Scoping Study for Precipitation Downscaling and Bias-Correction

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Executive Summary

Various methods exist for correcting biases in climate model precipitation data. This study has investigated four of these bias-correction methods, here called linear, non-linear, gamma and empirical, and extensively tested their performance and suitability for bias-correcting daily precipitation outputs from a Regional Climate Model (RCM) for use as inputs to hydrological models over six test regions spanning the Great Britain.

The RCM daily precipitation data were taken from the unperturbed variant of the Met Office Hadley Centre Regional Model Perturbed Physics Ensemble (HadRM3-PPE-UK), and observed daily precipitation data were taken from the Continuous Estimation of River Flows gridded precipitation dataset. Spatial downscaling (re-gridding) and correction of the fraction of rain-days were undertaken as pre-processing steps before the bias-correction procedure, which translated the RCM data from a 0.22° grid scale to the 1 km grid scale of the observed dataset.

Re-sampling tests were used to assess the performance of the bias-correction methods in terms of the first four statistical moments, and cumulative distribution functions (cdfs) were produced to compare the distribution of the bias-corrected precipitation with respect to the observed and pre-processed RCM precipitation. We found that whilst the first and second moments of the precipitation frequency distribution can be corrected robustly, correction of the third and fourth moments of the distribution is much more sensitive to the choice of bias-correction procedure and to the selection of a particular calibration period. Overall, our results demonstrate that, if both precipitation datasets can be approximated by a gamma distribution, the gamma-based quantile-mapping technique offers the best combination of accuracy and robustness. In circumstances where precipitation datasets cannot adequately be approximated using a gamma distribution, the non-linear method is more effective at reducing the bias but the linear method is least sensitive to the choice of calibration period. The empirical quantile mapping method can be highly accurate, but results were very sensitive to the choice of calibration time period. Examination of the seasonal variation of the non-linear bias-correction factors showed that the bias-correction applied to the HadRM3 daily precipitation varied with season, location, topography and precipitation intensity, suggesting that the method is capable of reproducing many features of the complex spatial and temporal patterns of UK daily precipitation. Taking the known limitations into account this study concluded that the gamma-based quantile-mapping technique is the most suitable for bias-correcting daily HadRM3 precipitation for use in hydrological modelling in the UK.

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Section I Introduction

The Future Flows and Groundwater Levels project was set up to provide estimates of the impact of climate change on UK river flows and groundwater levels. The project uses both probabilistic projections of climate change and transient regional climate model (RCM) runs from the UK Climate Projections 2009 (UKCP09) project (DEFRA, 2009). This report provides details on the pre-processing and bias-correction of the RCM precipitation data to correct systematic biases, prior to its use in hydrological modelling of river flow. This report is an extension of a manuscript submitted for publication in a peer-reviewed scientific journal by Lafon et al. (2012).

Precipitation is the key driver of river flow and groundwater levels. In order to make accurate estimates of the impacts of climate change on these processes the reliability of the driving precipitation is essential. The accuracy of global climate models (GCMs) is continually improving, however, it is not yet the case that they can produce realistic local scale precipitation. The most common problem associated with predictions of precipitation made using GCMs is that, at a daily time-scale, precipitation occurs more frequently than observed, but often with a lower intensity (Osborne and Hulme, 1998). A more recent study has shown that although total land precipitation amounts were well estimated by a set of 18 GCMs, the spatial patterns of frequency and intensity were more complex: most models overestimated the frequency of light precipitation (defined as 1–10 mm day^{-1}), but underestimated its intensity (Sun et al., 2006). In contrast, most models underestimated the frequency of heavy precipitation (>10 mm day^{-1}), but simulated the intensity well.

In order to make precipitation predictions at hydrologically-relevant spatial scales (i.e., daily and spatially variable at a few kilometres scale), it is necessary to employ some form of downscaling technique. Many such techniques have been reviewed in the literature, including statistical downscaling, which uses empirical relations between climate model outputs and historical observed data, and dynamical downscaling which involves the use of a regional climate model (RCM) (see Fowler et al., 2007 for a detailed review). RCMs offer a more physically-realistic approach to downscaling because they provide an explicit representation of the mesoscale atmospheric processes that produce heavy precipitation. When nested within a GCM, RCMs provide regional detail that is not only consistent with the parent GCM, but which is spatially-coherent. That is, a degree of spatial persistence of large-scale atmospheric features is automatically ensured, because the model generates these features dynamically. This feature is important in producing realistic forcing data for hydrological models because many floods and droughts are caused by spatially- and temporally-persistent rainfall patterns. Two major studies of the accuracy of RCM daily precipitation estimates used extreme precipitation statistics to compare the performance of several different RCMs nested within both ECMWF ERA-15 reanalysis data (Frei et al., 2003), and within the Hadley Centre HadAM3 GCM (Frei et al., 2006). They found that the RCMs were capable of reproducing important mesoscale patterns of observed daily precipitation, particularly during autumn and winter, and in response to topographic effects which could be much better represented at regional scales. Nevertheless, Frei et al. (2006) found large model biases, most notably in summer, when convective precipitation dominates.

Such evidence of bias in RCM daily precipitation has prompted many investigators to apply RCM-derived change factors to observed precipitation time series rather than using RCM daily outputs directly (e.g., Arnell et al., 2003). The biases in RCM daily precipitation may not be limited to bias in mean precipitation, but may affect precipitation variability and other derived measures that are of hydrological importance (Arnell et al., 2003, Diaz-Nieto and Wilby, 2005, Fowler et al., 2007). These effects include differences in variability and extreme values, and differences between the modelled and observed distribution of dry days, and periods of dry days. Many methods have been employed to adjust biases in RCM daily precipitation, each correcting a different range of statistical moments. We group these published techniques into the following four families: (i) linear (e.g. monthly and spatially varying change factor (e.g., Lenderink et al., 2007)); (ii) non-linear (e.g. monthly and spatially varying change factor and exponent (e.g., Leander and Buishand, 2007)); (iii) distribution-based quantile mapping (e.g., gamma distribution, Hay et al., 2002, Piani et al., 2010); (iv) and distribution-free quantile mapping (e.g., empirical distribution, Ashfaq et al., 2010, Wood et al., 2004, Wood et al., 2002).

We compare the range of established bias-correction techniques to determine which is the most reliable method for bias-correcting daily precipitation data over the whole of the UK. We apply each method to six regions in the UK and evaluate the performance using a range of statistics and tests. RCM daily precipitation was compared to an ‘observed daily gridded precipitation’ product derived by interpolation from Met Office rain gauges (Keller et al., 2006). Regional climate model daily precipitation was obtained from the HadRM3.0-PPE-UK ensemble of perturbed-physics experiments employed in the UK Climate Impacts Programme study (Jenkins et al., 2009).

This report is organised as follows. First, we investigate the suitability of spatial interpolation (‘smoothing’) methods as part of the downscaling procedure of the pre-processing of RCM precipitation. We then describe the four bias-correction methods applied in the study, along with the methodology used to assess the method performance. Next we present the test regions and the observed and RCM daily precipitation datasets. We test all four methods on all six test regions using a re-sampling approach similar to the jack-knife, which compare the sensitivity of the bias-correction procedure to the choice of calibration period. The results from this re-sampling procedure are presented for the first four statistical moments of the daily precipitation data (mean, standard deviation, skewness, kurtosis). Our results highlight some limitations of each of the methods, and indicate that the gamma-based quantile-mapping technique is most suitable for application to the UK as a whole.

Section II Methods

II. 1 Pre-processing

A number of pre-processing steps which are particularly important when bias-correcting daily precipitation are described below. It should be noted that these steps may not be necessary for other climate variables.

II. 1. 1. Spatial interpolation

To interpolate from 0.22º regional climate model data to 1 km data required for hydrological applications, we considered two alternatives: bilinear interpolation and cubic spline interpolation (Press et al., 1986). Bilinear interpolation smooths data within grid-boxes but the gradient of the interpolated function is discontinuous from grid-box to grid-box. As such, this interpolation method does not remove the 0.22º grid-box-related discontinuities in the RCM data. The alternative method, bicubic spline interpolation, in which thin-plate splines are fitted to the 0.22º dataset to permit interpolation to the 1 km level, was found to preserve the continuity in derivatives at grid-box boundaries, but an assessment of conservation of water following interpolation indicated the potential for serious underestimates on the order of 25 percent. This result is consistent with those obtained in several other studies looking at rainfall interpolation (Tait et al., 2006). As a result of these findings, it was considered unwise to perform interpolation without substantial further work beyond the scope of the present project.

II. 1. 2. Spatial downscaling (re-gridding)

A spatial downscaling step (re-gridding) was required as the observed data were available at a finer resolution than the RCM (Wood et al., 2002; Wood et al., 2004; Kay et al., 2006). For our study, each daily time series from each of the 1 km grid box of the observed data (see Section IV for more information) was associated with the HadRM3 daily time series from the nearest 0.22º grid square. A consequence of the re-gridding step is that during bias-correction the RCM daily precipitation data is corrected for topographic variations in precipitation which are present in the observed daily precipitation (i.e. some amount of spatial downscaling occurs during bias correction).

II. 1. 3. Wet/dry proportion matching

For each 1 km grid box, wet/dry proportion matching was carried out so that the frequency of rain days in the pre-processed dataset matched that in the observed record. This procedure is important because the frequency of low precipitation values in climate models is often found to be too high (Sun et al., 2006). Moreover, the occurrence of hydrological extremes (both floods and droughts) is linked to the sequencing of wet and dry periods. Using a similar method to (Hay et al., 2002), we calculated the fraction of dry days (days with zero rain) relative the whole period of the observed daily precipitation time series for each grid and imposed this fraction on the corresponding 1 km RCM daily precipitation (i.e. all values below the threshold associated with this fraction are set to zero; the same threshold is used for the whole RCM time series of this grid). This procedure was done independently each month.

II. 2 Correction Methods

In this section each bias-correction method used in this study is explained in detail. The first two methods, linear and non-linear, use the statistical properties of the observed data to calculate a linear and non-linear transform respectively, these transforms are then applied to the simulated data to correct the bias. In contrast, the third and fourth methods, gamma and empirical, involve ‘quantile mapping’, in which the probability distribution of the simulated dataset is mapped onto the probability distribution of the observed dataset using a gamma and empirical distribution respectively.

