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Regional Climate Data Tools

Final Report

Sutton and East Surrey Water on behalf of WRSE

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5194482-2

Notice

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Executive Summary

This is the final report of the Regional Climate Data project, which has developed new climate data sets to support regional water resources planning in England and Wales.

The two main data sets are:

- Stochastic daily time series of precipitation and potential evapotranspiration for more than 200 locations in England and Wales, based on Met Office HadUK observation data for precipitation and several Potential Evapotranspiration (PET) data sets, required for water resources modelling
- Bias corrected future climate change factors and daily time series based on UK Climate Projections 2018 Regional Climate Models under Representative Concentration Pathway (RCP8.5) and HadUK precipitation and temperature at the catchment scale

The first data set provides a set of 400 time series for each location for the assessment of climatological drought risk across England and Wales for a baseline climate without climate change. The same stochastic model is now applied to five regions of England and Wales and is an improved model compared to previous assessments for WRMP19[1]. Within each region these data are spatially and temporally coherent, providing plausible scenarios of a wide range of possible drought conditions. These data provide inputs to hydrological, groundwater and water resources systems models for the assessment of baseline deployable outputs and risks of very low rainfall over durations from 3 months to several years. Example outputs from the drought library are shown in Figure ES1.

A project development phase tested the performance of a new stochastic model, which was driven by a wider range of climate drivers including the North Atlantic Oscillation (NAO), Sea Surface Temperatures, Atlantic Multidecadal Oscillation, East Atlantic, East Atlantic West Russia and Scandinavia Indices. It also developed improved post-processing and sampling tools with the overall impact of improving the model fit to low rainfall by 25%[1]. Overall, the post-processing adjustments are minor, and the improved fit means that post-processing correction is not required for all sites. Case studies were used to test the workflow and compare the new stochastic model to older versions applied in WRMP19.

The second data set provides spatially coherent Regional Climate Model (RCM) change factors and accompanying daily time series to assess the impacts of climate change. These scenarios are based on Met Office UKCP18 Regional Climate Models under scenario Representative Concentration Pathway RCP8.5. The RCMs were bias corrected to match HadUK observations for more than 200 catchments in England and Wales. These data provide time series for modelling from 1981 to 2070, but it is anticipated that water companies will make use of the change factors and apply these to historical baseline and selected stochastic time series to assess future impacts.

A full Strengths Weaknesses Opportunities and Threats (SWOT) analysis on UKCP18 reviewed the available data sets for regional water resources modelling, with spatial coherence as a key criteria The RCMs provided the most suitable model outputs in this regard, despite other weaknesses. The bias-corrections applied were more advanced than the methods used for the previous Future Flows project, thereby creating a product that both fits the baseline climate and provides time series for future climate change at the catchment scale. However, it is clear the Met Office HadGEM global model and regional model are hotter than other models in the CMIP5 ensemble and the median projections from the UKCP probabilistic data, with predictably greater impacts on low flows.

Conclusions

This project was started before the development and publication of the Environment Agency Water Resources Planning Guidelines, which includes supplementary guidance on both stochastic data and climate change impacts assessment. Both data sets can be implemented in a way that is fully compliant with the guidelines and the interactions are summarised in Figure ES2.

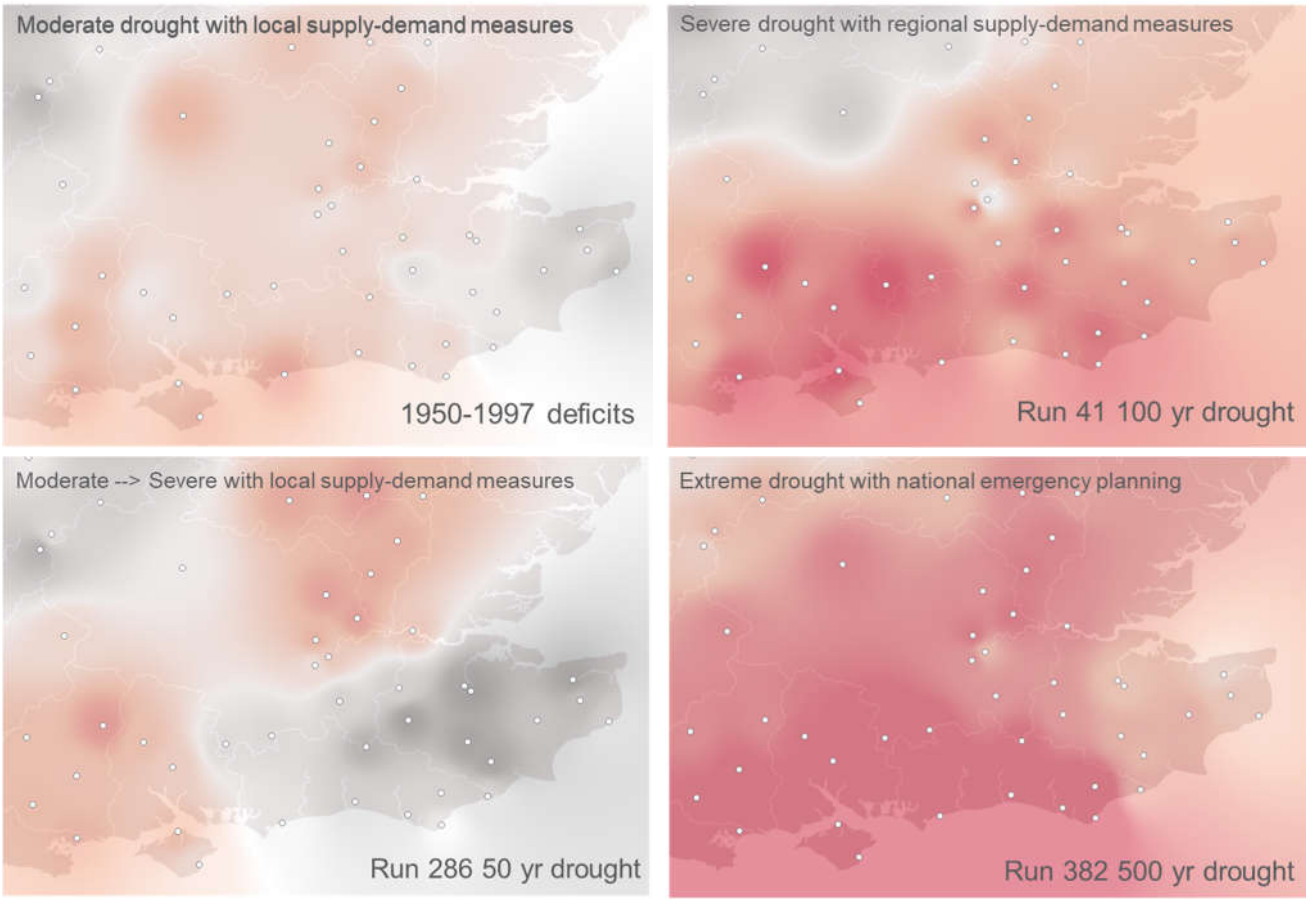
On stochastic analysis the Environment Agency favours a water resources systems assessment of drought, so that severe droughts (annual probabilities of 1%,0.5% and 0.2%) need to be defined in terms of system outputs. This means that the full 400 time series or a representative sub-sample need to be modelled.

On climate change the Environment Agency presents a comprehensive process-based approach, with updated modelling for zones at risk or where major investment is necessary. This modelling will include the application

[1] Based on the Mean Absolute Error of low rainfall in mm/month for three test regions and low rainfall metrics from 3 months to 36 months.

of the RCM factors provided by this project, but for the most detailed 'Tier 3' assessments, it is likely to require further scenarios to capture a larger range of climate change scenarios and stochastic analysis[2].

Figure ES1 – Baseline minimum rainfall and selected drought scenarios based on low rainfall in the south west of WRSE region



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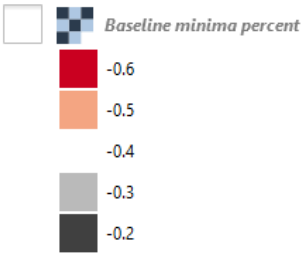
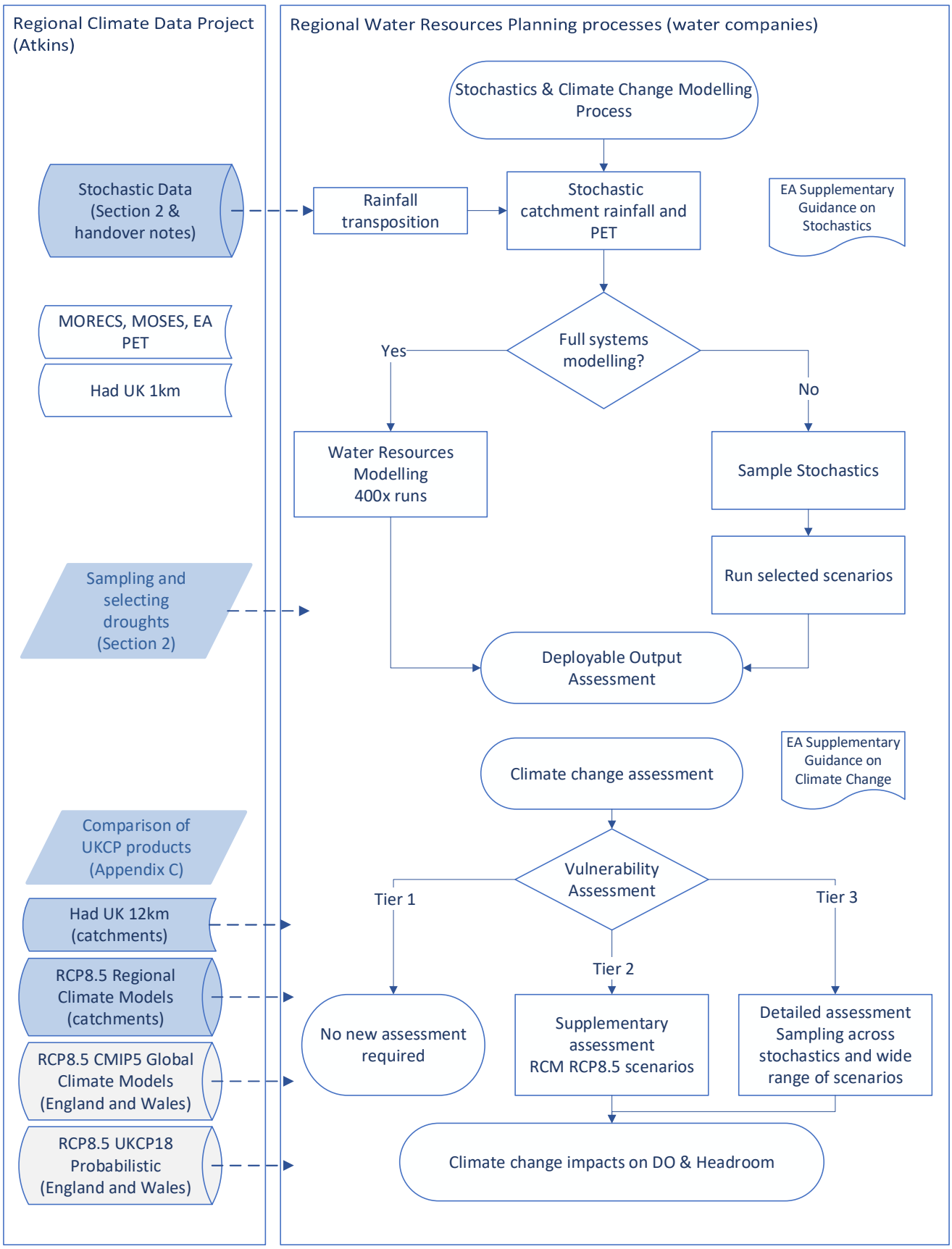


