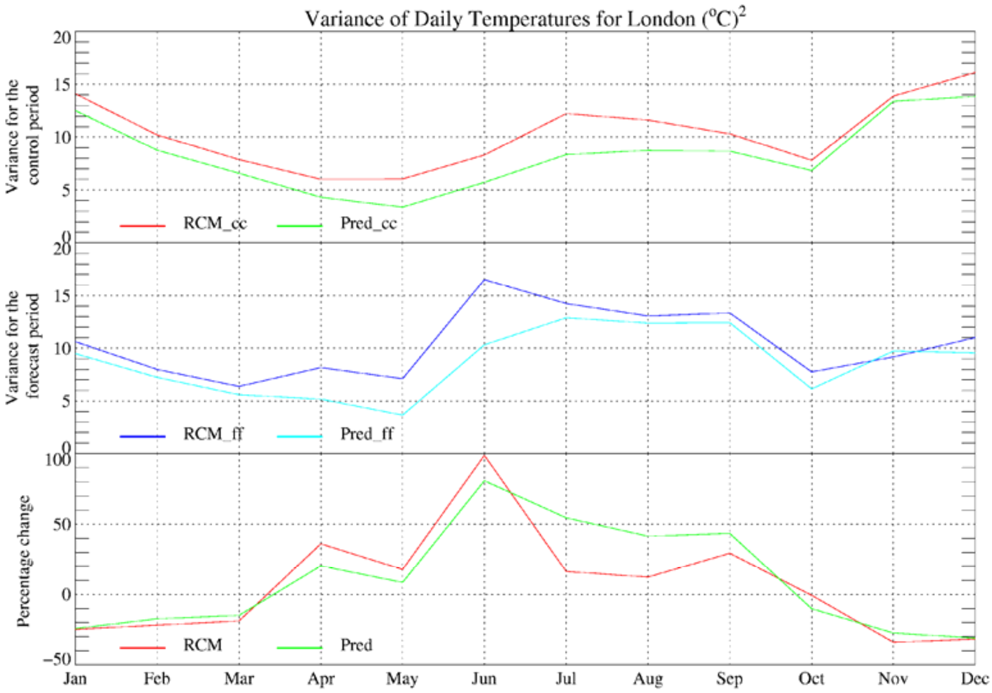

Figure 2: Variance statistics for daily surface air temperature for London.

a) Variance of daily anomalies during 1961-90 relative to the 1961-90 mean, simulated by the RCM (red curve) and predicted by SDSM (green curve) for each month.
b) As (a), but for daily anomalies during 2071-00 relative to the 2071-00 mean, for the RCM (dark blue) and SDSM (light blue)
c) Percentage change in the variance of daily anomalies between 2071-00 and 1961-90, simulated by the RCM (red) and predicted by SDSM (green).

The above technique of downscaling daily variability in temperature and precipitation to obtain changes in the mean and variance of the local daily distribution may also provide estimates of changes in the skewness of the daily distribution, and hence give some indication of changes in local climate extremes.

The ability of the SDSM model above, using large-scale temperature as the only predictor, to reproduce future changes in the skewness of the daily RCM surface temperature distribution was tested for London (Brown and Murphy, 2006). In general, it was found that SDSM performed well in predicting changes in the skewness (Figure 3). This suggests that in the case of temperature, the 'local scaling' of large-scale daily temperature anomalies may provide reasonable predictions of changes not only in the mean and variance, but also the skewness, of daily RCM temperature.