Each bias-correction method was implemented independently for each month, to preserve the month-to-month characteristics of the climate data. Hence each method is explained assuming it is applied to a specific month.

II. 2. 1. **Linear Bias-Correction Method**

Using the linear correction method, each of the RCM simulated daily precipitation amounts, P (having been corrected for the frequency of rain-days), is transformed into P^* such that $P^* = aP$, using a scaling factor, $a = \bar{O}/\bar{P}$, wherein $\bar{O}$ and $\bar{P}$ are the values of monthly mean observed and simulated precipitation, respectively. The linear correction method has the same mathematical structure as the ‘factor of change’ or ‘delta change’ method (Hay et al., 2000). A variant of this method, the change factor method, is employed in a wide range of studies (Arnell et al., 2003, Prudhomme et al., 2002, Prudhomme et al., 2010) as it has the advantage of simplicity and modest data requirement: only monthly climatological information is required in order to calculate monthly correction factors. However, correcting only the monthly mean precipitation can distort the relative variability of the inter-monthly precipitation distribution, and thus may adversely affect other moments of the probability distribution of daily precipitations (Arnell et al., 2003, Diaz-Nieto and Wilby, 2005).

II. 2. 2. **Non-Linear Bias-Correction Method**

Noting that a linear scaling factor adjusts the mean but not the standard deviation of monthly precipitation, Shabalova et al. (2003) and Leander and Buishand (2007) advocate the use of a power-law correction such that $P^* = aP^b$, where b is a scaling exponent. The constants a and b are calculated in two stages: (i) the scaling exponent, b, is calculated iteratively so that for each grid box in each month, the coefficient of variation of the simulated daily precipitation time-series matches that of the observed precipitation time-series. Here this is achieved using Brent’s method (Press et al., 1986); (ii) the prefactor, a, is then calculated so that the mean of the transformed precipitation values is equal to the observed mean.

In common with the linear method, this approach has the advantage that it requires observed data at monthly frequency, although it also requires monthly information on the coefficient of variation of precipitation. This approach results in the mean and the standard deviation of the daily precipitation distribution becoming equal to those of the observed distribution. Higher order moments are not corrected by the non-linear method.

II. 2. 3. **Gamma Distribution Bias-Correction Method**

The gamma distribution-based correction method assumes that the probability distributions of both observed and simulated daily precipitation datasets can be approximated using a gamma distribution, for example:

$$f(x; k, \theta) = x^{k-1} \frac{exp(-x/\theta)}{\Gamma(k)\theta^k}, \quad [1]$$

where $k > 0$ and $\theta > 0$ are the form and scaling parameters of a gamma distribution, respectively. In the present application, the parameters k and θ were estimated for each grid box for each month, using the method of moments:

$$k = \left(\frac{\bar{x}}{s}\right)^2, \quad [2]$$

$$\theta = \frac{s^2}{\bar{x}}\ , \qquad [3]$$

where $\bar{x}$ and s are the sample mean and standard deviation of x, respectively.

In order to perform the bias correction, each daily RCM precipitation amount was expressed as a quantile, $F(x; k, \theta)$, calculated as:

$$F(x; k, \theta) = \frac{\gamma(k, x/\theta)}{\Gamma(k)}, \qquad [4]$$

wherein γ is the lower incomplete gamma function, and *k* and θ are the parameters of the gamma distribution fitted to the RCM simulated precipitation. This quantile was then used to calculate the corrected precipitation amount by re-sampling from the gamma distribution fitted to the observed precipitation amounts. This method is designed to correct the first two statistical moments and was found to perform well when used to correct biases in GCM outputs at Global and European scales (Piani et al., 2010).

II. 2. 4. **Empirical Distribution Bias-Correction Method**

The empirical distribution-based correction method follows the same approach as the gamma distribution method, with the RCM-driven distributions transformed to match the observed distribution through a transfer function. However, unlike the gamma distribution correction method which assumes that the observed and simulated precipitation amounts follow a gamma distribution, the empirical method does not make any such *a priori* assumptions.

To implement the empirical distribution-based correction method, the range of observed precipitation values is divided into a number of discrete quantiles (in practice, 25, 50, 75 and 100 quantile divisions were used in the comparison presented here). For each quantile division, a linear correction factor was calculated by dividing the observed mean precipitation in that quantile by the RCM simulated mean precipitation in the same quantile. The number of quantile divisions controls the accuracy of the method: using fewer quantiles might omit much of the information contained within the observed record, while using too many quantiles might result in overfitting of the model to the data. The number of statistical moments corrected by the method depends on the number of quantiles used. This method has been shown to perform well when implemented in the United States (Wood et al., 2004, Wood et al., 2002).

II. 3 Re-sampling Procedure

During the study we quantified the sensitivity of each bias-correction method to the choice of correction period. We used a re-sampling technique similar to the jack-knife (Bissell and Ferguson, 1975), in order to cross-validate the bias-correction methods and to estimate the range of variability in the bias and standard error of the statistics of a bias-corrected daily precipitation dataset. We used a 40-year period (1961–2000), and re-computed the bias-correction factors having systematically removed contiguous ten-year periods beginning in 1961,1962,…,1991. This procedure provided a set of 31 bias-corrected datasets (i.e. the bias correction models were fitted on 30 ‘calibration’ years and applied to the 10 ‘validation’ remaining years), and by examining the central tendency and spread among these realisations, we evaluated the sensitivity of each method to the choice of time period. A similar procedure has been used to evaluate the robustness of a gamma-based quantile mapping technique in Northern Eurasia (Li et al., 2010).

Section III Test Regions

It is important that daily precipitation bias-correction methods are capable of correcting over the full extent of the spatial area of interest. The UK has a wide range of annual average precipitation and topography; hence, a method which successfully corrects biases in one region may not necessarily be as effective in another. To explore this question more comprehensively, the four bias-correction methods were each applied to six test regions.

The six test regions were chosen by comparing river catchments from the National River Flow Archive (NRFA) Hydrometric Register (Marsh and Hannaford, 2008). The starting point for choosing the catchments was the benchmark network, which is a subset of the NRFA stations which have a nearly natural flow regime and little impact from human activity (Bradford and Marsh, 2003). The catchments were compared using statistics such as elevation range and mean annual average rainfall. It had been hoped that it would be possible to choose six reasonably large catchments from the benchmark network which encompassed a range of these statistics. However, in some cases it was not possible to find sufficiently large catchments. In these cases stations outside the benchmark network were chosen, or one or more catchments were extended to form rectangular regions which were sufficiently large to accurately test the correction methods, but small enough so that they were still representative of the region. Details of the six test regions are given in Table 1 and their locations are shown in Figure 1.

Name	NRFA Catchment ID/s	Mean Annual Rainfall (mm/yr)	Elevation Range (m)	Easting Distance (km)	Northing Distance (km)	Location	Type
Northern Scotland	95001 B	2201	1409	130	20	Northern Scotland	R
Tay	15006 B	1461	1184	147	75	Eastern Scotland	C
Ribble	71001 B	1345	678	60	70	North West England	C
Conway	66011	2183	1028	39	30	North Wales	C
Severn	54001	924	809	115	76	Midlands of England	C
East Anglia	33019 B 36008	641 609	60 92	61	69	South East England	R

Table 1: Test Region Information: Information about the six test regions used in the study. NRFA catchment ID (followed by a B if the catchment is in the benchmark network), mean annual rainfall and elevation range all come from (Marsh and Hannaford, 2008). The easting and northing distances are the number of 1km grid squares required in each direction to encompass the region. The type indicates whether the region is delimited by a catchment outline (C) or a rectangle (R).

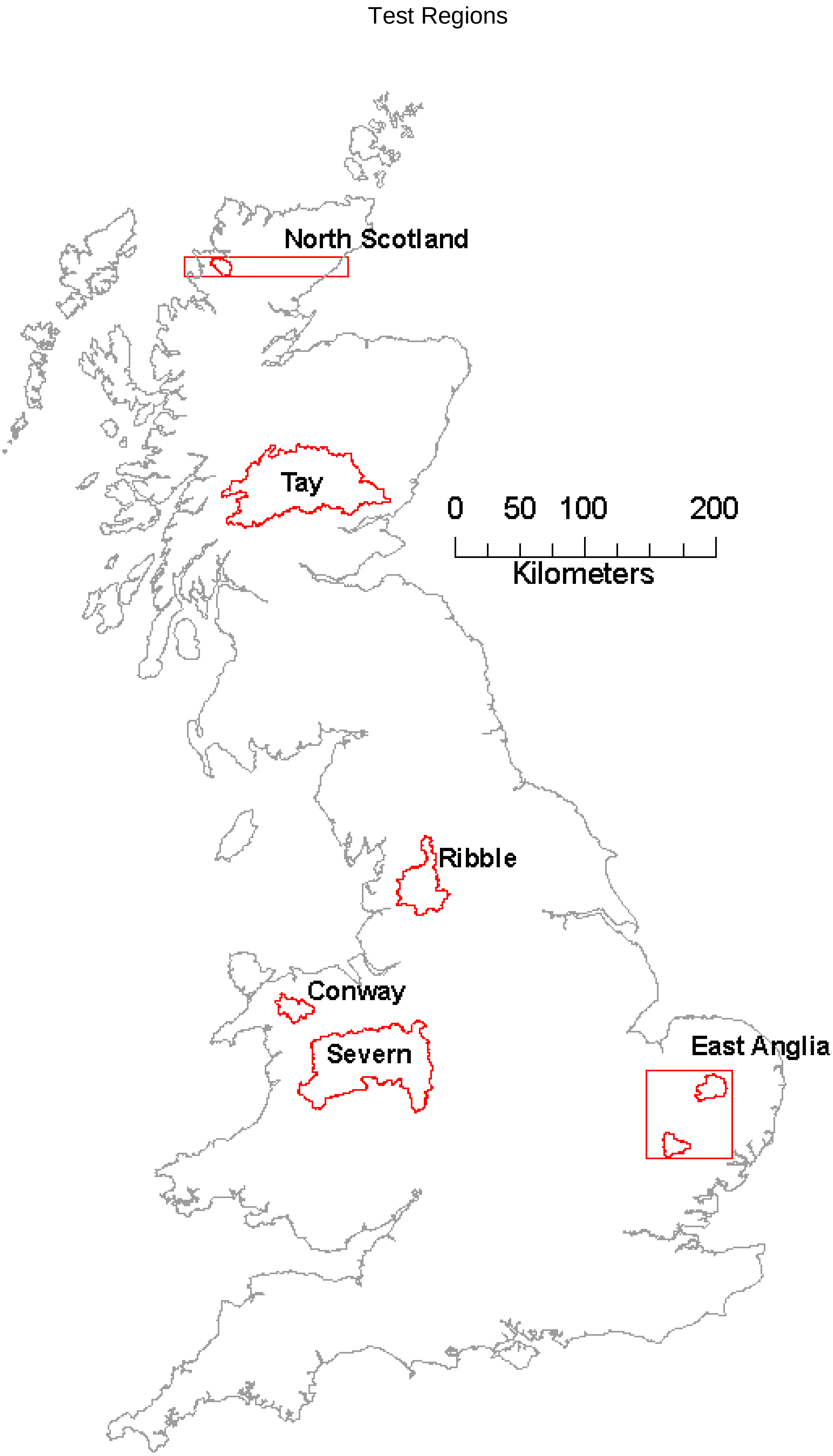

Figure 1: Location of Test Regions: Location of the six test regions in the UK. For the rectangular regions the catchments from which the statistics in Table 1 derive are shown inside the region.