Scenarios selected based on ordering the "worst droughts" in 400 stochastic runs

The estimated annual probabilities are for low rainfall for hydrological years in the south west WRSE region, centred on Hampshire

[2] For this reason, we provide CMIP5 global model factors and UKCP18 probabilistic data for England and Wales.

Figure ES2 - Regional Climate Data Project data and its relevance for Regional Water Resources Planning



1. Introduction

Water companies in England and Wales have a statutory duty to deliver water resources management plans (WRMPs), which include assessment of baseline water availability and the impacts of climate change of future water supply and demand. The National Framework for Water Resources sets out how regional planning groups should work together to assess strategic regional options for water supply and demand management schemes[3]. The draft Environment Agency Water Resources Planning Guideline provides a framework for the development of plans, including supplementary guidance on climate change, the use of stochastic data and assessment drought risks.

This project developed new climate data sets to support regional water resources planning in England and Wales. The two main data sets are:

- Stochastic daily time series of precipitation and potential evapotranspiration for more than 200 locations in England and Wales
    - These data were based on an improved stochastic model using HadUK precipitation at sites with good quality data from the 1950s to the present
    - For the assessment of baseline water resources drought without climate change
- Bias corrected future climate change factors and daily time series based on HadUK precipitation and temperature and the UK Climate Projections 2018
    - For the assessment of future climate change impacts on supply and demand
    - Provides climate change factors for perturbation of the baseline stochastic data
    - Provides daily bias-corrected precipitation and temperature time series from 12 Regional Climate Models for the assessment of future trends

All data provided are spatially coherent across England and Wales and can be used for the analysis of regional and national drought. This report is the final project report and is structured as follows:

- Section 1 provides background information on data used for the project and its application to regional water resources planning
- Section 2 describes the development of the baseline stochastic data, focusing on changes in the way the model was implemented (between WRMP2019 and this project, which informs WRMP24) and how to make use of the results
- Section 3 summarises the bias corrected Regional Climate Models and other climate change products provided by the project
- Section 4 provides conclusions and recommendations for further development of these tools
- A set of appendices provides more detailed information to support Sections 1-4. Appendix C is the main part of climate change report, which was provided prior to our workshop in March 2020.

1.1 Baseline data sets

The stochastic modelling was based on HadUK 1km daily data for specific locations, which were selected because those grid cells contained high quality observations from 1950 to the present. HadUK12 km daily precipitation and temperature data sets were used for the bias correction of climate models and were also averaged for selected river basins to provide a baseline data set for the 1981-2000 period[4].

Compatible Potential Evapotranspiration (PET) data sets were provided based on data provided by the water companies, typically Met Office Rainfall and Evaporation Calculation Systems (MORECS) data[5] or other proprietary water company data sets. The Environment Agency's new 1km PET data (released July 2020) was incorporated into some regional data sets but was delivered too late for the Water Resources South East (WRSE) programme. Appendix A provides more information about the data sets used in the project.

[3] https://www.gov.uk/government/publications/meeting-our-future-water-needs-a-national-framework-for-water-resources

[4] Hollis, D, McCarthy, MP, Kendon, M, Legg, T, Simpson, I. 2019: HadUK-Grid—A new UK dataset of gridded climate observations. Geosci Data J. 2019; 6: 151– 159. https://doi.org/10.1002/gdj3.78

[5] Hough, M. N. and Jones, R. J. A.: The United Kingdom Meteorological Office rainfall and evaporation calculation system: MORECS version 2.0-an overview, Hydrol. Earth Syst. Sci., 1, 227-239, doi:10.5194/hess-1-227-1997, 1997

1.2 Stochastic data sets

This project implements the stochastic multisite rainfall generators, originally developed by Serinaldi and Kilsby (2012) and developed further by Atkins on a series of projects to support Water Resources Management Plans in 2019 to provide daily rainfall and PET time series. The original model enabled the simulation of low and high rainfall scenarios more extreme than those observed as well as the reproduction of the distribution of the annual accumulated rainfall, and of the relationship between the rainfall and circulation indices such as North Atlantic Oscillation (NAO) and Sea Surface Temperature (SST) (Serinaldi and Kilsby, 2012). The model was developed under 3 projects during WRMP19 and has been developed further to include a larger number of climate indices and improved post-processing to provide drought sequences for all regions of England and Wales.

In this project's development stage, stochastics data were created for three regions (WRSE, United Utilities and Water Resource East) and in the delivery stage the final model was run for all five regions (West Country Water Resources Group, Water Resources North, Water Resources West, WRSE, WRE) and a total of 195 rainfall locations. This report uses the development data sets for selected hydrological case studies and the WRSE final delivery data set to show final results for the South East of England. The final delivery data sets for other regions form part of separate delivery contracts and are not described in detail in this report.

One of the innovations in the new data sets was to drive the stochastic model using a larger number of climate drivers, in addition to the North Atlantic Oscillation (NAO) index and Sea Surface Temperatures (SSTs). As these 'driver' data sets were only available from 1950 the new modelling provides a baseline from 1950-1997 (48 years). The data stop in 1997 to be consistent with data sets used for WRMP19 and to avoid including significant climate change in the baseline data. Environment Agency supplementary Water Resources Planning Guidelines stipulate that the baseline should stop by 2000, so as not to double count climate change in the stochastic data and future climate change scenarios.

The stochastic data delivered to water companies provides 400 model runs of replicates of the 1950-1997 climate. The data include 'wetter' and 'drier' time series that cover a wider range of possible conditions, including longer dry periods similar to those that occurred outside of the model calibration period, for example, at the end of the 19th century. Section 2 focuses on improvements to the stochastic methods developed as part of this project; further background research is included in Appendix B.1.

1.3 Selection of droughts

Regional groups will use the data sets in different ways, and many will run the full set of 400 time series through their hydrological and systems models to characterise water resources drought risk. Some companies may select time series or drought events based on rainfall or other hydrological characteristics, including severe droughts that are outside of the recent historical period (1950-1997).

To support rainfall drought analysis and selection of scenarios, we provide summary data for 16 rainfall metrics that were widely used in previous studies. These provide rainfall averages and minima for durations from 6 months to 36 months with different end dates to align with hydrological or calendar years. Example outputs for WRSE are shown in Section 2 and further information is provided in Appendix B.2.

1.4 Climate change scenarios

The climate change scenarios were derived from the UK Climate Projections 2018 (UKCP18), which provide a range of modelling products with the most emphasis on Representative Concentration Pathway 8.5 (RCP8.5), which is a higher emissions scenario. This scenario indicates warming of 1.4 to 4.1 ^{o}C in the 2070s above the 1981-2000 baseline for England and Wales[6] (therefore 2 to 5 ^{o}C above pre-industrial average temperatures). The main climate change products produced were:

(i) bias-corrected time series for 12 Regional Climate Models; and,

(ii) monthly change factors at the catchment scale for RCP8.5 and the 2070s (2061-2080).

It is anticipated that most users will apply the change factors to stochastic data in order to model a stochastic baseline and then add climate change.

In order to give a broader context, we also provide UKCP probabilistic data for several scenarios and CMIP5 Global Climate Models (GCMs) for England and Wales. The approach to climate change modelling was agreed at the first project workshop in March 2020. Further information on application of the climate scenarios is

[6] Based on 10th and 90th percentile of the UKCP probabilistic data for 2060-2079

provided in Section 3 and a full report on the pros and cons of different climate model data sets is included in Appendix C.

1.5 Regional Groups

There are five regional groups, which include water companies, Environment Agency, National Resources Wales and other representatives (including Natural England, energy and agriculture sectors). The water company representation in each regional group is summarised below:

- Water Resources North (WReN) – Northumbrian Water, Hartlepool (Anglian) Water, Yorkshire Water
- Water Resources West (WRW) – Severn Trent Water, United Utilities, South Staffordshire Water, Dŵr Cymru (Welsh Water)
- Water Resources East (WRE) – Anglian Water, Essex and Suffolk Water, Cambridge Water, Severn Trent Water, Affinity Water
- Water Resources South East (WRSE) – Affinity Water, Portsmouth Water, South East Water, Southern Water, SES Water, Thames Water[7]
- West Country Water Resources (WCWRG) – Bristol Water, Wessex Water, South West Water

Data sets are being provided for each group. The approach for combining these data sets is discussed in Section 4 and in the appendices.