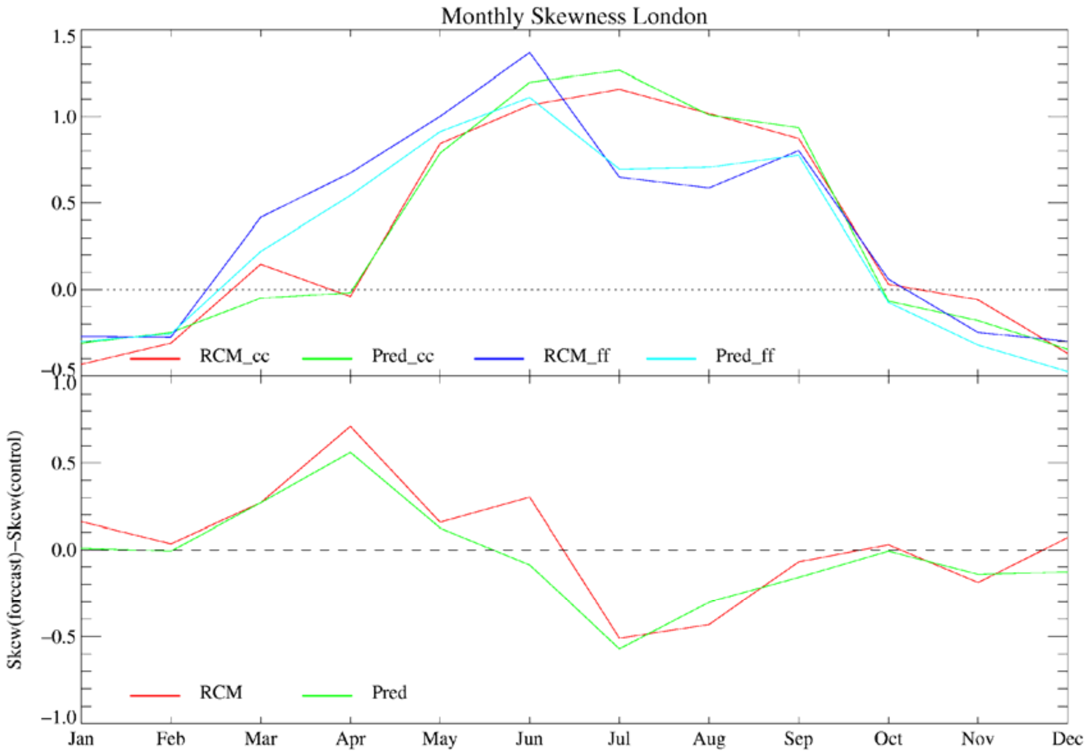

Figure 3: Skewness statistics for daily surface air temperature for London.

a) Skewness of daily anomalies simulated by the RCM during 1961-90 (red curve) and 2071-00 (blue curve) compared with corresponding SDSM predictions (green and light blue curves respectively). Daily anomalies are calculated relative to the mean of relevant time series (1961-90 or 2071-00).
b) Changes in skewness between the future and control period simulated by the RCM (red curve) and predicted by SDSM (green curve).

Initial work applying similar techniques to RCM precipitation over the UK, has found that large-scale precipitation is the leading predictor of daily RCM precipitation, although it is not quite as dominant as large-scale temperature above (James Murphy, personal communication, 2006). It is noted that due to the distribution of precipitation being non-Gaussian, SDSM uses the logarithm of precipitation fields. This initial work suggests that the 'local scaling' of large-scale daily precipitation anomalies may provide reasonable predictions of changes in the mean and variance of daily RCM precipitation, although to a lesser extent than for surface temperature.

Direct scaling of extremes

The applicability of the standard pattern scaling approach to extreme indices, using global mean temperature as a scalar, has been tested on the daily mean distributions of temperature and precipitation. These distributions have been taken from the PRUDENCE set of experiments performed with HadAM3P/HadRM3P (Rowell, 2005) also used in the SDSM approach (Brown and Murphy, 2006) described above.

Pattern scaling has been applied to reconstruct the B2 indices from the A2 and control ensembles and the reconstructed patterns have been compared to the model results.

For this comparison, two quantities will be considered: the inverse of the non linear fraction, measured as the ratio between the B2 climate response (estimated from the root mean square difference, rmsd) and the non linear component (also measured by the rmsd); and the pattern correlation between the reconstructed and the model B2 signal. Three independent scaled patterns have been obtained, one for each control-A2 pair in the ensemble.