Section IV Data

IV. 1 Observed Data

The observed precipitation dataset used in this study was the daily precipitation data from the Continuous Estimation of River Flows (CERF) project (Keller et al., 2006). The CERF precipitation dataset was created by the Centre for Ecology and Hydrology using observations from 17,812 UK Met Office raingauges. The observations were interpolated using the triangular planes method, a domain-based interpolation method, and normalised based on average annual rainfall (Jones, 1983). The dataset extends over England, Scotland and Wales, is projected on to the UK National Grid at a horizontal resolution of 1 km and encompasses the period 1961–2008.

IV. 2 Regional Climate Model Data

The RCM precipitation dataset used in this study was the daily precipitation data from the Met Office Hadley Centre Regional Climate Model Perturbed Physics Ensemble simulations for the 21st Century for the UK domain (http://badc.nerc.ac.uk/data/hadrm3-ppe-uk/). The HadRM3-PPE-UK dataset is composed of an ensemble of eleven variants of the Hadley Centre Regional Climate Model (HadRM3) ten of which are perturbed using different atmospheric parameterisations. In this study comparing bias-correction methods, only the unperturbed version of the model HadRM3.0, also known as afgcx, was used for most of the study. In this RCM run, the regional climate of the UK is simulated over the period 1950–2100, at 0.22° horizontal resolution (approximately 25 km). Lateral boundaries for the model are taken from the HadCM3 GCM using the SRES A1B emission scenario (rapid, regionally-convergent growth with a balance of fossil and non-fossil fuels).

Section V Results

V. 1 Method Performance

Each bias-correction method was implemented for each test catchment as presented in Section II, including the pre-processing steps of downscaling (re-gridding) and wet/dry proportion matching. The bias-corrected daily precipitation datasets were generated on the same 1 km grid as the observed daily precipitation data set.

The method performance was assessed by generating cumulative distribution functions (cdfs) on observed, pre-processed and bias-corrected daily precipitation for the period 1961–2000. All three daily precipitation datasets were extracted from a single grid square in each test region. Only one of the empirical method variations – that with 100 quantiles – was chosen for this comparison. The cdfs are shown in Figure 2 to Figure 5, for the linear, non-linear, gamma and empirical bias-correction methods respectively. The linear method improves the distribution of the daily precipitation overall, however, it causes overestimation of the highest intensity events in four of the six regions and underestimation of the low-intensity events in three regions. The non-linear method provides a better fit to the high and mid-intensity events but also underestimates the low intensity events to some degree in all regions. The gamma method produces a distribution which deviates from the observed record for all but the highest intensity events in all test regions. The empirical method produces cumulative distributions which are very well matched to the observed daily precipitation distributions in all regions.

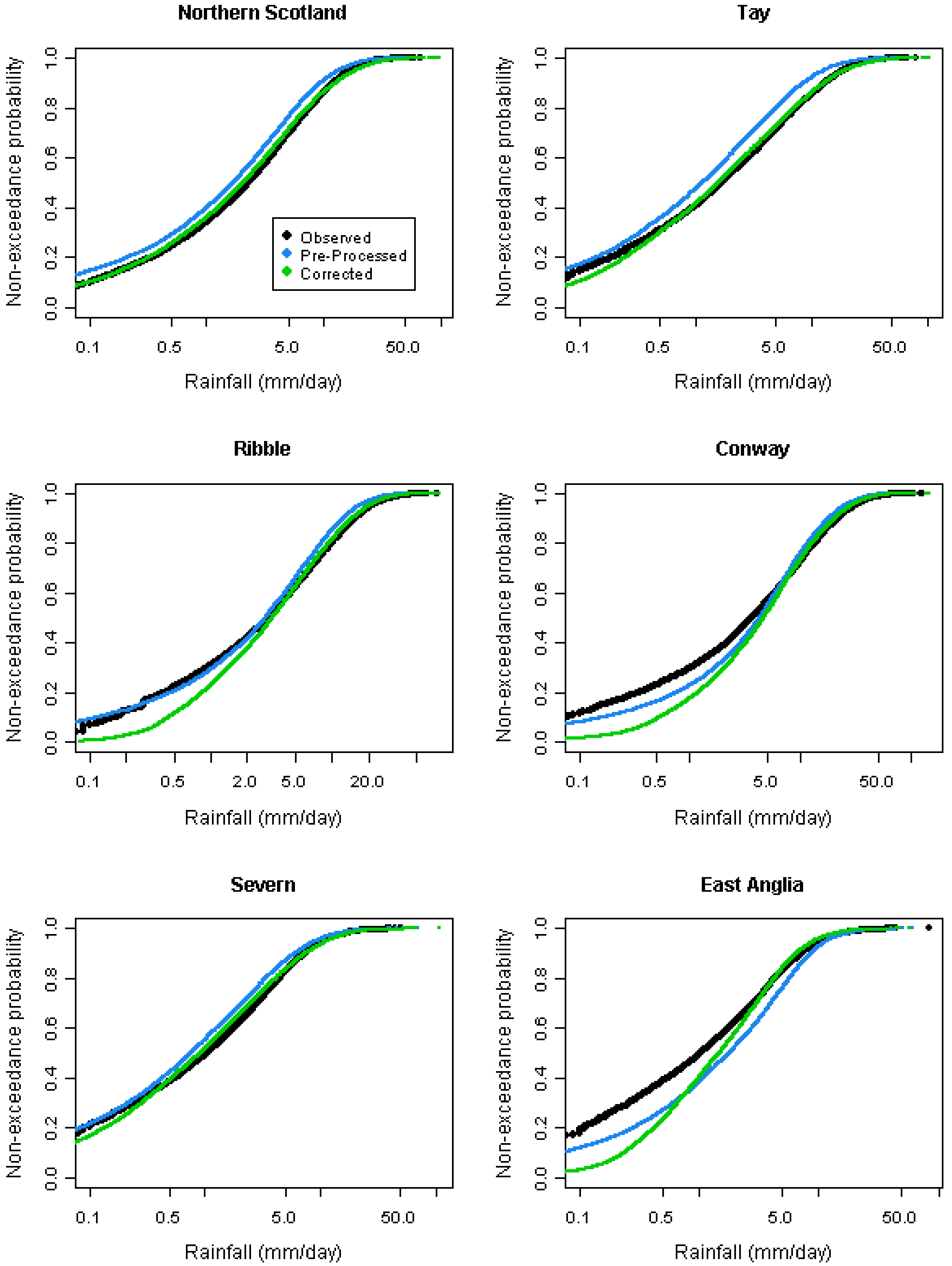

Figure 2: Linear Method Cumulative distribution Functions: Cumulative distribution functions (cdfs) of observed (black), pre-processed (blue) and linear bias-corrected (green) non-zero daily precipitation for the period 1961 – 2000. The data is from one grid square for each test region as follows: Northern Scotland (75, 10), Tay (75, 40), Ribble (30, 30), Conway (15, 15), Severn (60, 40) and East Anglia (35, 40). The cdfs are presented on a log scale to enable easier analysis of the extremes of the distribution.