1.6 Development of case studies

Each regional group proposed a case study as shown in Table 1-. These are "within" region studies that make use of regional stochastic data sets and catchment scale bias corrected Regional Climate Models as well as other standard UKCP18 products. Five case studies were completed; the WReN is ongoing.

Table 1-1 - Selected case studies

Region	Case study	Technical focus	Modelling resources
Water Resources in the South East (WRSE)	Western Rother	Stochastics & climate change	Catchmod model (Calibration period 1994-2009)
Water Resources East (WRE)	River Ouse	Stochastics Hydrological impacts	Stanford Watershed Model with analysis completed by Water Resources East
Water Resources West (WRW)	River Dee	Stochastics Hydrological impacts	Catchmod model of the Celyn sub-basin only
West Country Water Resources Group (WCWRG)	Wimbleball surface water and Ashton recharge	Climate change Hydrological impacts	Application of water company models for Wimbleball Reservoir inflow and Ashton recharge model
Water Resources North (WReN)	Langsett Group of catchments	Climate change Hydrological impacts	Catchmod model

The WReN Model provided was a HYSIM model, which is being changed to Catchmod as HYSIM is not an appropriate model for batch processing with 1000s of scenarios.

[7] The report was produced under contract from Seswater on behalf of the WRSE group. The same modelling approach was provided to other regions and the only differences were related to the choice of PET data used.

2. Stochastic data sets

2.1 Introduction

The key features of the new stochastic model and the specific data set are summarised in Table 2-1.

Table 2-1 - The differences between the WRMP19 stochastic data sets and the new Regional Planning stochastic data sets, using the example of the WRSE data set

Model component	WRMP 19 data sets	Regional Climate Data Project[8]	Rationale
Baseline precipitation data	Water company provided catchment average daily time series or time series from selected rainfall stations	195 HadUK 1km grid cells located over 'high quality' meteorological stations The same data source was used for all regions	Preference to use a single operational product for rainfall Focus on "grid cells" with quality data rather than interpolated data Flexibility to translate points to basins or demand areas as required
Number of precipitation series	40-65 sites per region Each region has a bespoke model	195 in total 50-80 sites per region (includes overlapping sites)	Each site is a 1km grid cell from the HadUK data set Improved coverage of key basins
Number of PET data sets	20-65 locations per region (river basin, MORECs or MOSES data)	Up to 200 basin daily PET data sets per region (River basin, MORECs, MOSES and new EA PET data).	Focused on use of PET data sets used in current hydrological and groundwater models
Climate drivers used	NAO, SST (and EAI for WRE)	NAO, SST, Kaplan SST, COBE SST, AMO, EAI< EA, EAWR, SCA and interactions between indicators (See Appendix B)	Marginally better fit and explanation of low rainfall in regions with weaker NAO influence (e.g. South East). Same model in all regions to support national scale work.
Model fitted to	1920-1997	1950-1997	High quality climate driver data available from 1950 only
Model validated against	1920-1997	1920-1997 1902-1949 (independent checks)	Demonstrates that contemporary stochastic model can fit early 20th century droughts
Number of replicate time series	200	400 (sub-sampled from 1000)	An increase in the number of replicates improves the fit to dry years
Length of replicate time series (and total years)	88 (17,600 years)	48 (19,200 years)	Broadly equivalent number of years
Bias correction	Simple scaling of driest 10% to match observed data	Less bias correction using a more sophisticated approach	Responds to previous peer review criticisms Avoids implausible droughts
Implementation of results	Drought library, selected events	Point to catchment transposition required.	Flexibility in application to different catchment models Meets EA supplementary guidance requirements

[8] The new stochastic model reduces Mean Absolute Errors of fitting extreme droughts by 25% across WRSE, WRE and UU regions and provides a large coherent rainfall and PET data set for regional water resources planning. It also reduces the need for bias correction.

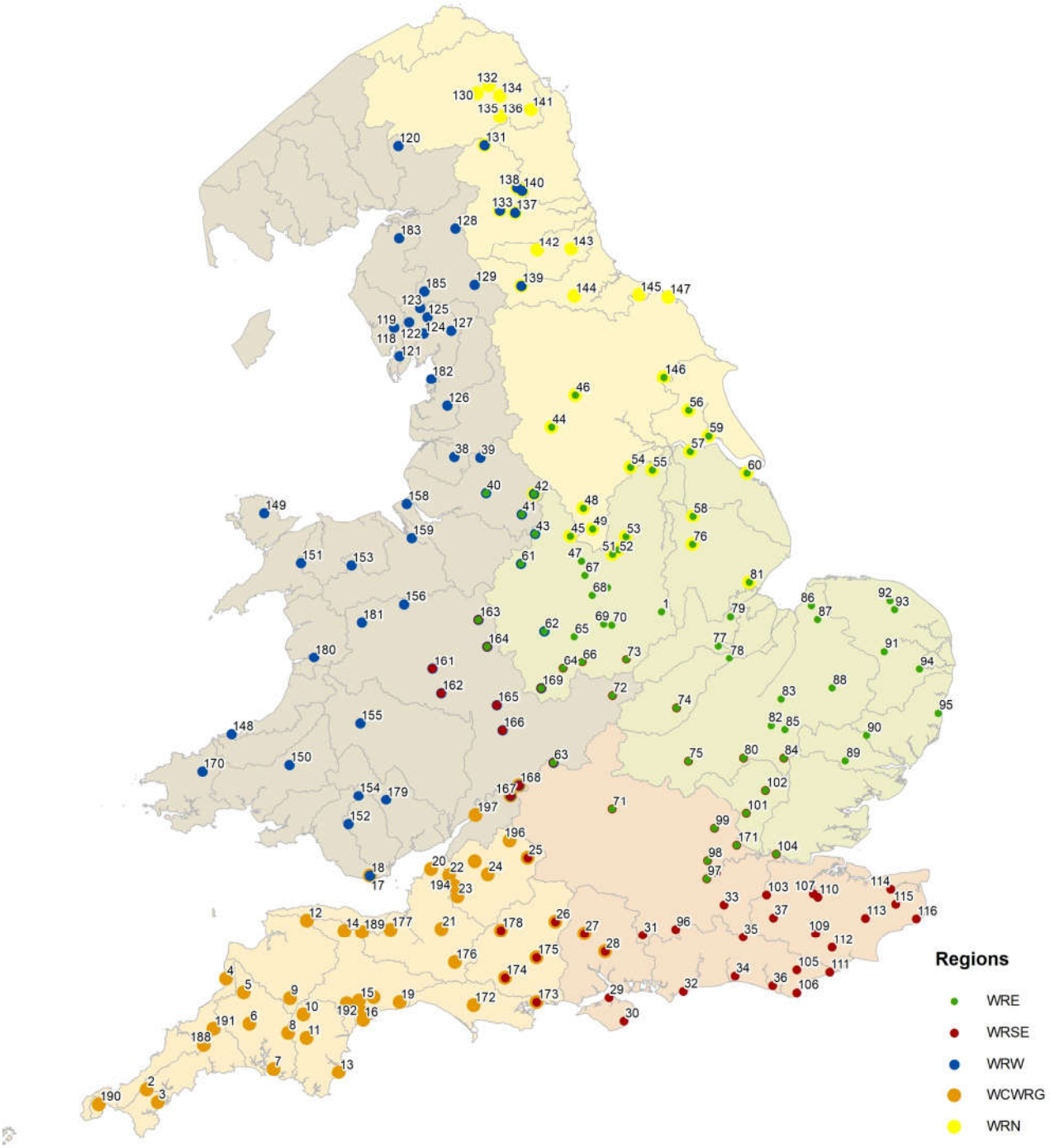


Figure 2-1 – Location of standard hydrometric areas and selected rainfall locations across England and Wales (illustrating overlapping sites that have modelled in more than one region)

2.2 Selection of rainfall locations

Rainfall locations (1km cells) were selected according to the following criteria:

- Sites with good quality data from 1950 to the present, to match the availability of the improved 'climate drivers' data set (Section 2.3), based on Met Office and CEH GEAR rainfall meta-data[9]
- An improved spatial coverage in England and Wales, particularly in locations with important regional water supplies
- Water company preferences to add further sites to provides improved spatial coverage and sites at higher elevations

A total of 195 sites were selected and assigned to one or more regional groups. The assignment to groups ensured that there was good overlap between regions so that the data could be brought together for national assessments as required. Stochastic time series were generated for selected locations rather than for river basins for several reasons.

- The original methodology was designed for point data, and this scale highlights the high variability of rainfall which is lower when averaging over large catchment areas
- It provides some flexibility to transpose these data to different spatial areas, whether these are catchments or water distribution zones for demand modelling
- Two out of three previous assessments used point locations, so this approach provides a clearer audit trail from the WRMP19 work to the present study
- Hydrological modelling strategies were developed in parallel to this study, so the full set of catchment boundaries were not available for all regions at the start of this study

2.2.1. Comparison of HadUK data and CEH GEAR data

In the previous WRMP19 stochastic weather generators used CEH GEAR rainfall data but this has now been replaced with Met Office HadUK gridded rainfall. We undertook a comparison of these data as inputs for the stochastic weather generator and the results were presented to the Technical Steering Group at the project workshop in March which confirmed the decision to use HadUK data (Figure 2-2). The two data sets are very similar but individual days may be different due to the different quality assurance procedures applied to each data set. Going forward the HadUK data is the operational data set that will be used by water companies in England and Wales, which is endorsed by the Environment Agency

