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Applicability of pattern scaling for filling the 
ENSEMBLES GCM-RCM matrix

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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 geographical pattern of the change is independent of the forcing. Thus the local response of a climate variable is assumed to be linearly related to the global mean temperature change, with the scaling coefficient only dependent on position. This condition is largely satisfied for temperature and to a lesser degree precipitation (Mitchell et al., 1999; Mitchell, 2003).

In this study, we assess the applicability of pattern scaling methods to provide climate projections at the RCM scale for a full range of driving GCMs. The availability of GCM simulations raises the possibility of using anomalies at the GCM scale, rather than the global mean temperature change, as the predictor of the local climate response. Thus the change in the RCM for a given variable is expressed as:

\[ \Delta RCM_{xsy} = A_{xs} \Delta GCM_{xsy} \]  

where the scaling coefficient \( A \) depends on position \( (x) \) and season \( (s) \), but not year or period \( (y) \) or forcing scenario \( (e) \); \( \Delta RCM \) is the change in the RCM and \( \Delta GCM \) is the corresponding change for the given variable in the nearest GCM grid box. This ‘local scaling’ method for downscaling precipitation was developed by Widmann et al. (2003). The physical basis for it is that regional patterns of precipitation are produced predominantly by the interaction between large-scale systems and the stationary topography.

In this paper we examine whether this simple local scaling relationship can be used to predict the local change for untried GCM-RCM pairs, i.e. to what extent the scaling coefficient \( A \) can be assumed to be independent of the driving GCM. In addition, we examine the accuracy of this technique both for time-mean variables and for measures of variability and extremes, focussing on temperature
and precipitation. Recommendations regarding the applicability of this technique for filling the ENSEMBLES GCM-RCM matrix are made.

**Model data**

In this study we use data from two multi-model ensembles. Firstly we use the Met Office Hadley Centre’s GCM-RCM perturbed physics ensemble, available from the Quantifying Uncertainty in Model Predictions project (hereafter referred to as the QUMP ensemble, Murphy et al., 2007). This consists of 11 coupled ocean-atmosphere GCMs, generated by varying uncertain parameters in the atmospheric physics and surface schemes in the HadCM3 model, and a corresponding 11-member ensemble of the Hadley Centre RCM. The invariance of a local scaling relationship across these different model versions has been explored, for changes at the end of the century (2069-2099 minus 1959-1989) for the A1B scenario. The GCM changes are at the 300 km scale, whilst the RCM changes are at the 25 km scale. We note that since the different members of the QUMP ensemble are all based on a single parent model, this dataset does not allow an assessment of the accuracy of local scaling across structurally different driving GCMs.

The second multi-model dataset used is that from the PRUDENCE project, in which different RCMs are forced with boundary conditions from different driving GCMs (Deque et al., 2007). In particular, we use a subset of the data consisting of two RCMs, namely the DMI HIRHAM and SMHI RCAO models, each driven by two GCMs, namely HadAM3H and ECHAM4. This 2x2 matrix allows an assessment of the extent to which a local scaling relationship is invariant across different driving GCMs. In this case, changes are calculated as the difference between the 2070-2100 and 1960-1990 periods for the A2 scenario, with the GCM data degraded to a common resolution of 300 km and the RCM data at a 50 km resolution. We note that there is a slight mismatch between the ECHAM4 experiments used to drive the DMI and SMHI RCMs (Ole Christensen, personal communication, 2008). Only data for the ECHAM4 experiment that was downscaled by SMHI are available, and thus are used here to assess the performance of local scaling for both RCMs. Although the climatologies of the two ECHAM4 experiments are expected to be similar, the slight experimental mismatch may lead to an apparent reduced scaling performance for the DMI compared to the SMHI model.
Correlation between GCM and RCM changes across the QUMP ensemble

Figures 1, 2, and 3 show the extent to which changes in various metrics of the daily precipitation and temperature distributions in the RCM are correlated with those in the GCM across the QUMP ensemble, for the British Isles (BI). In particular results are shown for the mean, variance and skewness of daily rainfall (MEANRAIN, VARRAIN and SKEWRAIN), the number of dry days (PDRY), and the mean and variance of daily temperature (TMAX and VAR-TMN). In the case of precipitation intensity measures a logarithmic transform is applied.