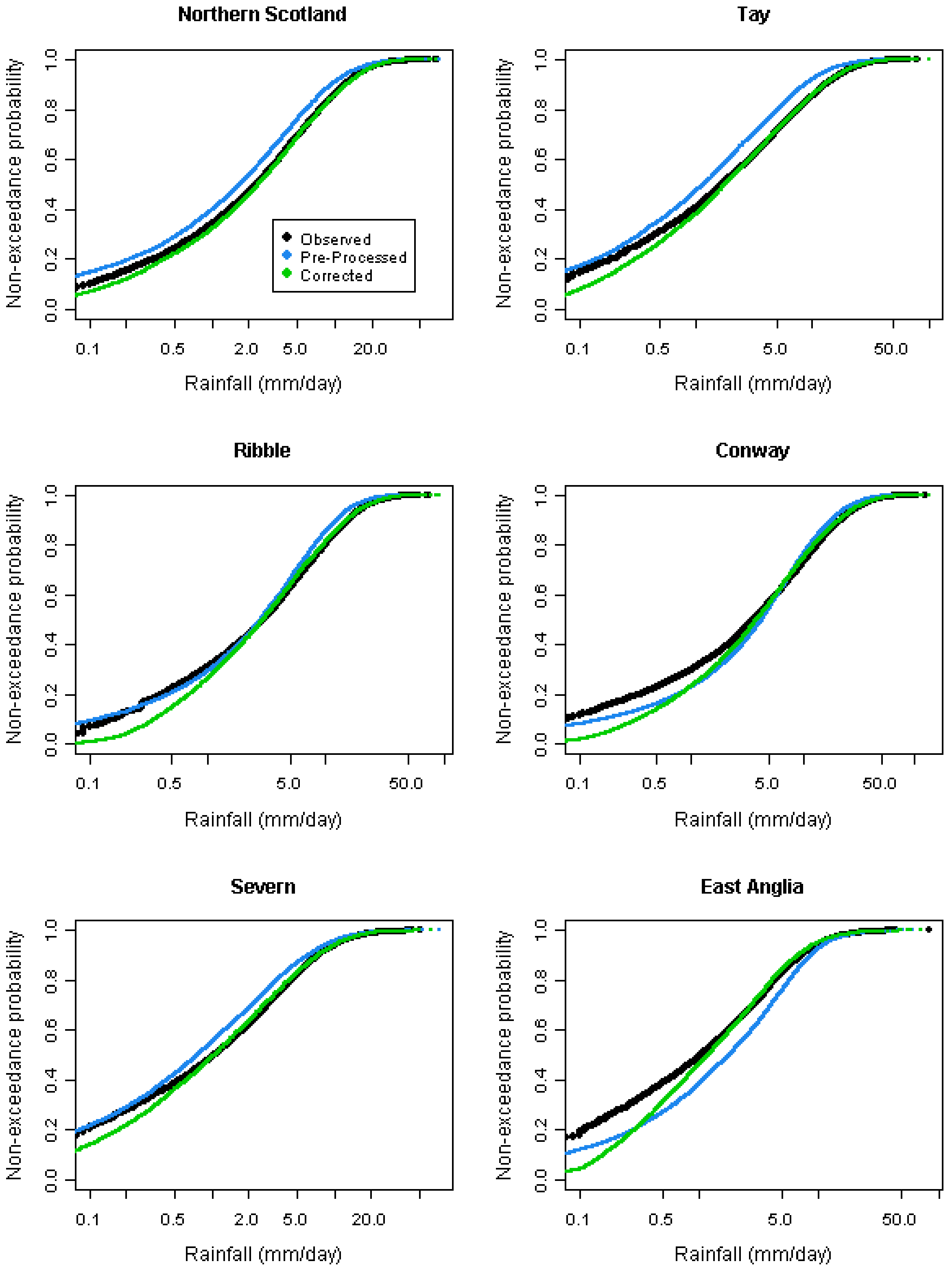

Figure 3: Non-Linear Method Cumulative distribution Functions: As for Figure 2 but with non-linear bias-corrected data.

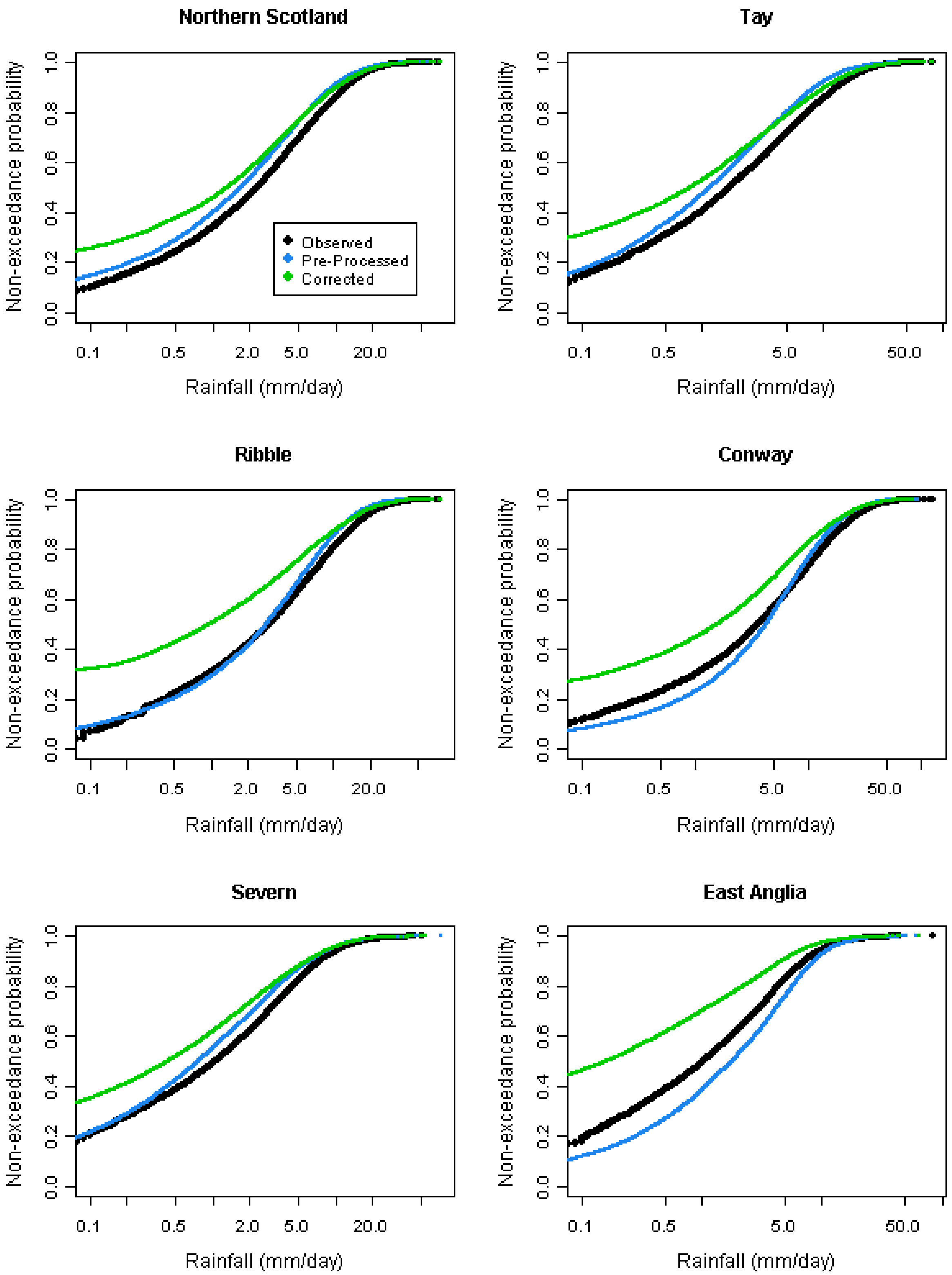

Figure 4: Gamma Method Cumulative distribution Functions: As for Figure 2 but with gamma bias-corrected data.

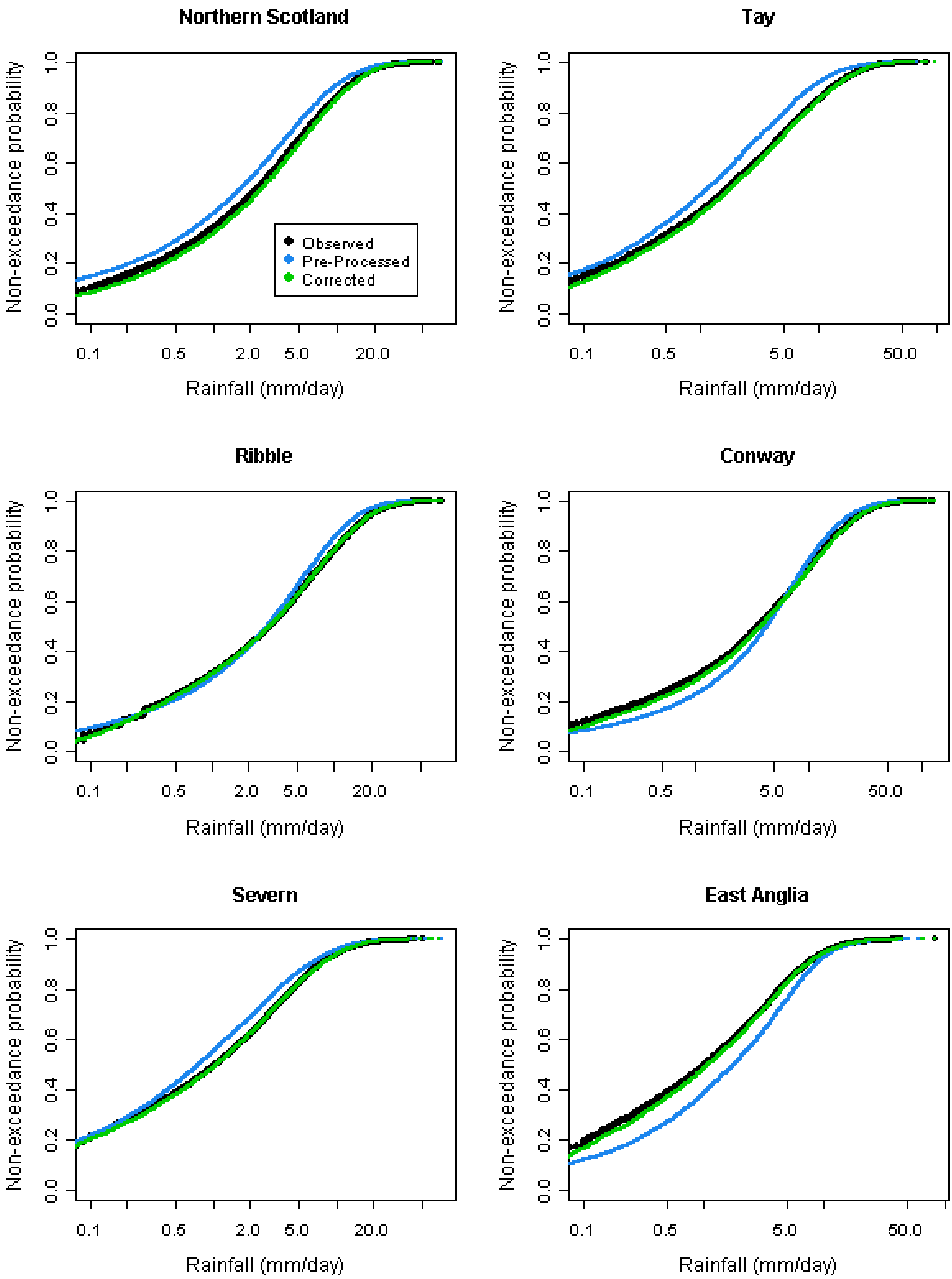

Figure 5: Empirical Method Cumulative distribution Functions: As for Figure 2 but with empirical bias-corrected data using 100 quantiles.