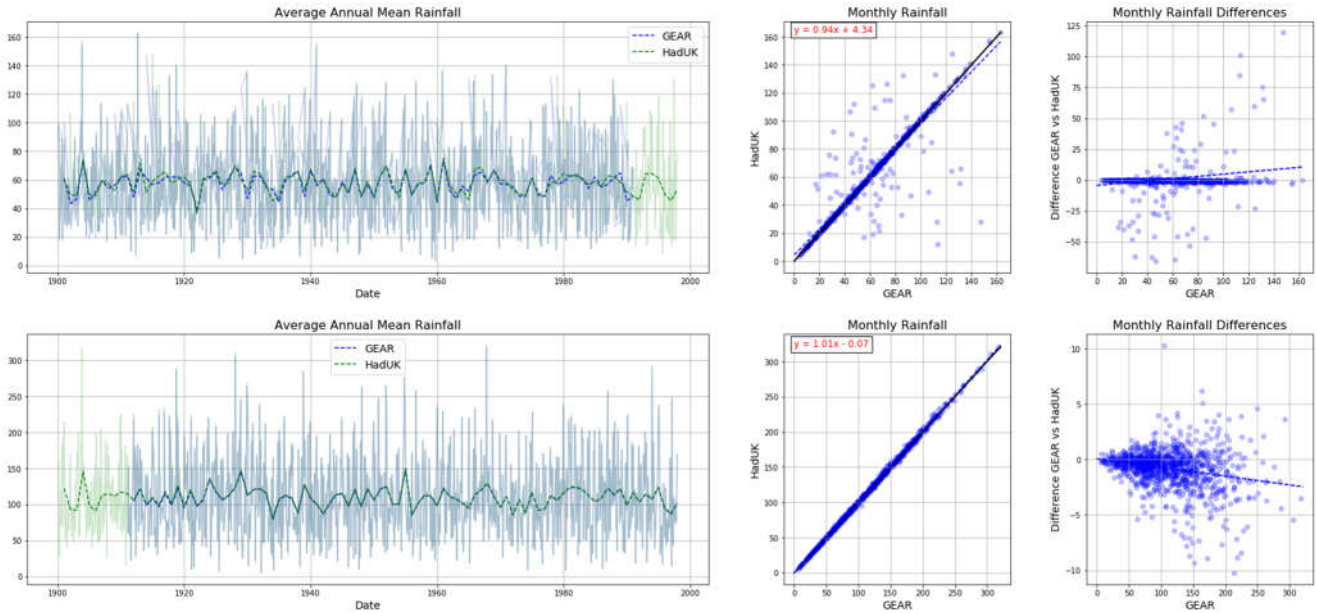


Figure 2-2 - Comparison of GEAR and HadUK observed monthly rainfall data. Averaged across the WRE region (top) and United Utilities (bottom).

[9] The rainfall "sites" were selected by processing CEH GEAR rainfall metadata and comparing this information with HadUK metadata to identify locations with meteorological stations and good quality rainfall records between 1950 and the present (i.e. a low percentage of missing data and long periods of continuous time series)

2.2.2 Transposing from site locations to river basins

In many cases, the selected rainfall locations will be those used for hydrological modelling. As these data are drawn from the HadUK 1km data set, they will also be broadly consistent with HadUK12km catchment average precipitation used for the climate change modelling (Section 3).

Hydrologists utilise a range of methods for transposing from points to basins. In previous studies stochastic data sites have been linked to sites used for catchment modelling using a 1:1 scaling relationship (WRE for WRMP19) or based on multiple linear regression (UU for WRMP19).

In developing the case studies we have used Thiessen polygons and a scaling factor to convert stochastic series to catchment series for "target" river catchments, as follows:

$$R_{target}^{day} = \frac{AARt}{AARs}\,(\,w1.R_{s1}^{day} + w2.R_{s2}^{day} + wn.R_{sn}^{day})$$

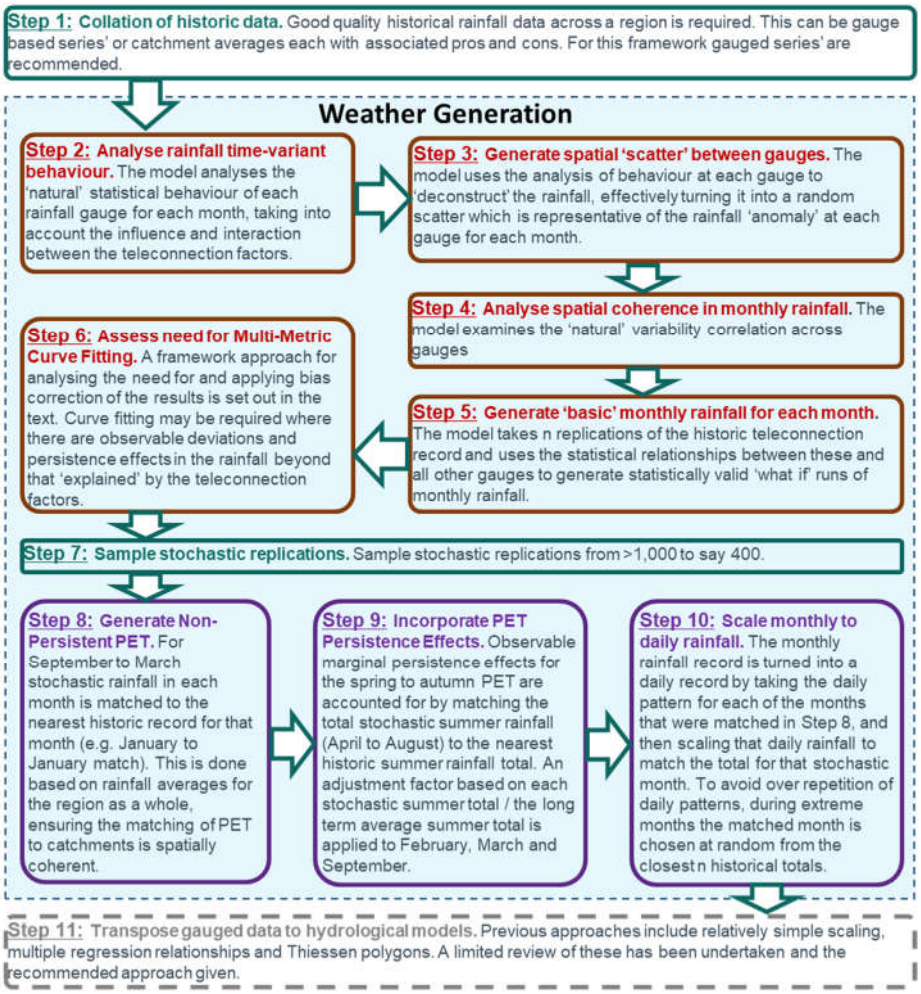
Where R is the rainfall on any day for "target" catchments or stochastic sites 1 to *n*, AAR is the Average Annual Rainfall for the target basin (*AARt*) or weighted average of stochastics (*AARs*), *w*1…*n* are Thiessen weights. Therefore, catchment rainfall is estimated based on the weighted average from stochastic sites and scaled by Average Annual Rainfall (AAR). This approach may need refining in areas of complex relief or variable seasonality and in such cases monthly weights may be required

2.3 Further development of stochastic methods

The stochastic weather generator outlined in this framework uses the observed relationships between climate data and regional climatic drivers to produce replicates of the historical climate. The model works by analysing and modelling the underlying rainfall behaviour in relation to climatic drivers as well as 'random chance'.

The basic concept behind this approach is that the historic record provides only one set of actual weather conditions (i.e. the one that did occur) out of the possible range of conditions that might have occurred given the climatic drivers. The implicit assumption behind this approach is that the historical record included in the model is reasonably 'typical' in terms of its overall statistical behaviour.

Figure 2-3 outlines the key steps involved in generating stochastic precipitation and PET data, outlined in further detail in the following sections.



Notes: "Gauge based series" refers to point observations or grid cells, which include one or more meteorological stations. We use the HadUK 1km data as the basis for this work. In Step 5 the models are fit to a large number of sites, which is distinctly different to generators focused on single sites or a small number of sites. For more details see Appendix B.

Figure 2-3 - Overview of stochastic weather generator

2.3.1 Summary of updates for this framework

The approach applied for this framework is similar in its core to the stochastic weather generators previously applied as part of WRMP19 for several water companies and regional groups. However, some key testing and improvements have been carried out at various stages of the modelling process to improve the results as much as possible. These are summarised below and compared in more detail to the previous approach in the following sections:

- **Inclusion of additional teleconnection factors**[10], the model previously used NAO and SST as the climatic drivers (WRE also included an East Atlantic Index). For this framework we have analysed the inclusion of several additional factors.
- **Inclusion of seasonal and interaction terms between the factors to explain rainfall.** Previous iterations of the model considered month, SST and NAO as independent 'main effects' parameters. For this work we have allowed the inclusion of interactions between these, notably to allow for monthly variations but also to enable interactions between the teleconnections.
- **Multi-metric curve fitting approach.** This was a post-processing step to improve the final model fit; it was arguably a contentious component of the previous approach. As part of this framework we have retained the ability to bias correct but amended the method to limit the adjustment and ground the approach in probabilistic methods.

[10] A teleconnection is a causal connection or correlation between meteorological or other environmental phenomena which occur a long distance apart.

- **Adjustment to the daily resampling approach**. The previously applied approach matched each stochastic rainfall month to the closest historical month. This can lead to over-representation of a daily pattern during extreme events where the stochastic total gets repeatedly matched to the lowest historical total and therefore the same daily pattern is selected. To account for this, a small amendment has been incorporated to match to one of a random selection of the 'n' closest historical months. This reduces the chance that one daily pattern is seen repeatedly.