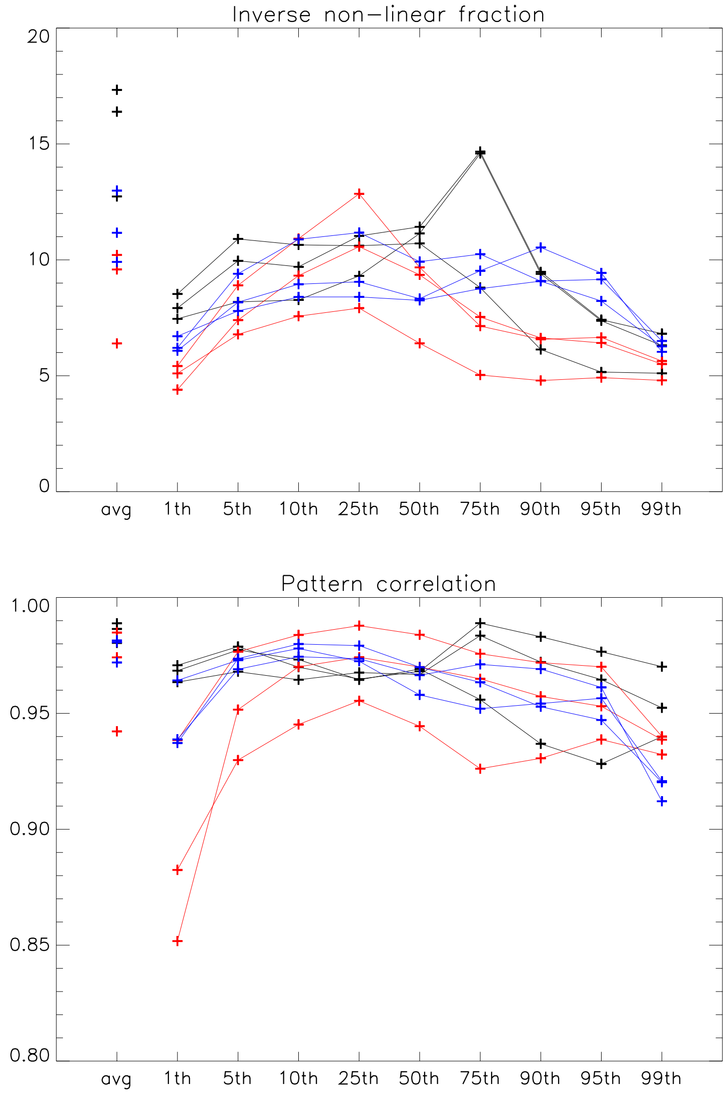

Figure 4: Inverse of the non-linear fraction and correlation for the B2 daily mean temperature distribution reconstructed by pattern scaling. The three sets of curves correspond to three independent estimates for DJF (blue), JJA (red) and annual (black). The meaning of the symbols is the following: *n*th (where n=(1,5,10,25,50,75,90,95,99)) indicates the *n*-th percentile, avg is the mean of the distribution.

The daily distributions have been described by a set of percentiles which include measures of the tails. A good description of the daily intensity distribution should ensure that intensities for longer time scales could also be scaled in the same way. However, this study should be extended to include measures of frequency and persistence. Finally, no attempt has been done to evaluate the signal-to-noise ratio, due to the lack of a long RCM control run, however, the extreme indices will be compared to the mean to infer the possibility of pattern scaling.

The results obtained from scaling daily temperature are reported in Figure 4. Three sets of curves for winter, summer and the whole year are shown. The response pattern has been obtained by a least squares method applied to the three decadal periods in each experiment. Global temperature change has been used to scale the response pattern as in equation (1). It is found that the method reproduces local temperature change well, with the B2 response being at least 5 times higher than the non-linear component across the full set of percentiles. The non-linear fraction for high percentiles is greater although of a similar order of magnitude than for the corresponding average (which shows seasonal dependence, DJF percentiles scaled better those for JJA). Pattern correlations are also very high, with percentiles in the same range as the averages. Both the non-linear fraction and correlation results suggest that the efficiency of the simple scaling extends to the tails of the temperature distribution, without great loss of predictive power.