Reliability of the four bias-correction methods was assessed using a re-sampling procedure (see II. 3) for each method and each test region. The procedure was applied between the years of 1961–2000, i.e., 31 ten-year runs were produced for each method and each test region as validation periods. The observed, the RCM and the bias-corrected daily precipitation data were compared using each of the ten-year validation periods, which were excluded from the calculation of the bias-correction factors and transfer functions (i.e. the 30-year calibration period does not contain the 10-year of the validation period; this is equivalent to a cross validation methodology on an independent sample of the calibration sample). Relative errors between seasonal bias-corrected and observed statistics were calculated for each of the sets of 31 validation runs and averages errors estimated. As described in section II. 2. 4. the accuracy of the empirical method depends on the number of quantiles used. To explore this further the above procedure was carried out for four variations of the empirical method with 25, 50, 75 and 100 quantiles in each case.

To provide an indication of the degree of improvement (i.e., how well the statistical properties of observed daily precipitation are captured by the RCM-driven daily precipitation) that can be achieved using bias-correction methods instead of a simple pre-processing of RCM daily precipitation data, the same procedure as described above for the bias-correction methods was used to calculate the statistics for the pre-processed daily precipitation (which does not include any account of elevation other than from the wet/day frequency).

The results of the re-sampling performance tests are shown in Figure 6. It can be seen that most of the bias-correction methods in most regions produce an improvement in at least the lower order statistical moments. The linear method consistently improves the average but rarely improves the higher order moments. In some cases it actually produces a slightly poorer correspondence with the higher order moments than the pre-processed daily precipitation. In most of the test regions the non-linear and gamma methods show similar performance with a reduction of errors achieved at higher order moments. However, both of these methods struggle to improve the higher order moments in the summer season, with the non-linear method being the worse of the two. This trend is most apparent in the East Anglia region where summer precipitation is dominated by convective storms. The empirical method offers the most hope for improving the higher order moments, however, it can be seen that the performance of this method can be erratic, and produces some unexpectedly high values in the lower order moments in all test regions. This issue is discussed further in section V. 2. 1.

The Gamma method was seen not to well capture low intensity rainfall distribution; when used as cross-validation however (results of Figure 6) it shows overall good results suggesting it is much less sensitive to the choice of calibration period than linear and non-linear methods and hence likely to be more robust when used outside the calibration range (e.g. when looking at future time horizons).

Northern Scotland

	PrePro	Lin	N-Ln	Gam	E 25q	E 50q	E 75q	E 100q
Ave Win	0.26	0.06	0.05	0.03	1532.83	708.18	3.1E+05	376.09
Ave Spr	0.17	0.03	0.04	0.04	0.06	0.05	0.04	0.04
Ave Sum	0.23	0.02	0.03	0.03	0.03	0.03	0.03	0.03
Ave Aut	0.39	0.03	0.03	0.05	170.22	83.69	3.2E+05	49.22
Sdv Win	0.21	0.34	0.04	0.06	6504.02	4002.50	3.8E+06	3001.65
Sdv Spr	0.17	0.06	0.07	0.05	0.16	0.13	0.11	0.11
Sdv Sum	0.17	0.09	0.03	0.02	0.05	0.04	0.04	0.04
Sdv Aut	0.24	0.22	0.01	0.02	627.87	405.89	3.5E+06	333.80
Cvr Win	0.25	0.25	0.01	0.03	0.04	0.13	0.27	0.23
Cvr Spr	0.04	0.05	0.03	0.02	0.10	0.08	0.07	0.07
Cvr Sum	0.10	0.11	0.01	0.02	0.03	0.02	0.02	0.01
Cvr Aut	0.24	0.23	0.01	0.03	0.12	0.13	0.16	0.19
Skw Win	0.19	0.19	0.18	0.13	0.08	0.16	0.25	0.26
Skw Spr	0.13	0.13	0.13	0.11	0.12	0.17	0.23	0.23
Skw Sum	0.10	0.10	0.17	0.12	0.07	0.06	0.06	0.06
Skw Aut	0.14	0.15	0.13	0.07	0.11	0.14	0.17	0.18
Krt Win	0.20	0.20	0.17	0.13	0.08	0.15	0.24	0.21
Krt Spr	0.13	0.13	0.11	0.10	0.11	0.15	0.20	0.20
Krt Sum	0.10	0.10	0.15	0.12	0.08	0.07	0.06	0.06
Krt Aut	0.13	0.13	0.14	0.08	0.10	0.13	0.15	0.17

Tay

	PrePro	Lin	N-Ln	Gam	E 25q	E 50q	E 75q	E 100q
Ave Win	0.25	0.03	0.03	0.03	0.06	0.09	0.66	0.07
Ave Spr	0.25	0.03	0.03	0.03	0.04	0.04	6.51	0.03
Ave Sum	0.26	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Ave Aut	0.28	0.02	0.02	0.02	0.04	0.24	30.37	0.08
Sdv Win	0.20	0.11	0.04	0.03	0.11	0.29	4.08	0.22
Sdv Spr	0.20	0.08	0.01	0.02	0.04	0.03	34.51	0.03
Sdv Sum	0.18	0.15	0.02	0.03	0.04	0.03	0.02	0.02
Sdv Aut	0.20	0.17	0.03	0.03	0.08	1.71	161.13	0.58
Cvr Win	0.15	0.09	0.01	0.02	0.02	0.02	0.02	0.02
Cvr Spr	0.09	0.11	0.04	0.05	0.03	0.02	0.02	0.02
Cvr Sum	0.12	0.16	0.02	0.03	0.03	0.02	0.01	0.01
Cvr Aut	0.21	0.14	0.01	0.02	0.03	0.03	0.03	0.02
Skw Win	0.20	0.14	0.08	0.07	0.07	0.09	0.10	0.10
Skw Spr	0.11	0.12	0.06	0.06	0.09	0.07	0.06	0.06
Skw Sum	0.10	0.09	0.19	0.08	0.06	0.04	0.03	0.03
Skw Aut	0.27	0.22	0.07	0.08	0.06	0.06	0.06	0.06
Krt Win	0.17	0.13	0.08	0.07	0.10	0.12	0.12	0.13
Krt Spr	0.12	0.13	0.06	0.07	0.10	0.09	0.07	0.08
Krt Sum	0.11	0.11	0.16	0.07	0.07	0.06	0.04	0.04
Krt Aut	0.26	0.21	0.07	0.08	0.05	0.06	0.05	0.05

Ribble

	PrePro	Lin	N-Ln	Gam	E 25q	E 50q	E 75q	E 100q
Ave Win	0.15	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Ave Spr	0.14	0.04	0.04	0.06	0.06	0.05	0.03	0.04
Ave Sum	0.16	0.02	0.03	0.03	0.03	0.02	0.02	0.02
Ave Aut	0.27	0.02	0.02	0.02	0.02	0.01	1875.66	0.01
Sdv Win	0.14	0.08	0.02	0.01	0.03	0.03	0.02	0.02
Sdv Spr	0.14	0.14	0.04	0.02	0.10	0.08	0.05	0.06
Sdv Sum	0.20	0.12	0.02	0.02	0.06	0.05	0.05	0.05
Sdv Aut	0.20	0.05	0.02	0.02	0.05	0.04	1.0E+04	0.03
Cvr Win	0.06	0.10	0.01	0.03	0.02	0.02	0.01	0.01
Cvr Spr	0.12	0.18	0.01	0.04	0.03	0.02	0.02	0.02
Cvr Sum	0.09	0.14	0.01	0.04	0.03	0.03	0.03	0.03
Cvr Aut	0.14	0.07	0.01	0.01	0.03	0.02	0.02	0.02
Skw Win	0.14	0.16	0.03	0.08	0.05	0.05	0.03	0.03
Skw Spr	0.18	0.20	0.09	0.05	0.07	0.08	0.07	0.07
Skw Sum	0.08	0.09	0.14	0.04	0.07	0.07	0.08	0.08
Skw Aut	0.19	0.15	0.06	0.08	0.06	0.07	0.08	0.08
Krt Win	0.16	0.19	0.03	0.09	0.07	0.06	0.04	0.04
Krt Spr	0.20	0.22	0.06	0.06	0.07	0.07	0.07	0.07
Krt Sum	0.10	0.10	0.12	0.04	0.07	0.07	0.07	0.07
Krt Aut	0.18	0.14	0.05	0.07	0.06	0.07	0.07	0.07

Conway

	PrePro	Lin	N-Ln	Gam	E 25q	E 50q	E 75q	E 100q
Ave Win	0.27	0.03	0.03	0.02	0.03	0.03	0.02	0.03
Ave Spr	0.29	0.04	0.05	0.05	0.07	0.05	0.04	0.04
Ave Sum	0.31	0.05	0.06	0.04	0.05	0.05	0.05	0.05
Ave Aut	0.27	0.02	0.02	0.03	0.01	0.01	2.46	0.01
Sdv Win	0.23	0.09	0.02	0.03	0.04	0.04	0.03	0.03
Sdv Spr	0.25	0.21	0.04	0.03	0.13	0.09	0.06	0.07
Sdv Sum	0.24	0.15	0.04	0.04	0.06	0.06	0.05	0.05
Sdv Aut	0.25	0.03	0.03	0.07	0.03	0.02	14.28	0.02
Cvr Win	0.11	0.13	0.01	0.04	0.01	0.01	0.01	0.01
Cvr Spr	0.20	0.24	0.01	0.05	0.05	0.03	0.02	0.02
Cvr Sum	0.16	0.19	0.02	0.06	0.02	0.02	0.01	0.01
Cvr Aut	0.03	0.03	0.01	0.04	0.02	0.02	0.01	0.01
Skw Win	0.18	0.17	0.02	0.13	0.05	0.05	0.04	0.04
Skw Spr	0.27	0.27	0.10	0.09	0.06	0.08	0.08	0.08
Skw Sum	0.11	0.10	0.20	0.04	0.04	0.04	0.03	0.04
Skw Aut	0.04	0.04	0.04	0.08	0.05	0.07	0.08	0.07
Krt Win	0.24	0.24	0.04	0.17	0.05	0.06	0.06	0.06
Krt Spr	0.29	0.28	0.08	0.11	0.04	0.06	0.06	0.06
Krt Sum	0.12	0.11	0.18	0.04	0.05	0.05	0.04	0.04
Krt Aut	0.04	0.04	0.03	0.09	0.04	0.06	0.07	0.06