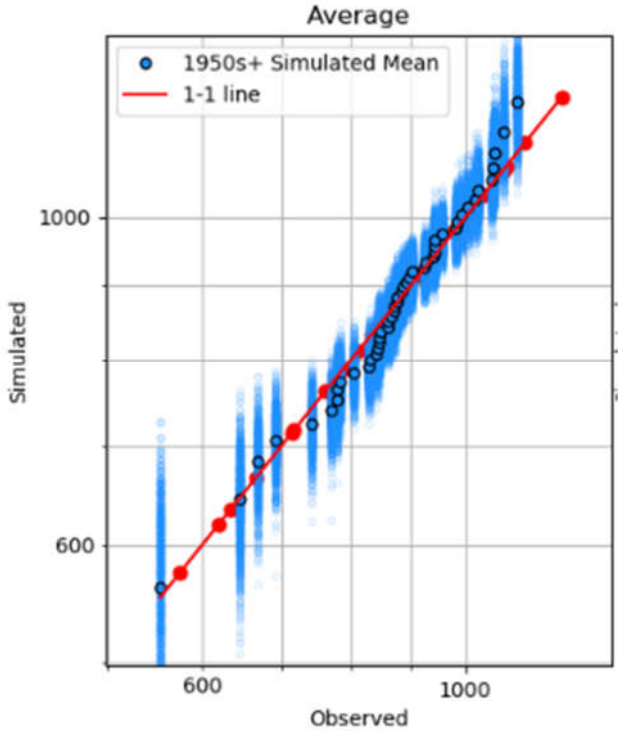
2.3.2 Validation of outputs

At each stage of the weather generation process the outputs are validated using a range of visualisations and rainfall total metrics. The standard rainfall metrics include:

- Longer than annual total rainfall:
  - 18 months ending September
  - 24 months ending September and December
  - 30 months ending September
  - 36 months ending September and December
- Annual total rainfall:
  - 12 months ending September and December
- Winter – Summer total rainfall:
  - December – August
  - January – August
- Summer total rainfall:
  - April – September
  - April – August
  - June – August
  - July – September
- Autumn total rainfall:
  - August – October
  - September – November
- Winter total rainfall:
  - October – March
  - November - February

Checking these rainfall metrics ensures the time coherence of the generated data is retained through the process. To ensure the spatial coherence of the outputs, the data are examined at varying spatial scales including regional average, sub-regional average and site data. For each rainfall metric and spatial scale, ranked rainfall 'Q-Q type' plots[11] and cumulative percentile plots are produced as shown in Figure 2-4 and Figure 2-4.

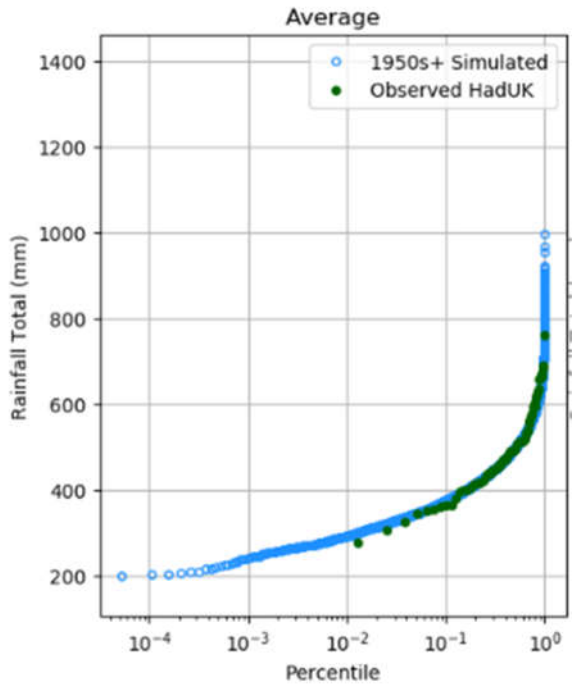
[11] Strictly speaking Q-Q plots would show the probabilities of the data but we show the ranked precipitation values for easier interpretation



These curves show the Q-Q plots of the observed versus simulated total rainfall (mm) (i.e. ranked years from driest to wettest for each simulation compared with the historic record). The black circles represent the mean of the simulation and the individual simulations form the blue 'scatter'. The red line represents the 1-1 mapping between the simulated and observed values – i.e. if the black circles plot on the red line, then the average of the simulations is the same as the historic ranked value (i.e. the historic value falls close to the 'expected' ranked value based on the stochastic).

For additional context, the bold red dots on the 1-1 line indicate observed values that have not contributed to the simulated data (i.e. occurred before 1950).

Figure 2-4 - Example 'Q-Q' ranked rainfall plot



These curves show the cumulative percentile plots of the stochastic and observed rainfall. The blue dots show all the simulated data sorted from driest to wettest. The green dots show the sorted observed data from driest to wettest.

The observed data may contain more points than used to generate the stochastics. For example, in the plot the observed record includes data prior to 1950.

Figure 2-5 - Example percentile plot 2.4 Weather Generation Methodology

2.3.3 Monthly rainfall generator

The core monthly rainfall generator is implemented in R and is an adaptation of the principles originally proposed by Serinaldi and Kilsby (2012) and later applied for several water companies and regional groups as part of WRMP19.

The R module initially uses the GAMLSS package in R[12] to fit generalised linear models (GLMs) to de-seasonalised rainfall probability distributions for each calendar month at each rainfall site. Each GLM contains two components, describing the mean and standard deviation for each rainfall site based on the month, explanatory factors and observed 'natural variability'.

Previous Approach

The previously applied stochastic weather generator approaches used Month, Sea Surface Temperature (SST) and North Atlantic Oscillation (NAO) as explanatory factors for the mean and standard deviation. In other words:

$$\mu_a = f_n(Month) + f_n(SST) + f_n(NAO) + \varepsilon_a$$
$$\sigma_a = f_n(Month) + f_n(SST) + f_n(NAO)$$

Where:

- μ_a = the mean of the rainfall for site a
- σ_a = the variance (standard deviation squared) for site a
- $f_n(Month)$ = the function of the month, which is a categorical factor so acts as a separate month intercept at each site
- $f_n(SST)$ = function of the observed sea surface temperature anomaly
- $f_n(NAO)$ = function of the North Atlantic Oscillation index anomaly
- ε_a = the amount of 'error' (random variability) at site a

Updated Approach

We have incorporated several updates to the R module as part of this framework. These include:

- Consideration of the interaction between the explanatory variables in the equation describing mean rainfall at each site;
- Inclusion of additional explanatory factors;
- The inclusion of a cubic spline time dependent term.

Interaction terms between the explanatory variables allow the model to identify more complex patterns and relationships between the climatic drivers. At a simple level, the interaction between Month and SST (signified with a colon as, $f_n(Month{:}SST)$) allows the model to identify a varying degree of influence between sea surface temperature and rainfall across the year.

In general, when fitting a model, a balance is sought between including the factors and relationships that provide the best explanation of the observed data and constructing a model with the fewest unnecessary terms (termed *the Principle of Parsimony*). However, in this case where the model is fitted to multiple rainfall series individually it was felt more importance should be given to maintaining the consistency of the model formula between sites and in fact between each of the regional groups. Therefore, when analysing the inclusion of additional terms, we have erred on the side of retaining any factors or interactions even if only found to have a significant impact on rainfall at a limited number of locations.

Additional teleconnection factors analysed for this framework include:

- Alternative sources of SST anomaly, notably Kaplan SST V2 and COBE-SST2 in addition to the HadSST2 previously used;
- Atlantic Multi-decadal Oscillation (AMO);
- East Atlantic Index (EAI), previously used by the Met Office in the WRE stochastic weather generation;
- East Atlantic (EA);
- East Atlantic West Russia (EAWR);
- Scandinavia (SCA).

Detailed comparison of the source of these factors and relationship with rainfall across the country were carried out prior to inclusion in the weather generator. Further detail is given in Appendix B.

Prior to 1950 the availability and quality of teleconnection data is significantly reduced, and most of the additional factors listed above are not available before this time. Therefore, further analysis was carried out to compare the model fit and outputs as a result of generating data using the full 20th Century historical record but

[12] 'Generalised Additive Models for Location, Scale and Shape', https://www.gamlss.com/

with a more limited teleconnection dataset compared to a fuller set of teleconnection explanatory factors with data from 1950s onwards. The details of this comparison are summarised in Appendix B. The analysis concluded that while the 1950s model does not include some of the key droughts in the 20th Century, in most cases this model performed as good as, or marginally better, when viewed against the observed data in the 20th Century[13].

Finally, a time dependent cubic spline term has been included in the mean rainfall formula. This is a pragmatic approach that recognises that the model is not capable of fully capturing all the physical processes influencing weather. Therefore, the cubic spline term identifies and accounts for the remaining *structured change* in the residuals after fitting to the teleconnection variables.

Following these updates, the final GAMLSS model for each rainfall series is defined by:

$$\begin{aligned}\mu_a = f_n(Month) &+ f_n(NAO) + f_n(SST) + f_n(AMO) + f_n(EA) + f_n(EAWR) + f_n(SCA) + f_n(Month{:}\,NAO)\\ &+ f_n(Month{:}\,SST) + f_n(Month{:}\,AMO) + f_n(Month{:}\,EA) + f_n(Month{:}\,EAWR) + f_n(Month{:}\,SCA)\\ &+ f_n(NAO{:}\,SST) + f_n(NAO{:}\,AMO) + f_n(NAO{:}\,EA) + f_n(NAO{:}\,EAWR) + f_n(NAO{:}\,SCA)\\ &+ f_n(SST{:}\,AMO) + f_n(SST{:}\,EA) + f_n(SST{:}\,EAWR) + f_n(SST{:}\,SCA) + f_n(AMO{:}\,EA)\\ &+ f_n(AMO{:}\,EAWR) + f_n(AMO{:}\,SCA) + f_n(EA{:}\,EAWAR) + cs(time, df = 5) + \varepsilon_a\end{aligned}$$

$$\sigma_a = f_n(Month) + f_n(NAO) + f_n(SST) + f_n(AMO) + f_n(EA) + f_n(EAWR) + f_n(SCA)$$

Where:

- μ_a = the mean of the rainfall for site a
- σ_a = the variance (standard deviation squared) for site a
- $f_n(factor)$ = the function of the main effects for each factor
- $f_n(factor1{:}\,factor2)$ = the function of the interaction between factor 1 and factor 2
- $cs(time, df = 5)$ = the cubic spline time dependent term to account for residual structure change in the data
- ε_a = the amount of 'error' (random variability) at site a

2.3.4 Curve fitting

In the previous weather generator, a multi-metric curve fitting approach was applied to the monthly stochastic rainfall outputs. This identified observed anomalies with a deviation of the statistical behaviour of the historic climate from the predictions of the model. The rationale behind applying such a correction is that the observed deviations represent all the other potential climatic influences not represented in the model. This can, in part, be backed up by research suggesting the influence of blocking behaviours not closely linked to NAO or SST that impacts regions of the country, most notably in the South and East.