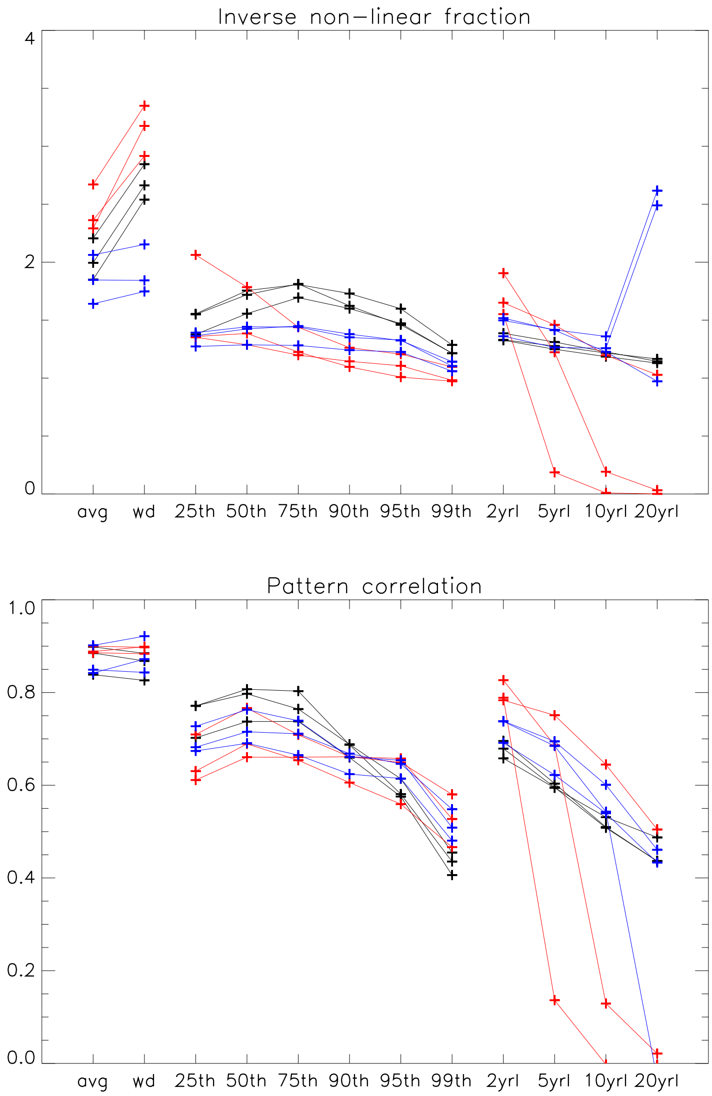

Figure 5: Inverse of the non-linear fraction and correlation for the B2 daily mean precipitation distribution reconstructed by pattern scaling. The three sets of curves are

three independent estimates for DJF (blue), JJA (red) and annual (black). Symbols as in Figure 4, plus wd, fraction of wet days and *n*yrl with n=(2,5,10,20) are the return levels corresponding to n-years return period.

The case for precipitation is different, as shown in Figure 5. For this case, a logarithmic transformation has been applied to the intensity indices. The response patterns for mean, wet day fraction and percentiles have been calculated as for temperature (least squares fit of three decadal periods) while the return levels have been scaled using the 30-year time-slice pattern. Wet day fraction has been defined with respect to 1 mm/day threshold and the distribution of percentiles is also defined with respect to the same threshold. Values of the estimated non-linear fraction for mean and wet days indicate a signal two times larger than the non-linear component. At the 50 km resolution, these results are likely to be heavily affected by the variability of precipitation, which will act to increase the non-linear component of the signal. For the percentiles, the non-linear component obtained is of the same order of magnitude as the signal. Correlations for mean and wet days are larger than 0.8. The correlations for percentiles up to the 90^{th} are larger than 0.6, while for the largest percentiles correlations are much lower.