Severn

	PrePro	Lin	N-Ln	Gam	E 25q	E 50q	E 75q	E 100q
Ave Win	0.17	0.01	0.01	0.01	0.02	0.02	1235.97	0.10
Ave Spr	0.15	0.03	0.04	0.05	0.04	0.04	0.04	0.04
Ave Sum	0.16	0.04	0.04	0.05	0.02	0.02	0.04	0.04
Ave Aut	0.20	0.02	0.02	0.02	0.05	0.04	0.73	0.03
Sdv Win	0.13	0.06	0.02	0.02	0.04	0.03	7690.10	0.64
Sdv Spr	0.10	0.09	0.06	0.04	0.07	0.07	0.07	0.07
Sdv Sum	0.10	0.07	0.02	0.03	0.05	0.03	0.03	0.03
Sdv Aut	0.15	0.08	0.04	0.03	0.10	0.08	4.01	0.07
Cvr Win	0.08	0.06	0.01	0.01	0.02	0.01	0.01	0.01
Cvr Spr	0.09	0.10	0.02	0.01	0.03	0.03	0.03	0.03
Cvr Sum	0.07	0.10	0.04	0.07	0.06	0.04	0.02	0.03
Cvr Aut	0.11	0.08	0.02	0.02	0.04	0.04	0.03	0.03
Skw Win	0.09	0.08	0.04	0.04	0.05	0.04	0.04	0.04
Skw Spr	0.11	0.10	0.17	0.10	0.06	0.07	0.09	0.09
Skw Sum	0.09	0.09	0.13	0.06	0.11	0.09	0.06	0.06
Skw Aut	0.12	0.11	0.05	0.06	0.06	0.08	0.09	0.09
Krt Win	0.13	0.11	0.08	0.09	0.07	0.06	0.06	0.06
Krt Spr	0.10	0.10	0.14	0.08	0.05	0.06	0.07	0.07
Krt Sum	0.09	0.09	0.11	0.06	0.13	0.11	0.08	0.08
Krt Aut	0.12	0.11	0.05	0.06	0.05	0.07	0.08	0.08

East Anglia

	PrePro	Lin	N-Ln	Gam	E 25q	E 50q	E 75q	E 100q
Ave Win	0.31	0.01	0.01	0.01	0.02	0.22	0.02	0.37
Ave Spr	0.39	0.02	0.03	0.04	0.05	0.04	0.03	0.03
Ave Sum	0.21	0.02	0.03	0.03	0.03	0.02	0.02	0.02
Ave Aut	0.07	0.01	0.01	0.01	0.02	0.02	0.01	0.01
Sdv Win	0.27	0.05	0.01	0.02	0.04	1.29	0.04	2.30
Sdv Spr	0.16	0.20	0.05	0.02	0.14	0.12	0.09	0.10
Sdv Sum	0.05	0.16	0.03	0.02	0.06	0.04	0.03	0.03
Sdv Aut	0.04	0.05	0.02	0.01	0.04	0.04	0.03	0.03
Cvr Win	0.04	0.06	0.01	0.02	0.02	0.02	0.01	0.01
Cvr Spr	0.17	0.22	0.01	0.03	0.06	0.05	0.05	0.05
Cvr Sum	0.14	0.18	0.03	0.05	0.04	0.03	0.02	0.02
Cvr Aut	0.03	0.06	0.01	0.02	0.02	0.02	0.02	0.02
Skw Win	0.06	0.05	0.09	0.07	0.05	0.05	0.05	0.05
Skw Spr	0.16	0.17	0.21	0.09	0.09	0.12	0.14	0.14
Skw Sum	0.11	0.11	0.31	0.20	0.05	0.05	0.07	0.07
Skw Aut	0.09	0.08	0.16	0.11	0.04	0.04	0.05	0.05
Krt Win	0.06	0.06	0.10	0.07	0.06	0.06	0.05	0.05
Krt Spr	0.18	0.19	0.19	0.07	0.06	0.09	0.12	0.12
Krt Sum	0.11	0.11	0.29	0.17	0.05	0.05	0.06	0.06
Krt Aut	0.08	0.07	0.14	0.10	0.04	0.04	0.05	0.05

Figure 6: Statistical Comparison of Correction Methods: A comparison of the performance of the bias-correction methods for each test catchment using the re-sampling tests. Relative errors between RCM-driven (pre-processed and bias-corrected) and observed daily precipitation are given for each season and five key statistics. PrePro, Lin, N-Ln, and Gam refer to the pre-processing, linear, non-linear and gamma methods respectively. E 25q, E 50q, E75q and E100q are the empirical

method with 25, 50, 75 and 100 quantiles. Ave, Sdv, Cvr, Skw and Krt are the statistical moments; average, standard deviation, coefficient of variation (standard deviation divided by average), skewness and kurtosis. Win, Spr, Sum and Aut are winter (December, January, Febuary), spring (March, April, May), summer (June, July, August) and autumn (September, October, November) respectively. Dark green, yellow and blue colours represent low, medium and high relative errors respectively.

V. 2 Improvements to the Distribution Based Methods

V. 2. 1. Empirical Distribution Method

Figure 6 shows that the empirical method can generate daily precipitation time series which, when compared to observations using the first two statistical moments, show large discrepancies. In order to determine the reason for these differences it was necessary to examine the bias-correction factors calculated for each percentile of the distribution. It was found that in some months, in localised areas of the test regions, the bias-correction factors for certain percentiles (generally the lower percentiles) were of the order of a million. These high correction factors occur when, in a certain quantile, the pre-processed precipitation is significantly lower than the observed precipitation. An example of this in the Tay test region is shown in Figure 7 and the reasons for these high correction factors are discussed further in section VI. 1. In view of the unrealistic values produced using this bias correction method the decision was taken not to proceed with this technique in the present project.

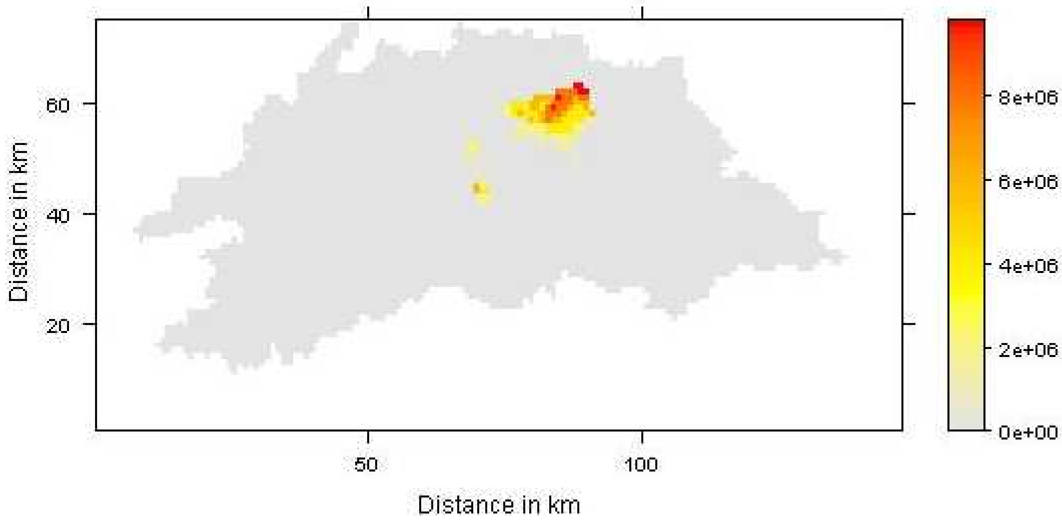

Figure 7: Empirical Method Bias-Correction Factors – Tay Region: Map of Tay region bias-correction factors for January, percentile 14, from the empirical method 75 quantile run for the time period 1971-1980. The colour key for the bias-correction factors is given on the right hand side.

V. 2. 2. Gamma Distribution Method

The gamma method is one of the best performing methods according to Figure 6, as it generates daily precipitation time series whose moments (both lower and higher) consistently show small relative errors compared with observations. However Figure 4 shows that the distribution of the gamma bias-corrected daily precipitation does not match the distribution of the observed precipitation. Further assessment revealed whilst the observed and pre-processed daily precipitation data could not be approximated using a gamma distribution at the 1-km grid scale, the goodness-of-fit of the gamma distribution could be greatly improved by using area-averaged rainfall data (at the scale of RCM grids) rather than 1 km rainfall data. As a result of this finding, the bias-correction procedure was amended so that prior to bias correction the observed data were aggregated to 25 km spatial resolution in line with the underlying resolution of the RCM data.

Using the observed gridded rainfall averaged at HadRM3-PPE scale and gridded rainfall from each HadRM3-PPE members for 1961-1990, catchment/ regional average for the regions of Table 1 and three additional regions were calculated. Parameters of the best-fit gamma distribution were estimated using the method of moments, and the goodness of fit to the gamma distribution was assessed using a Chi-squared test, the results of which are given in Table 2. The p-value represents the probability of obtaining a value of the Chi squared statistic at least as extreme as that which was observed between the precipitation time-series and its best-fit gamma distribution, under the assumption that the time-series are drawn from the best-fit gamma distribution. Applying a typical significance threshold of 0.05 shows that in over 80 percent of cases the rainfall distributions were indistinguishable from the best-fit gamma distribution at the 0.05 significance level (i.e. 95% confidence level)

Table 2: Goodness of fit statistics for Chi-squared test comparing CERF and RCM rainfalls with gamma distribution. Bold type indicates that the data are indistinguishable from those drawn from a gamma distribution at the 0.05 significance level. The full HadRM3-PPE ensemble members is used here, associated acronyms given in the second line (afgcx, afixa etc...) N_g gives the number of catchments/regions for which a gamma distribution provides a reliable fit for each RCM experiment.