A curve-fitting adjustment essentially moves the stochastic predictions so that the observed record falls closer to the 'expected' distribution of generated data. However, the implicit assumption of such an approach is that the anomalies demonstrated by the more severe droughts (i.e. greater than a 1 in 20-year return period) are 'typical' for the climate in that region. Statistically speaking there is no reason why the events that occurred in the 20th Century should be statistically 'typical' and it could be argued that without sufficient evidence there is no basis for bias correction.

This highlights the trade-off between a fully theoretical model and a model that needs to be used for practical application. While it could be argued that there is limited evidence to justify correcting the outputs, from a very practical sense it is important that the generated outputs adequately represent and extend the range of droughts observed in the historical record for water resources modelling and testing purposes.

Additionally, while the model had been updated to include more teleconnection factors it is still primarily a pragmatic approach using the best tools and data available at this time. It is recognised that other influences will also be affecting weather across the country, and therefore, making small post-process adjustments to improve the model fit is a practical approach. It is worthwhile noting that the adjustments made are very small compared to the bias in climate modelling that underpins UKCP18 (Appendix C).

In line with this assessment, we have retained the bias correction step with some key improvements to the method. The new approach makes use of our previous understanding and experience from applying the method during WRMP19 while aiming to reduce the amount of adjustment needed/applied and to provide a

[13] A key element of the approach is to validate the generated data against observed rainfall from the full 20th Century record rather than just 1950 onwards.

stronger framework around which to select adjustments. The following two sub-sections compare the multi-metric curve fitting approach previously applied and the updated approach developed as part of this framework.

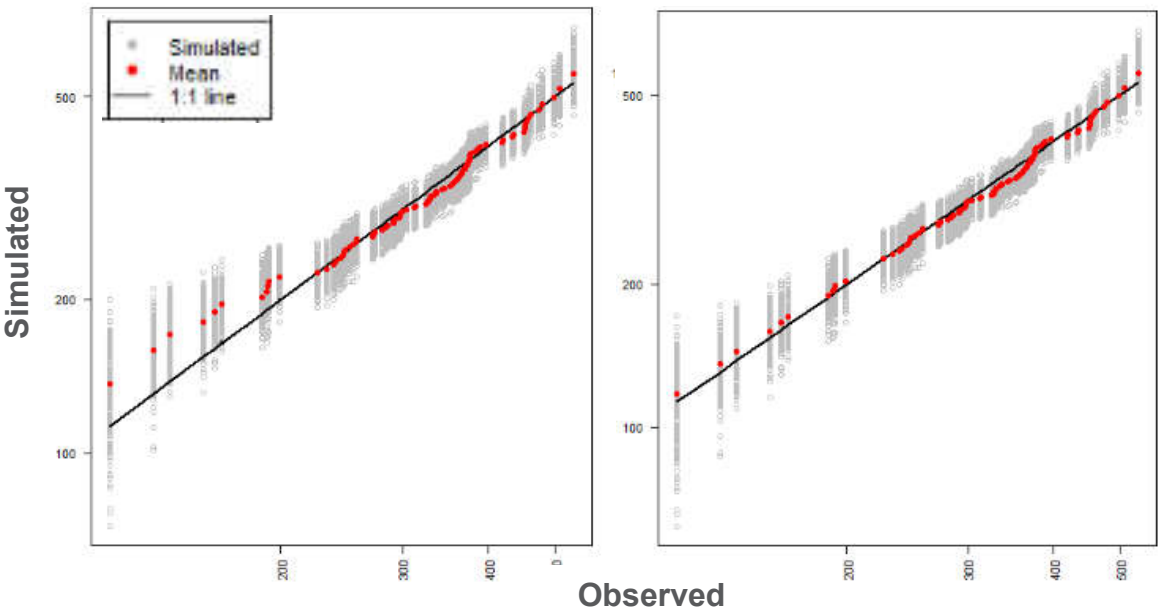
Previous approach

The previous multi-metric curve fitting approach identified persistent deviations between the stochastic and historic data using a series of rainfall total metrics. This approach relied on an element of 'skill' in its application so that each adjustment was carried out in the right order to prevent interference with the spatial and temporal coherence of the model.

The approach was primarily a manual process which involved analysing outputs at multiple metrics and scales after each adjustment. However, following extensive application and testing, two key guidelines around implementing this approach were identified:

- Carrying out adjustments based on a sub-regional average rather than each individual rainfall site helped to maintain spatial coherence across the region;
- Adjusting longer term metric totals before moving on to the shorter duration events reduces the likelihood of causing unacceptable deviation across other metrics.

Figure 2-6 illustrates the previous application of the curve fitting process for one metric across one sub-regional average.



The figure on the left shows the raw output from the monthly rainfall generator with the adjusted output on the right. The adjustment takes the bottom 15% of ranked data (in this case the lowest 13 points) and calculates the difference between the mean stochastic total (i.e. the red dot) and the historical value (i.e. the black line) to move the stochastic data 90% of the way towards the historical value.

Figure 2-6 - Example of multi-metric curve fitting adjustment

Updated approach

As part of this project a number of improvements have been made to the previous multi-metric curve fitting approach. The updated approach aims to:

- Minimise the amount of adjustment applied;
- Apply a structured probabilistic statement to define any adjustment carried out;
- Provide a framework for suggesting the metrics against which to adjust (as far as this is possible).

In the updated probabilistic curve fitting approach at least 1,000 replications are initially generated from the monthly generator. This means that when viewed in terms of the Q-Q plots there are enough simulated points at each ranked observed total (i.e. each vertical spread of data) to treat the stochastic simulations as a distribution and construct a probability statement around the chance that the observed value falls within the X% prediction interval specified by the stochastic data.

In this way an observed value is considered to deviate from the predicted stochastic data if it falls outside the X% prediction interval, i.e. the stochastic data suggests there is a less than (100-X)% chance of this being observed naturally. If this is the case, then the adjustment module calculates the adjustment needed to apply to the stochastic data so that the observed value falls just within the defined prediction interval.

Figure 2-7 illustrates the application of this approach for one metric using a 50% prediction interval (i.e. observed values outside the prediction interval occur with less than 50% chance).

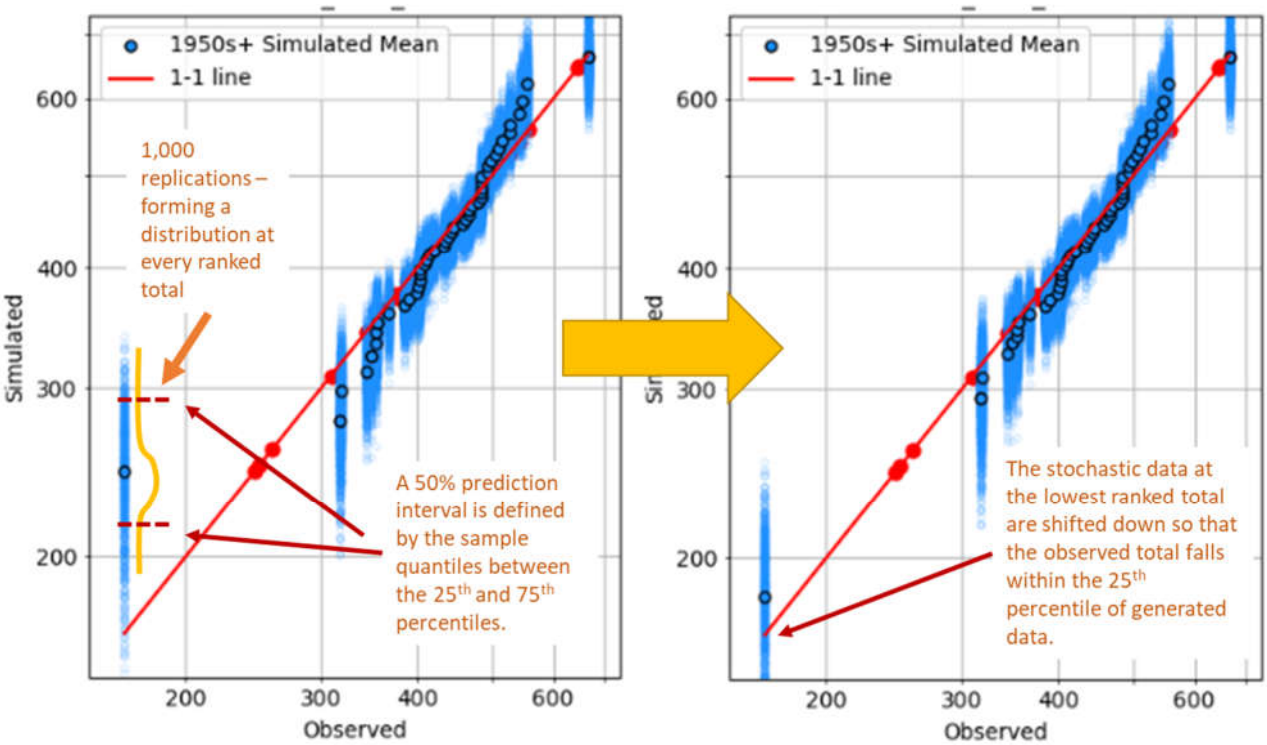


Figure 2-7 - Example of probabilistic curve fitting approach

Following initial testing, a 50% interval was felt to represent the fairest balance between minimising unnecessary adjustment while still achieving a noticeable improvement.

The key improvements to the previous approach are:

- Adjustments are applied on a ranked point by point basis rather than across the bottom X% of data;
- The stochastic simulations are adjusted so that the observed value meets the prediction interval rather than approaching the mean.

Framework for selecting adjustments

As part of this project we have developed a set of guidelines for, when necessary, selecting and applying the curve-fitting. These make use of several factors including our understanding and experience from applying the

previous multi-metric curve fitting, greater automation in the coded modules and crucially the proposed approach considers the simulated data within the context of the longer historical record[14].

The process defined below can be implemented with varying degrees of automation and control however it is important to note that even at the most automated a certain level of 'skill' and regional knowledge is still required to present appropriate periods and metrics. To remove all levels of automation the model could be run by completely specifying the metrics to adjust.

Step 1: Define a series of 'periods' to test

Periods define the broad durations within which to examine specific rainfall metric totals. Using our previous experience these are recommended to start with longer term durations and reduce in length.