The key results, in order of the strength of any linear relationship, are as follows:

- For changes in monthly mean Tmax, ΔRCM and ΔGCM are highly correlated for all grid boxes and in all months.
- For changes in monthly mean rainfall, ΔRCM and ΔGCM are significantly correlated across much of the BI in all months.
- For changes in the number of dry days, ΔRCM and ΔGCM are significantly correlated, with a stronger relationship over land in summer.
- For changes in the variability of daily temperature, ΔRCM and ΔGCM are significantly correlated across much of the BI, although with a weaker relationship over southern Britain in summer.
- For changes in the variability of daily rainfall, ΔRCM and ΔGCM are significantly correlated across the BI in winter, but not summer.
- For changes in the skewness of daily rainfall, there is no significant correlation between ΔRCM and ΔGCM.

These correlation results suggest that local scaling may perform well in predicting the change for an untried RCM ensemble member, in particular for mean temperature, and to a lesser extent for mean rainfall and measures of daily variability. The lack of any significant correlation for the skewness of daily rainfall suggests that the skill of local scaling may reduce on considering precipitation extremes. This is explored further in the following section.
Figure 1: Linear correlation between $\Delta$RCM and $\Delta$GCM across 11 members of the QUMP ensemble and 4 non-overlapping time periods, for MEANRAIN, VARRAIN, SKEWRAIN, PDRY, VAR-TMN, TMAX, for January. Regions where the correlation coefficient is not significantly different from zero at the 10% level are masked in white.
Figure 2: As in Figure 1 but for July.
Figure 3: Linear correlation between ΔRCM and ΔGCM across 11 ensemble members and 4 time periods, for each month, for 6 selected UK stations. Results are shown for MEANRAIN, VARRAIN, SKEWRAIN, PDRY, VARMN, TMAX. The grey shading indicates the region of non-significance at the 10% level.
Performance of local scaling for the QUMP ensemble

In this section, we assess the performance of local scaling in predicting the change for a randomly selected member of the QUMP ensemble. This corresponds to downscaling from 300 km to 25 km. At each grid box and for each variable, the scaling coefficient $A$ is calculated using linear regression (with zero intercept) applied to 10 (out of the 11) ensemble members. The resulting relationship is used to predict the RCM change for the remaining ensemble member. In this analysis the scaling coefficient is assumed to be a function of position only, and not dependent on the physics perturbations in the different ensemble members.

Local scaling performance is assessed using the inverse non-linear fraction (InvF), which is given by the ratio of the RCM response (in the randomly selected member) to the non-linear component (calculated from the difference between the RCM response and that estimated from local scaling):

$$\text{InvF} = \sqrt{\frac{1}{(1 - A\frac{\Delta \text{GCM}}{\Delta \text{RCM}})^2}}$$

where $A$ is the local scaling coefficient, given by the linear regression relationship $\Delta \text{RCM}_k = A . \Delta \text{GCM}_k$ fitted to 10 (out of 11) ensemble members ($k$), at each grid point; $\Delta \text{RCM}$ and $\Delta \text{GCM}$ are the corresponding changes in the remaining ensemble member. InvF≥2 corresponds to a non-linear component of less than half the signal, and this is used here as a measure of good scaling performance.

The fraction of grid boxes across the British Isles showing good scaling performance, for various measures of daily variability and extremes, are shown in Figure 4. A logarithmic transform has been applied to precipitation intensity measures. In addition, 3x3 spatial pooling has been used in the calculation of the local RCM indices as this has been shown to reduce grid box noise (Kendon et al., 2008).

The results for the British Isles indicate:

- Local scaling performs well for mean and extremes of daily temperature in both seasons, with no significant loss of skill on moving to the tails of the distribution. Both changes in extreme and mean temperature in the GCM are good predictors of the RCM extreme temperature change.