Basin	*p-value*											
	CERF	*afgcx*	*afixa*	*afixc*	*afixh*	*afixi*	*afixj*	*afixk*	*afixl*	*afixm*	*afixo*	*afixq*
NS	**0.33**	0.02	**0.63**	**0.20**	**0.72**	**0.32**	**0.29**	**0.09**	**0.63**	**0.54**	**0.20**	**0.52**
Tay	0.00	**0.37**	**0.16**	0.00	**0.12**	0.01	0.00	**0.81**	**0.49**	**0.34**	**0.92**	0.01
Ribble	0.01	**0.40**	0.01	**0.16**	**0.55**	0.00	0.00	0.00	0.04	0.05	**0.12**	0.03
Yorks	**0.40**	**0.47**	**0.39**	**0.07**	**0.54**	**0.86**	**0.97**	**0.90**	**0.99**	**0.50**	**0.81**	**0.93**
Conwy	**0.06**	**0.66**	**0.23**	**0.23**	**0.98**	**0.14**	0.01	**0.25**	**0.87**	**0.76**	**0.81**	**0.52**
Severn	**0.57**	**0.94**	**0.49**	**0.80**	**0.67**	**0.38**	**0.38**	**0.77**	**0.46**	0.00	**0.06**	**0.61**
EA	**0.69**	**0.09**	**0.77**	**0.56**	**0.06**	**0.82**	**0.77**	**0.15**	**0.71**	**0.47**	**0.15**	**0.74**
Exe	**0.22**	**0.43**	0.00	**0.58**	**0.57**	0.00	0.00	**0.24**	0.01	**0.82**	**0.09**	0.00
Thames	**0.86**	**0.69**	**0.98**	**0.31**	**0.50**	**0.61**	**0.73**	**0.78**	**0.63**	**0.22**	**0.54**	**0.62**
N_g	**7**	**8**	**7**	**8**	**9**	**6**	**5**	**8**	**7**	**7**	**9**	**6**

The clearest evaluation of the success of the RCM-scale bias-correction procedure used here is obtained through the examination of cumulative distributions of rainfall values in the observed, RCM, and bias-corrected time-series, respectively. These plots are given in Figure 8. Note that the raw RCM data (i.e. before a wet-day correction was applied) is shown in the graphs. The quantile-mapping method accurately corrects the higher quantiles of the distribution and considerably improves the accuracy of the lower quantiles. In each case the distributions of the bias-corrected data are brought closer to those of the observed data, validating the RCM-scale gamma approach. A slight mismatch remains at low quantile values (typically when values of precipitation rate are less than 1 mm per day). This mismatch is not likely to be important when the data are used in hydrological models in circumstances where daily evaporation rates are greater than 1 mm per day. There appears to be no consistent spatial pattern in the results.

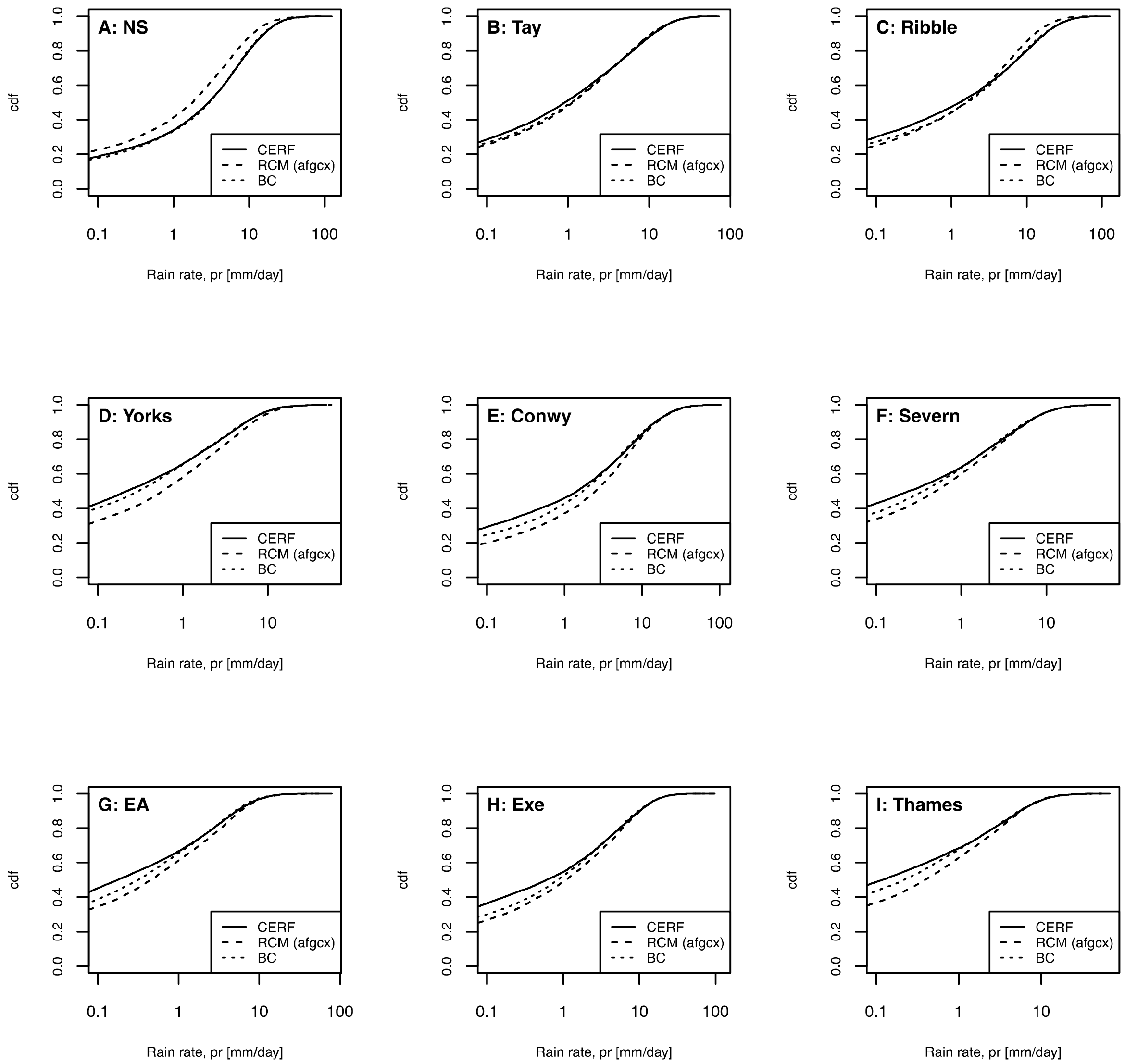

Figure 8: RCM-scale Gamma Method Cumulative Distribution Functions: Cumulative distribution functions (cdfs) of observed (solid), and gamma bias-corrected (dotted) non-zero daily precipitation for the period 1961 – 2000. Cumulative distribution function of original RCM data (before wet-dry correction is applied) is shown with dashed line.

Section VI Summary, Discussion and Further Work

VI. 1 Method Performance

The performance of each bias-correction method was broadly as expected.

The linear method performed the worst overall, where the majority of the improvement to the daily precipitation was confined to the first statistical moment. This is as expected as the linear method is a simple scaling method which only corrects the mean of the distribution. Hence, in agreement with (Leander and Buishand, 2007) we suggest that the linear method is suitable only where the estimation of hydrological extremes is not important.

The non-linear method performed well in the re-sampling tests. At the lower order moments it was often the best of the four methods, especially in the autumn and winter seasons. At the higher order moments it did not offer such a significant improvement, but again in the autumn and winter seasons it performed similarly to the distribution-based methods in four of the six test regions. However, this method did not perform as well in the summer season at higher order moments. In all the test regions the relative difference between the observed and non-linear bias-corrected skewness and kurtosis in the summer season is greater than that between the observed and pre-processed daily precipitation time series. This means that the non-linear bias-correction method could be introducing additional uncertainties in the summer daily precipitation distribution. It is well known that the summer season is the often the most difficult when it comes to bias-correction (Li et al., 2010). In their study of non-linear bias-correction for the Rhine basin (Terink et al., 2010) found that the length of period chosen to calculate bias-correction factors had an effect on the accuracy of the bias-correction in summer months. They found that periods of less than 65 days led to worse bias-corrections for July and August. In our study the bias-correction period is monthly, ~30 days, hence this could be a factor in the poor performance of the non-linear method in the summer months. In terms of bias-correcting the distribution of daily precipitation the non-linear method performed well for daily precipitation intensities over ~1 mm but underestimated the lowest intensity precipitation in the majority of test regions.

The gamma method performed well in the re-sampling tests (performed on 1-km scale bias correction) showing a low sensitivity to the choice of calibration period and accurately captured the distribution of observed daily precipitation when the observed data were aggregated to the same spatial scale as the RCM data (see Section V. 2. 2.). Its overall performance in the re-sampling tests was similar to the non-linear method. However, it was better at the higher order moments in the summer in all regions other than East Anglia.

The empirical method performed with mixed success. Where it performed as intended e.g. the 25, 50 and 100 quantile tests in the Ribble region (see Figure 6), the empirical method was successful at correcting all statistical moments, with greater strength at the lower order moments. However, in all regions there was at least one of the empirical tests which did not perform as intended, seen by the high relative differences between the observed and bias-corrected lower order moments in some seasons. It was found that these statistics were caused by unusually high bias-correction factors in the mid to low quantiles of the empirical distribution. These high correction factors occur when, in a certain quantile, the pre-processed precipitation is significantly lower than the observed precipitation. It is known that the climate model precipitation often has a 'drizzle' effect whereby too much low intensity precipitation is simulated (Sun et al., 2006). This effect is what leads to mid to low quantiles containing precipitation which is significantly lower than the observed precipitation and hence, excessively high correction factors from the empirical method. In theory the empirical method should be able to correct all moments of the simulated distribution but, as shown here, if the shape of the two distributions is too different then the performance of the empirical method is erratic.

The bias correction method used to derive FF-HadRM3-PPE for precipitation is the quantile mapping method based on the RCM-scale Gamma distribution after a wet-day correction was applied to the whole series. Monthly correction models (wet day and gamma) were calibrated on 1961-1990 period. The correction was applied to all the ensemble members of HadRM3-PPE to generate 1950-2099 daily precipitation grids of the same scale than HadRM3-PPE. The downscaling to 1-km was done subsequently at through the snow-melt processing described in Morris (2012).

VI. 2 Further Work

We have identified three main areas for further work; increased record lengths, varying correction factor windows, and alternative distributions and fitting methods.

The presence of significant natural variability in precipitation means that, for all methods, uncertainty on the 95^{th} percentile can be greatly reduced by increasing the record length. This is true for all correction methods hence all methods may benefit from increased historical record length available for calculating correction factors. It may be possible to increase the observed record length by using a pooling technique (using data from long record stations to estimate data elsewhere) similar to that used in the Flood Estimation Handbook (Hydrology, 1999). RCM daily precipitation could be extended by pooling data from different model ensemble members over the historical period e.g. 1950 – 2000 as was demonstrated in Kendon et al (2008).