Step 2: Define specific metrics within each period

Each defined period may contain more than one specific rainfall total metric against which to analyse any deviation. For example, a typical series of periods and metrics might include:

- **Longer than annual periods**, containing the 24-month rainfall total ending September and 18-month rainfall total ending September;
- **Annual periods**, containing 12 months rainfall total ending September (the hydrological year) and 12 months ending December (calendar year);
- **Winter – Summer periods**, containing 9 months rainfall total ending August and 8 month ending August
- **Summer periods,** containing rainfall total metrics covering April – August, March – September etc.
- **Winter periods,** containing rainfall total metrics covering November – February, October – March.

Step 3: Run automated bias correction process to identify metrics displaying significant deviation

Starting with the first period, each of the metrics defined within this period are analysed and, at most, one metric selected for curve fitting based on analysis of persistent deviation across all the sub-regions between the simulated and observed data for each of the metrics. If none of the defined metrics within a period are considered to display significant deviation, then this period is skipped, and no bias corrections carried out. The module identifies significant deviation between the simulated and observed data by comparing the equivalent percentile totals for each dataset and for each metric. This allows the simulated data at each metric to be considered within the context of the longer observed record (i.e. pre 1950).

Step 4: Apply probabilistic curve fitting

Probabilistic curve fitting is applied across the selected metric within the period to bring observed values within the 50% prediction interval of the simulated data.

Step 5: Analyse any remaining deviation in the results against the next defined 'period' and metrics

Repeat the process for shorter duration drought periods.

Worked example

After generating the raw stochastic monthly rainfall data for a region, we produce the Q-Q and percentile plots of the data across the range of rainfall total metrics.

Step 1 above, sets out how to define the series of 'periods' to analyse for deviation. We will take these as:

- Longer than annual
- Annual
- Winter – Summer
- Summer
- Winter

In order to define which metrics to place within each period (Step 2 above), we look at the output plots and select metrics where there appears to be significant deviation. For example, within the 'longer than annual' period we look at the 36, 30, 24 and 18-month rainfall totals ending September and December. Little deviation is observed at the 36 and 30-month durations (see Figure 2-8) and so we do not include these within the period. Similarly, while some deviation can be seen in the 24 months ending December metric this deviation in

[14] This is particularly relevant now that the model is generated using observed data from 1950 onwards rather than earlier in the 20th Century.

part covers the range of events in the historic record prior to 1950 and would be counterproductive to correct against (see Figure 2-9).

The 24-month ending September and 18 month ending September metrics potentially show some deviation and so are included within this period.

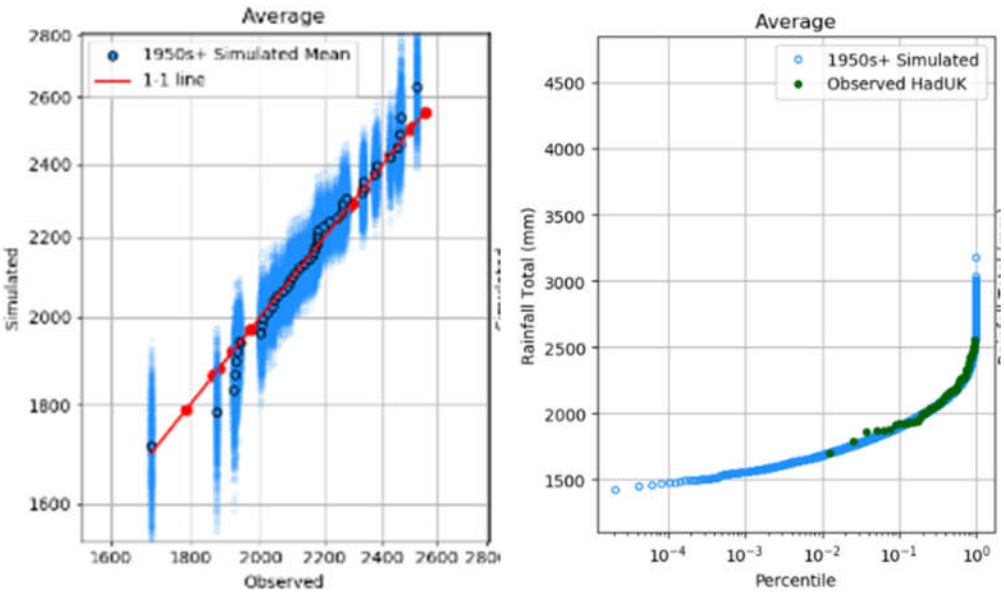


Figure 2-8 - Simulated vs observed data across 30 months ending September for Q-Q plot (left) and percentile plot (right). The bold red dots on the Q-Q plot show where observed data points prior to 1950.

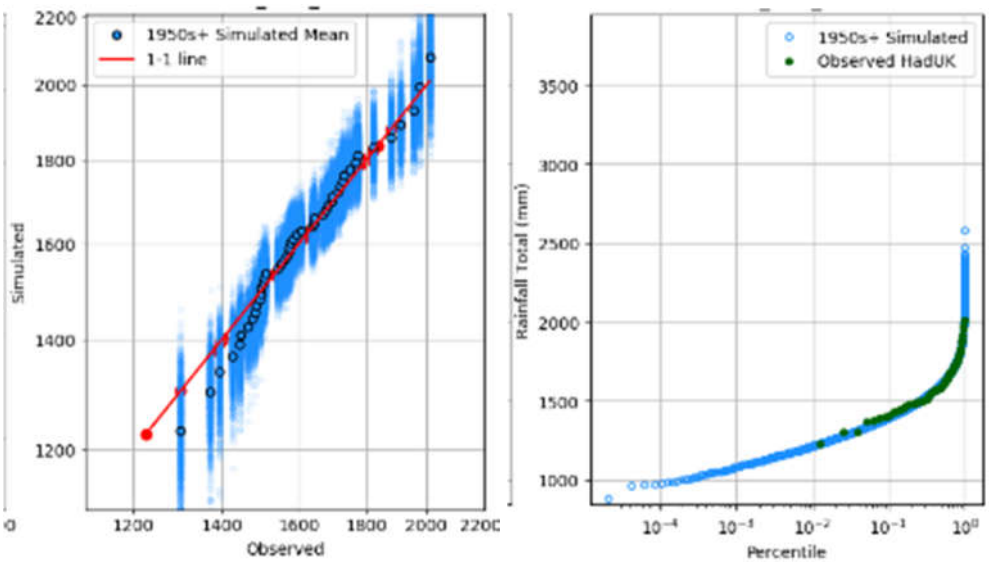


Figure 2-9 - Simulated vs observed data across 24 months ending December for Q-Q plot (left) and percentile plot (right). While the lowest ranked simulated data deviate from the observed the range covered by the simulated data can be taken to account for the lowest observed point in the record which is prior to 1950 (i.e. the bold red point). This can be seen in the percentile plot on the right where the stochastic and observed appear to show a good fit.

This process is continued across each of the periods to define the metrics to consider. It may be that only one potential metric within a period shows any deviation and, in this case, just one metric would be included. Or, alternatively, the period could be removed entirely from the bias correction process if no metrics are considered to show deviation.

Once steps 1 and 2 are completed the automated bias correction process can be run to numerically calculate the extent of any deviation at each of the lower percentiles and apply adjustments to selected metrics. This

provides two levels of check against the need for curve-fitting. For instance, in the example above, although the 24 months ending September and 18 months ending September are included within the 'longer than annual' period the automated curve-fitting module does not find significant deviation against the percentiles for these metrics and so this period is not adjusted.

2.3.5 Sampling

The probabilistic curve fitting approach outlined above requires at least 1,000 replications to be generated in order to produce adequate distributions at each ranked level. This is equivalent to approximately 48,000 stochastic years and although it would be possible to generate daily sequences for this full series this would significantly increase the memory and processing time required for the resampling stage. Additionally, many regional groups and companies will already be looking to sample from the stochastic datasets to reduce the burden on their water resources models.

A sampling sub-module has therefore been developed to randomly sample replications from the 1,000 samples to 400[15] which is equivalent to just under 20,000 years and is approximately equal to the length of datasets that most companies and regional groups have worked with for previous stochastic datasets. As each replication is equally as likely to have occurred as another a simple random sample is enough to ensure that the final stochastic dataset is representative of the original sample. Moreover, this can be checked by comparing the output plots before and after sampling to ensure that the sampling has not biased the results at any metric as shown in Figure 2-10.

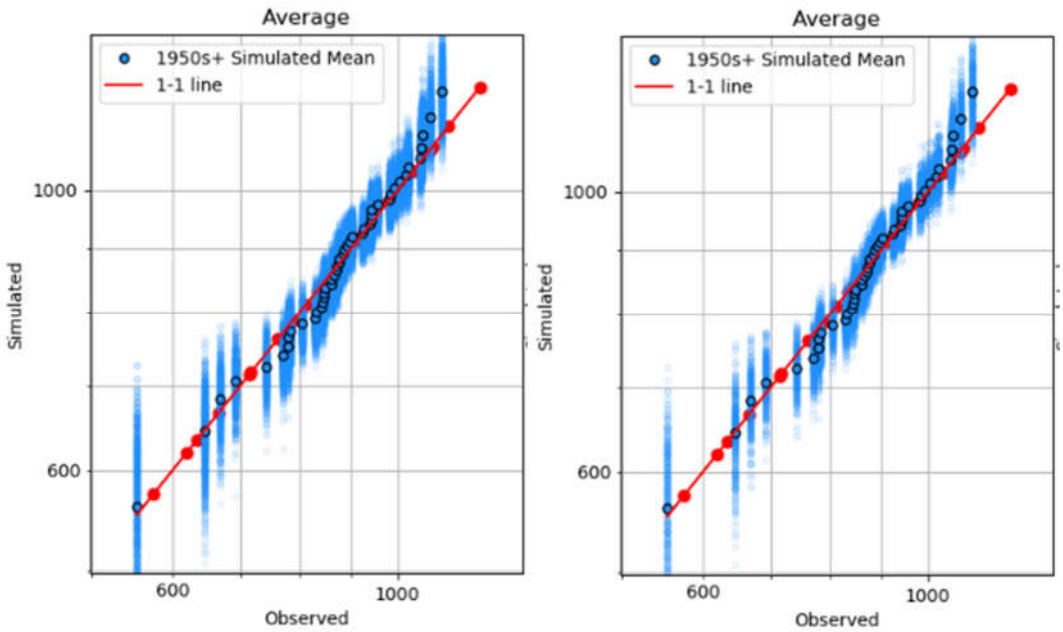


Figure 2-10 - Example Q-Q plots before sampling (left, 1000 runs) and after sampling (right, 400 runs). This confirms that the sampling process has not biased the stochastic distributions.