- Local scaling performs less well for the variability of daily temperature, although there is still significant skill. In this case the change in daily variability in the GCM is a better predictor than the mean temperature change.
Figure 4: Fraction of grid boxes across the British Isles showing good scaling performance, in the context of predicting the RCM change for a randomly selected member of the QUMP ensemble. Good scaling performance is defined as an inverse non-linear fraction InvF ≥2. Results are shown for seasonal statistics of (left) daily precipitation and (right) daily temperature, for DJF (blue) and JJA (red). The seasonal statistics correspond to: mean = seasonal mean, stddev = standard deviation of daily variability, wd freq = frequency of wet days (≥1 mm day⁻¹), and PX = xth percentile of the daily distribution. In the top panels the GCM predictor (∆GCM) is given by the appropriate seasonal statistic of the daily distribution, and in the bottom panels by the seasonal mean.
• Local scaling generally performs less well for rainfall compared to temperature indices. Good skill is seen most consistently across the region for wintertime rainfall variability and extremes, and the summertime occurrence of dry days. Further analysis (not shown here) indicates that these indices correspond to those for which the climate change signal is significant compared to natural variability. Relatively low skill is seen for rainfall variability and extremes in summer, where internal variability dominates any climate change signal.

• For rainfall indices, the change in the corresponding statistic of the daily rainfall distribution rather than the seasonal mean change provides the best GCM predictor.

In summary, local scaling performs well in predicting the change for an untried RCM ensemble member in the case of temperature (including extremes). For rainfall, local scaling also performs well for those indices which show significant changes compared to natural climate variability. Thus significant non-linearities appear to be explained by the dominance of internal variability.

Performance of local scaling for untried time periods

In this section we assess the relative performance of local scaling in predicting the change for an untried transient time period compared to an untried RCM ensemble member. In the case of an untried time period, the change in a single GCM-RCM pair for the 2069-99 period is used to estimate the change for the earlier 2039-69 period assuming a linear scaling, and this is then compared to the actual model result. Results for the British Isles are shown in Figure 5.

In general, local scaling performs similarly or less well in terms of predicting the local change for an intervening time period compared to a different ensemble member. In particular, local scaling gives poor performance in estimating transient changes in summertime rainfall indices and temperature variability. These results may reflect the greater relative influence of natural variability compared to the climate change signal for earlier time periods.
Figure 5: Fraction of grid boxes across the British Isles showing good scaling performance in predicting the change for (top) a randomly selected ensemble member and (bottom) a transient time period. Results are shown for MEANRAIN, VARRAIN, SKEWRAIN, PDRY, VAR-TMN, TMAX, for January (blue) and July (red).
Performance of local scaling for different driving GCMs

In the above results the performance of local scaling has been assessed for the QUMP ensemble, where the different ensemble members are all derived from the same underlying parent model. A more stringent test, and one which is more applicable in the context of the ENSEMBLES project, is whether local scaling can be used to predict the change in an RCM forced by a different driving GCM. This is addressed here using data from the PRUDENCE project.

Changes in seasonal mean precipitation and temperature in the DMI and SMHI RCMs, driven by the HadAM3H and ECHAM4 GCMs, are shown in Figures 6, 7, 8 & 9. The corresponding changes in the driving GCMs, at a common resolution of \(~300\text{km}\), are also shown. In general, it can be seen that the pattern of change in the RCM resembles the pattern of change in the corresponding driving GCM. Thus the local climate response is strongly conditioned by the large-scale forcing. However, local detail varies between different RCMs driven by the same GCM, indicating a significant influence from local processes in some regions. For example, summertime precipitation change over the Alps varies considerably between the DMI and SMHI RCMs. We note that differences between the RCMs when driven by HadAM3H over the Baltic Sea are due to erroneous SSTs in this region, which were only corrected for in the SMHI runs. In addition, differences between the RCMs when driven by ECHAM4 may reflect the slight mismatch between the driving experiments noted above. However, these differences are generally small supporting the assertion that the climatologies of the two ECHAM4 driving experiments are similar.

In general these results suggest that local scaling may be skillful in estimating the local change in an RCM for a different driving GCM, where the scaling coefficient varies between different RCMs. The fact that the driving GCM is a key source of uncertainty in the local climate response has also been found in previous studies (e.g. Rowell, 2006; Deque et al., 2007). This implies the importance of sampling uncertainty in the driving GCM in any ensemble approach, and in the context of the ENSEMBLES project, of fully representing this by using statistical techniques to fill the GCM-RCM matrix.