In this study we calculated monthly bias-correction factors using daily precipitation from the same month for the full range of the bias-correction period (e.g., ten years for the re-sampling tests in a cross-validation procedure, and forty years for the extra non-linear tests, i.e. on all available observed record). We then applied the appropriate monthly bias-correction factor to daily precipitation data. Both Leander and Buishand (2007) and Terink et al (2010) calculated non-linear bias-correction factors for five day periods using a sixty-five day moving window centred on the period of interest, for the Meuse and Rhine basins respectively. Terink et al (2010) carried out a sensitivity analysis and found that periods less than sixty-five days led to worse results in the summer months. It may be possible to improve the performance of all four bias-correction methods by varying the window length used to calculate correction factors and also considering the use of a moving window.

We have shown that the observed and pre-processed RCM daily precipitation used in this study were well represented by a gamma distribution when aggregated to the RCM scale and when fitted using the method of moments. However, a superior fit may be achieved by using the method of L-moments which is well suited to datasets with extreme outliers such as high intensity precipitation events (Hosking and Wallis, 1997). In addition to this it may be useful to test alternative distributions such as the Generalised Extreme Value distribution which may produce a better fit to the precipitation data used in this study.

Section VII Conclusion

In this study four methods for bias-correcting HadRM3 daily precipitation data were tested over six regions spanning the UK, in order to determine the best bias-correction method for use in hydrological modelling applications.

Re-sampling tests were used to assess the performance of the bias-correction methods in terms of the first four statistical moments and cumulative distribution functions were produced to compare the distribution of the bias-corrected daily precipitation with respect to the observed and pre-processed daily precipitation distributions. The linear method was shown to produce improvements in only the first two statistical moments, as was expected since it is the simplest of the four methods based solely on scaling the mean of the distribution. This method improved the distribution for mid-intensity daily precipitation, in some cases closely matching the observed, but did not do as well for the extremes. In most cases the empirical method produced an improvement in all the statistical moments, however its performance was erratic and it sometimes produced unrealistically high correction factors (and associated very large errors on the first moment in cross-validation). Despite this unreliability, in areas where it did work correctly, the empirical method improved the daily distribution at all precipitation intensities. The performance of the non-linear and gamma methods was similar in terms of the statistical moments with large improvements in the low order moments and moderate to significant improvements in the higher order moments. The non-linear method improved the majority of the daily precipitation distribution, only deviating significantly from the observed precipitation at daily intensities of less than 1 mm.

Following this initial testing phase the linear and empirical methods were ruled out. The linear method was deemed unsuitable as it did not improve the higher order moments of the distribution. Hence, daily precipitation generated in this way would not be suitable for hydrological modelling where accuracy at the extremes is important. The empirical method was discarded due to its unstable behaviour leading to unrealistically high bias-correction factors. However, as this method performed well in all other ways it is possible that with refinement it could be a dependable and accurate technique for bias-correcting daily precipitation.

The gamma method was subjected to a further test to determine whether the observed and pre-processed daily precipitation fit a gamma distribution. The results of the Chi-squared test showed that a gamma distribution was an adequate fit to both the observed and pre-processed daily precipitation in all the test regions, but only if the data were first aggregated to the scale of the RCM.

Taking the known limitations, such as uncertainty in daily precipitation intensities of less than 1 mm per day, into account this study concludes that the RCM-scale gamma-distribution-based bias correction method is the most suitable for use with daily HadRM3 data for hydrological modelling applications in the UK.

Section VIII References

Arnell, N., Hudson, D. A. & Jones, R. G. 2003. Climate change scenarios from a regional climate model: Estimating change in runoff in southern Africa. Journal of Geophysical Research*,* **108,** 4519, doi.

Ashfaq, M., Bowling, L. C., Cherkauer, K., Pal, J. S. & Diffenbaugh, N. S. 2010. Influence of climate model biases and daily-scale temperature and precipitation events on hydrological impacts assessment: A case study of the United States. Journal of Geophysical Research*,* **115,** D14116, doi.

Bissell, A. F. & Ferguson, R. A. 1975. The jackknife-toy, tool, or two-edged weapon? Statistician*,* **24,** 79-100, doi.

Bradford, R. B. & Marsh, T. J. 2003. Defining a network of benchmark catchments for the UK. Water & Maritime Engineering*,* **156,** 109-116, doi.

Defra. 2009. *UK Climate Projections* [Online]. Available: http://ukclimateprojections.defra.gov.uk/content/view/12/689/ [Accessed 16th Sept 2010].

Diaz-Nieto, J. & Wilby, R. L. 2005. A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom. Climatic Change*,* **69,** 245-268, doi.

Fowler, H. J., Blenkinsop, S. & Tebaldi, C. 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology*,* **27,** 1547-1578, doi.

Frei, C., Christensen, J. H., Déqué, M., Jacob, D., Jones, R. G. & Vidale, P. L. 2003. Daily precipitation statistics in regional climate models: Evaluation and intercomparison for the European Alps. Journal of Geophysical Research*,* **108,** 4124, doi.

Frei, C., Schöll, R., Fukutome, S., Schmidli, J. & Vidale, P. L. 2006. Future change of precipitation extremes in Europe: Intercomparison of scenarios from regional climate models. Journal of Geophysical Research*,* **111,** D06105, doi: doi:10.1029/2005JD005965.

Hay, L. E., Clark, M. P., Wilby, R. L., Gutowski, W. J., Leavesley, G. H., Pan, Z., Arritt, R. W. & Takle, E. S. 2002. Use of regional climate model output for hydrolgic simulations. Journal of Hydrometeorology*,* **3,** 571-590, doi.

Hay, L. E., Wilby, R. L. & Leavesley, G. H. 2000. Comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. Journal of the American Water Resources Association*,* **36,** 387-397, doi.

Hosking, J. R. M. & Wallis, J. R. 1997. *Regional frequency analysis: an approach based on L-moments.*, Cambridge University Press.

Hydrology, I. O. 1999. *Flood Estimation Handbook (five volumes),* Wallingford, Centre for Ecology and Hydrology.

Jenkins, G. J., Murphy, J. M., Sexton, D. S., Lowe, J. A., Jones, P. & Kilsby, C. G. 2009. *UK Climate Projections: Briefing report,* Exeter, UK, Met Office Hadley Centre.

Jones, S. B. 1983. The Estimation of Catchment Average Point Rainfall Profiles (IH Report Number 87). *Report.* Wallingford: Institute of Hydrology.

Keller, V., Young, A. R., Morris, D. & Davies, H. 2006. Environment Agency R & D Project W6-101 Continuous Estimation of River Flows (CERF) Technical Report: Estimation of Precipitation Inputs. Wallingford: Centre for Ecology and Hydrology.

Kendon, E. J., Rowell, D. P., Jones, R. G. & Buonomo, E. 2008. Robustness of future changes in local precipitation extremes. Journal of Climate*,* **21,** 4280-4297, doi: 10.1175/2008JCLI2082.1.

Lafon, T., Dadson, S., Buys, G. & Prudhomme, C. 2012. Bias correction of daily precipitation simulated by a regional climate model: a comparison of methods. International Journal of Climatology**,** n/a-n/a, doi: 10.1002/joc.3518.

Leander, R. & Buishand, T. A. 2007. Resampling of regional climate model output for the simulation of extreme river flows. Journal of Hydrology*,* **332,** 487-496, doi.

Lenderink, G., Buishand, A. & Van Deursen, W. 2007. Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. Hydrology and Earth System Sciences*,* **11,** 1145-1159, doi: 10.5194/hess-11-1145-2007.

Li, H., Sheffield, J. & Wood, E. F. 2010. Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. Journal of Geophysical Research*,* **115,** D10101, doi: 10.1029/2009jd012882.

Marsh, T. J. & Hannaford, J. 2008. UK Hydrometric Register (Hydrological Data UK Series). Wallingford: Centre for Ecology and Hydrology.

Morris, D. 2012. Derivation of water available from precipitation - Science Report/Project Note - SC090016/PN5. *Future Flows and Groundwater Levels.* Wallingford: CEH.

Osborne, T. J. & Hulme, M. 1998. Evaluation of the European daily precipitation characteristics from the atmospheric model intercomparison project. International Journal of Climatology*,* **18,** 505-522, doi.

Piani, C., Haerter, J. O. & Coppola, E. 2010. Statistical bias correction for daily precipitation in regional climate models over Europe. Theoretical and Applied Climatology*,* **99,** 187-192, doi.

Press, W. H., Teukolsky, S. A., Vetterling, W. T. & Flannery, B. P. 1986. *Numerical Recipes in FORTRAN: The Art of Scientific Computing,* Cambridge, CUP.

Prudhomme, C., Reynard, N. & Crooks, S. 2002. Downscaling of global climate models for flood frequency analysis: where are we now? Hydrological Processes*,* **16**, doi.

Prudhomme, C., Wilby, L. R., Crooks, S. M., Kay, A. L. & Reynard, N. S. 2010. Scenario-neutral approach to climate change impact studies: application to flood risk. Journal of Hydrology*,* **390,** 198-209, doi: 10.1016/j.jhydrol.2010.06.043.

Shabalova, M. V., Van Deursen, W. & Buishand, T. A. 2003. Assessing future discharge of the river Rhine using regional climate model integrations and a hydrological model. Climate Research, **23,** 233-246, doi.

Sun, Y., Solomon, S., Dai, A. & Portmann, R. W. 2006. How often does it rain? Journal of Climate, **19,** 916-934, doi.

Tait, A., Henderson, R., Turner, R. & Zheng, X. 2006. Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. International Journal of Climatology **26,** 2097-2115, doi: 10.1002/joc.1350

Terink, W., Hurkmans, R. T. W. L., Torfs, P. J. J. F. & Uijlenhoet, R. 2010. Evaluation of a bias correction method applied to downscaled precipitation and temperature reanalysis data for the Rhine basin. Hydrology and Earth System Sciences, **14,** 687-703, doi.

Wood, A. W., Leung, L. R., Sridhar, V. & Lettenmaier, D. P. 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Climatic Change, **62,** 189-216, doi.

Wood, A. W., Maurer, E. P., Kumar, A. & Lettenmaier, D. P. 2002. Long-range experimental hydrologic forecasting for the eastern United States. Journal of Geophysical Research, **107,** 4429, doi.