Similar features are generally observed for the return level (the exceptions for higher return levels for some ensemble members, i.e. where the results are close to zero, are probably due to insufficient data to reliably estimate the return levels). In fact, where the return levels are reliably estimated, the results are as good as or better than for the 95^{th} and 99^{th} percentiles. This result is remarkable considering the events described by the return levels are less frequent than those described by the highest percentiles and should make possible the application of scaling to the tail of the precipitation distribution. These features will be investigated further in future work.

The results obtained so far seem to indicate that pattern scaling should not be applied to precipitation. However, these findings should be updated when longer RCM simulations (like those planned in ENSEMBLES RT2B) will be available, since it has been shown (Mitchell, 2003) that the use of multiple periods for estimating the response pattern strongly improves the signal-to-noise ratio.

In this study, we have not included extreme indices describing persistence or frequency. The work by Good *et al.* (2006) has shown that, for some indices, the assumption of linear scaling with temperature should be abandoned in favour of a stronger relationship (which implies positive feedbacks with increasing temperature).

Conclusion

The following diagram illustrates graphically the possible strategies that can be applied to downscale GCM scenarios which have not been used to force a RCM. The approaches work under the assumption that at least one GCM scenario has been used to drive a regional climate model.

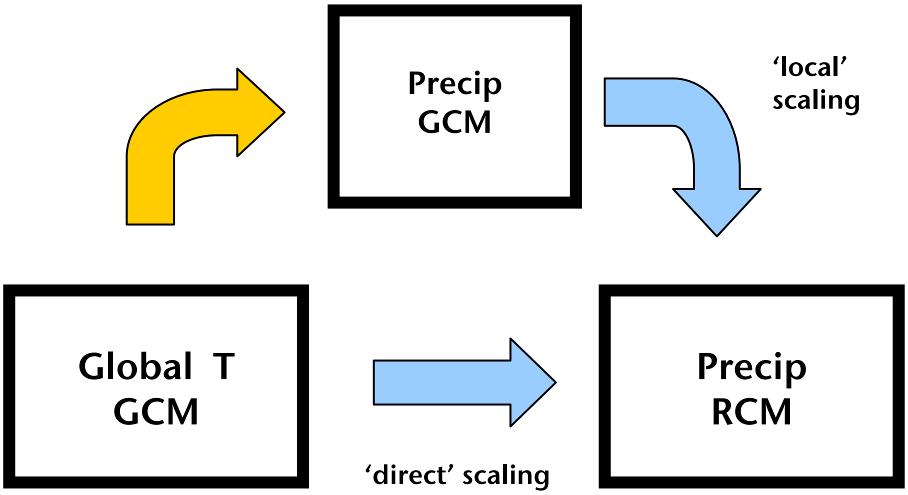

Figure 6: Possible strategies for pattern scaling of precipitation indices from GCM to RCM resolution

The two suggested methods correspond to the blue arrows in the figure:

1. 'local' scaling from GCM to the corresponding RCM variable, both considered on the same time scale
2. 'direct' scaling from global temperature of the required RCM index; usually a linear scaling law is assumed but the method can be extended to more general power laws (Good *et al.*, 2006)

In this report, it has been shown that both methods work for temperature, while additional research is needed for precipitation indices. There is also the need to extend this study to indices describing frequency or persistence of events. It is worth noting that the results shown above are for the relationship between a GCM with 150km horizontal resolution with an RCM on a 50km horizontal grid. Since the ENSEMBLES RT2B experiments will be at ~300km resolution for the GCMs and 25km for the RCMs, 'local' scaling methods could be affected by the increased gap in resolution between GCMs and RCMs.

Finally, the ENSEMBLES RT2B set of experiments will give us the opportunity for a systematic study such as those carried out for GCM pattern scaling (e.g. Mitchell *et al.*, 1999, Mitchell 2003), from better evaluation of response patterns due to the 150 year runs, and, possibly, from verification with multiple scenario RCM runs.

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