In order to assess the likely skill of local scaling for filling the ENSEMBLES matrix, the dependence of the scaling coefficient $A$ on the RCM and the driving GCM was tested. In particular, the ratio $\Delta_{\text{RCM}}/\Delta_{\text{GCM}}$ was examined for the different PRUDENCE integrations, again with $\Delta_{\text{GCM}}$ calculated at the same scale for both GCMs. The results for seasonal mean precipitation are shown in Figure 10.
Figure 6: Change in seasonal mean precipitation in the (top) HadAM3H and ECHAM4 GCMs, and the (middle) DMI and (bottom) SMHI RCMs for the corresponding driving GCMs, for DJF. Changes correspond to the difference between the 2070-2100 and 1960-1990 periods for the SRES A2 scenario. The HadAM3H data has been aggregated onto the ECHAM4 grid.
Figure 7: As in Figure 6 but for JJA.
Figure 8: As in Figure 6 but for temperature in DJF.
Figure 9: As in Figure 6 but for temperature in JJA.
Figure 10: The scaling coefficient calculated as the ratio $\Delta RCM/\Delta GCM$, for seasonal mean precipitation, for (top) DMI driven by HadAM3H, (middle) SMHI driven by HadAM3H and (bottom) SMHI driven by ECHAM4. Results are shown for (left) DJF and (right) JJA.
Key results:

- The scaling coefficient varies between different RCMs. This is seen to be particularly the case over Europe in summer for mean precipitation where the RCM has a major influence on the local precipitation change.

- The scaling coefficient also varies between different driving GCMs. For seasonal mean precipitation, this is particularly the case over the Scandinavian mountains and southern Europe in winter, and parts of the far north and far south of Europe in summer.

- The scaling coefficient varies more between different driving GCMs than different RCMs for seasonal mean precipitation change across much of the region.

The ability of local scaling to predict the change for an untried GCM-RCM pair depends on the extent to which the scaling coefficient $A$ can be assumed to be independent of the driving GCM. Thus any significant variation of $A$ with the driving GCM will lead to error in the approach. Such a dependence may be explained by either (1) the dominance of local processes i.e. $\Delta RCM$ is independent of $\Delta GCM$; or (2) a complex non-linear interaction between the large-scale forcing and the local climate variable. In the following analysis we assess the performance of local scaling in predicting the change for a different driving GCM, which essentially examines the validity of the assumption of independence.

For each RCM and each grid box, local scaling has been applied to reconstruct the change for the ECHAM4 driven experiment using the HadAM3H driven experiment. The performance of local scaling is then assessed by considering the inverse non-linear fraction:

$$\text{InvF} = \sqrt{\frac{1}{\left(1 - \frac{\Delta RCM_H \Delta GCM_E}{\Delta RCM_E \Delta GCM_H}\right)^2}}$$

where $\Delta RCM_E$ is the change, for a given variable and grid box, in the RCM when driven by ECHAM4, $\Delta RCM_H$ the corresponding change in the RCM when driven by HadAM3H, and $\Delta GCM_E$ and $\Delta GCM_H$ are the changes in the ECHAM4 and HadAM3H GCMs respectively. In this formulation the scaling coefficient is a function of the position and also the RCM, but is assumed to be independent of the driving GCM, forcing scenario and time period.

We note that the scaling coefficient is sensitive to the respective resolutions of the RCM and GCM data. In order to use the scaling relationship derived from one GCM-RCM pair to estimate the change for a different driving GCM, the GCM data must be on a common grid. Thus in this analysis the HadAM3H data
have been aggregated onto the same grid as the ECHAM4 data (corresponding to \( \sim 2.8125^\circ \) in longitude and latitude).

Figures 11 and 12 show the inverse non-linear fraction for seasonal mean precipitation and temperature, for each of the RCMs. In general, the two RCMs show similar results, giving us confidence that the performance of local scaling found here is expected to apply more generally to other models. In the following assessment, we focus primarily on the results for the SMHI-RCM as these are unaffected by the ECHAM4 experimental mismatch. A value of \( \text{InvF} \geq 2 \) is used as indicative of good scaling performance.

Assessment of local scaling performance for seasonal mean variables:

- Local scaling performs well in estimating the change in seasonal mean temperature for a different driving GCM, for both seasons, across much of Europe.

- For temperature changes over some coastal regions, local scaling using the nearest GCM grid box as the predictor does not work well. This may relate to a mismatch between the land/sea classification of the RCM and corresponding GCM grid boxes. In this case, initial work suggests that the appropriate predictor for a coastal RCM land point is not the nearest GCM grid box if this is a marine point, but rather the adjacent GCM land grid box.

- Local scaling performs well in estimating the change in seasonal mean precipitation for a different driving GCM over much of northern Europe in winter and central Europe in summer. This coincides with those regions where the climate change signal is significant compared to natural variability (Kendon et al., 2008).

- There is evidence that local scaling does not perform well for precipitation changes in the lee of mountains. In particular, local scaling does not work well in the vicinity of the Scandinavian mountains in both seasons, and to the south-east of the Alps in summer. This may relate to the dominance of local processes in these regions.

Finally, in this section we examine results for measures of daily variability and extremes. The performance of local scaling in predicting the change in the SMHI-RCM for a different driving GCM for various statistics of the daily precipitation and temperature distributions is shown in Figures 13 and 14. Results are shown for the 8 PRUDENCE regions: BI = British Isles, IP = Iberian Peninsula, FR = France, ME = Mid Europe, SC = Scandinavia, AL = Alps, MD = Mediterranean, EA = Eastern Europe. As above, a logarithmic transform has
Figure 11: Inverse non-linear fraction on estimating the change in seasonal mean precipitation for the ECHAM4 driven experiment, using the HadAM3H driven experiment. Results are shown for the (left) DMI and (right) SMHI RCMs, for (top) DJF and (bottom) JJA.
Figure 12: As in Figure 11, but for seasonal mean temperature.
been applied to precipitation intensity measures and 3x3 spatial pooling has been used in the calculation of the local RCM indices. Due to only monthly mean data being available for the ECHAM4 GCM, seasonal mean precipitation (temperature) change in the GCM is used as the predictor for all statistics of the RCM daily precipitation (temperature) distribution. Thus these results are comparable with the bottom panels in Figure 4 for QUMP, for the British Isles region.

Key results in the context of predicting the local change for an untried GCM-RCM pair:

- In general, local scaling works better for temperature compared to precipitation indices.

- Local scaling works well for mean and upper percentiles of daily temperature. An exception is Scandinavia in winter, where poor performance may be explained by local snow/ice changes.

- Changes in daily temperature variability in the RCM do not scale well with the GCM seasonal mean temperature change. From the QUMP results (Figure 4), however, we would expect some improvement in scaling skill on using changes in daily variability in the GCM as the predictor.

- Changes in low percentiles of daily temperature in the RCM do not scale well with the GCM seasonal mean temperature change over northern European regions during winter. We note that, in the case of the British Isles, this behaviour was not seen for the QUMP ensemble.

- Local scaling works well for mean precipitation over northern European regions in winter and central European regions in summer, as seen in Figure 11. Again, this seasonal and regional dependence in scaling skill appears to be explained, at least in part, by the extent to which the climate change signal is discernible above natural variability.

- For other precipitation indices, changes in the RCM generally do not scale well with the GCM seasonal mean precipitation change. From the QUMP results (Figure 4), we would expect improved scaling skill on using changes in the corresponding statistic in the GCM as the predictor. An additional factor, which may explain a reduction in skill for precipitation extremes, is the increase in uncertainty due to natural variability. In particular, single 30 yr climate change experiments may not be sufficient for characterising the tail of the precipitation distribution (Kendon et al., 2008).

We note that for the British Isles region, the performance of local scaling in estimating the change for a different driving GCM in PRUDENCE (top left plot
Figure 13: Fraction of grid boxes across each of the 8 PRUDENCE regions showing good scaling performance, in the context of predicting the change in the SMHI-RCM for a different driving GCM. Good scaling performance is defined as an inverse non-linear fraction InvF ≥2. Results are shown for the following seasonal statistics of daily precipitation: mean = seasonal mean, stddev = standard deviation, wd freq = frequency of wet days (≥1 mmmday⁻¹), and Px = xth percentile; for DJF (blue) and JJA (red). In each case, the predictor (ΔGCM) is given by the seasonal mean precipitation change in the nearest GCM grid box.
Figure 14: As in Figure 13, but for seasonal statistics of daily temperature.
in Figures 13 and 14) is similar to that for a different ensemble member in QUMP (bottom plots in Figure 4). An exception however is for the variability and low percentiles of daily temperature in winter. Any differences between QUMP and PRUDENCE results may be due to a number of factors:

1. For PRUDENCE, the scaling coefficient is allowed to vary with the RCM, whereas for QUMP it is assumed to be independent of the physics perturbation in each ensemble member.

2. In the QUMP ensemble, all members are derived from the same underlying parent model; whilst the PRUDENCE results sample local changes for structurally different driving GCMs.

3. The QUMP results correspond to a greater downscaling step: 300 to 25 km for QUMP versus 300 to 50 km for PRUDENCE.

Conclusion

In this study we have considered a pattern scaling technique, which we have termed 'local scaling', whereby the change in the GCM at the nearest grid box is used as a predictor of the change in the corresponding RCM variable. This technique can be used to estimate the local RCM change for the full range of driving GCMs, providing at least one has been downscaled. Thus it is applicable for filling the ENSEMBLES GCM-RCM matrix.

In this context, we have found that the appropriate scaling method is as follows:

- The local scaling coefficient $A$ depends on the position and the RCM. It is assumed to be independent of the driving GCM, time period and scenario. Note in order to use the scaling relationship derived from one GCM-RCM pair to estimate the change for a different driving GCM, the GCM data must be aggregated onto a common grid.

- The predictor is given by the change in the corresponding GCM variable at the nearest GCM grid box. A possible exception to this may be in coastal regions, where the appropriate predictor for a land RCM grid box may not be the nearest GCM grid box if this corresponds to a marine point. In this case the nearest GCM land grid box may be a better predictor.

- The best predictor for estimating the change in a given index of the daily distribution in the RCM is the change in the same index in the GCM. We note that for extremes of daily temperature, the change in seasonal mean temperature in the GCM performs equally well.
• A logarithmic transform applied to precipitation intensity indices gives improved skill.

• Applying 3x3 spatial pooling to RCM daily data reduces grid box noise, and improves scaling performance.

In terms of the performance of local scaling for estimating changes in an untried GCM-RCM pair we find:

• Local scaling performs well for estimating changes in the daily temperature distribution. In particular skill extends to the upper tails of the distribution without loss of predictive power.

• Local scaling does not perform well for estimating changes in low temperature extremes over northern regions in winter.

• Local scaling performs reasonably well (non-linear component < 50%) in estimating changes in seasonal mean rainfall where the climate change signal is significant compared to natural variability. An exception to this may be in the lee of mountains where local processes dominate.

• For precipitation extremes, there is increased uncertainty due to natural variability, and this may lead to a reduction in local scaling performance. Further analysis using the appropriate daily statistic in the GCM as predictor, however, is needed to fully assess local scaling performance for measures of precipitation variability and extremes. In addition using results from a three member initial condition ensemble for each set of boundary conditions will lead to a more robust estimate of extreme precipitation change, and potentially improved scaling performance.

In summary this local scaling technique is showing promising results in terms of its applicability for filling the ENSEMBLES GCM-RCM matrix. In particular, significant non-linearities in the downscaling relationship appear to be largely explained by the dominance of internal climate variability. This technique has the advantage of simplicity but also generality, with other more complex downscaling methods using multiple predictors likely to vary from region to region.

Further assessment of this technique will be possible once data from the ENSEMBLES RT2B scenario runs become available. In particular, there are a number of RCMs that will be driven by multiple GCMs. In this case daily data from the driving GCMs will allow the appropriate statistic of the daily distribution to be used as the GCM predictor.
References