2.3.6 Generate daily sequences

The method to produce stochastic PET and daily rainfall sequences essentially follows the same approach as undertaken for the previous stochastic weather generator with a minor update in Figure 2-11, which describes the resampling approach. PET and daily rainfall sequences are generated from the observed record on a 'nearest neighbour' basis. This means that the regional average rainfall for each stochastic month is compared against the observed record for that month and matched to the closest historic month. PET is taken as absolute from the matched month while the daily rainfall sequences are scaled to total the stochastic month total (in effect, a multiplier to wet days rather than changing the number of wet days per month).

As shown in the flow chart a couple of additions have been made to this process. Firstly, summer PET is matched based on the 'nearest neighbour' summer rainfall total (April – August) rather than on a month by month basis. This was implemented because previous versions of the stochastic weather generator summer

[15] 400 replications are the default although this can be easily amended as preferred.

persistence effects around PET were not being adequately simulated when matched on a month by month basis.

Secondly, following feedback from the regional groups, it was identified that the previous matching process could often lead to repetitions of just one or two daily rainfalls, and subsequently repeated flow sequences in extreme events. This is because extreme stochastic months that are lower than the lowest observed month were always matched to the same month. To minimise the impact of this, a small update has been included to the process so that stochastic values that fall in the bottom 20th percentile of observed values are matched randomly to one of the closest four observed months rather than the absolute closest. We have analysed the impact of this update as part of one of the case studies examples.

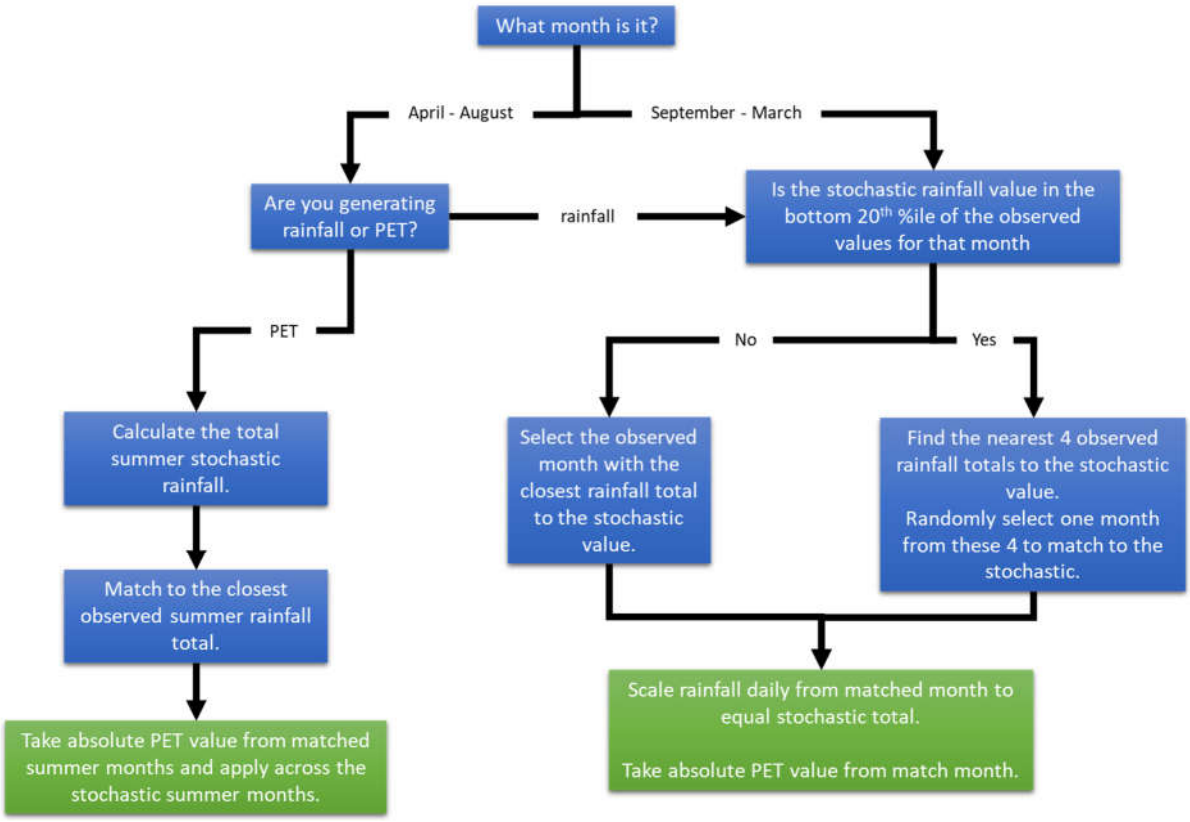


Figure 2-11 - Stochastic PET and daily rainfall resampling

2.4 Results from final delivery dataset for WRSE region

This section provides further information on results and how they can be used for water resources planning[16].

2.4.1 Analysis of regional drought

In the WRSE dataset there were 57 sites including the Severn Trent locations (43 sites of direct relevance to the South East),

For many water resources planning applications all 400 time series will be run through water resources models but for other applications a sub-set of stochastic runs may be selected. To aid this selection summary tables for all metrics were provided as well as an Excel template to illustrate analysis for calendar year droughts (Appendix B).

[16] The stochastic results for 57 sites across WRSE were provided as text files and supported by a handover note and a large number of ranked rainfall and percentile plots. Uploaded 15th May 2020.

Choice of metrics

The standard drought metrics are summarised below. These data were provided by site and by metric for the stochastics and for HadUK observed data for the 1950-1997 period and earlier 1902-1949 period to provide an independent check of the stochastic model fits.

Table 2-2 - Standard drought metrics (✓ - rainfall metrics provided)

Climate metrics		Hydrological metrics
Seasonal metrics	Annual and multi-year metrics	All timescales
Winter	Jan – Dec ✓	Q min
4 month Nov – Feb✓	*Oct – Sept (hydrological year)✓	Q min 7 day
Oct – March (winter half year)✓		Q mean (Oct-March)
Summer	Multi-year metrics	Q mean (June, July, Aug)
June – Aug✓	2 year calendar✓	Q mean (April-Sept)
April – Aug✓	3 year calendar✓	Q5
July – Sept✓	2 year hydrological✓	Q95
April – Sept (summer half year)✓	3 year hydrological✓	Q50
Winter to summer	18 months April – Sept ✓	
Jan – Aug✓		
Autumn	30 months April – Sept ✓	
Sept - Oct✓		

Low rainfall in sub-regions

The Drought Vulnerability Framework (DVF) is a form of sensitivity analysis that presents the rainfall deficits for a catchment or region over a range of durations and overlays the impacts in terms of low river flows or other water availability indicators. Figure 2-11 plots the results of the stochastic analysis in a similar way to facilitate comparisons with previous DVF work. This figure summarises rainfall deficits for 3 months to 36 months for five sub-regions in the South East of England.

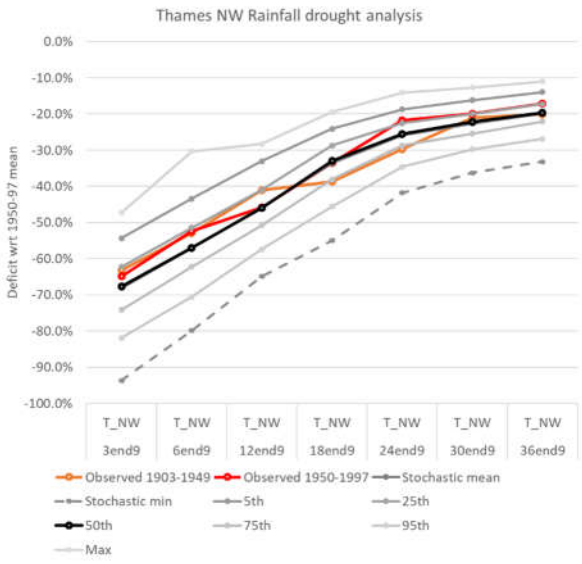
The black line plots the median of the stochastic data and the grey lines indicate the 5th to 95th percentile range of the stochastic data and the maximum deficit (dotted). The observed data 1950-1997 that were used for calibration are shown in red and an independent data set of the same length 1902-1947 provides a check and useful comparison. This earlier period includes more extreme droughts in the southern region over short and longer durations.

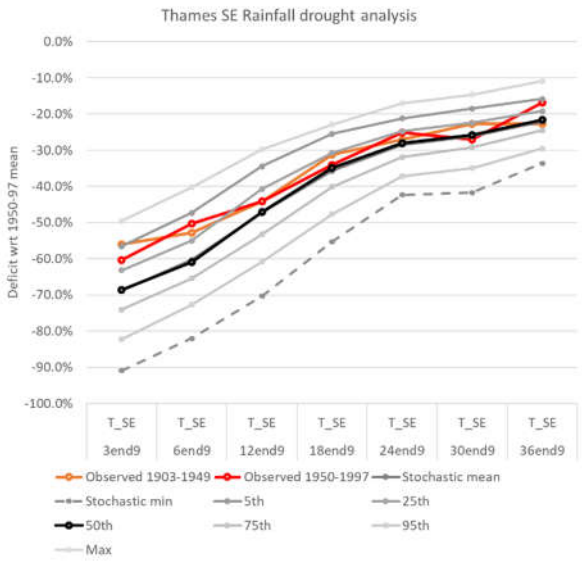
The observed data generally sit between the 25th and 75th percentiles of the stochastic data. Overall the stochastic model is providing a good fit, which improves for longer duration drought.

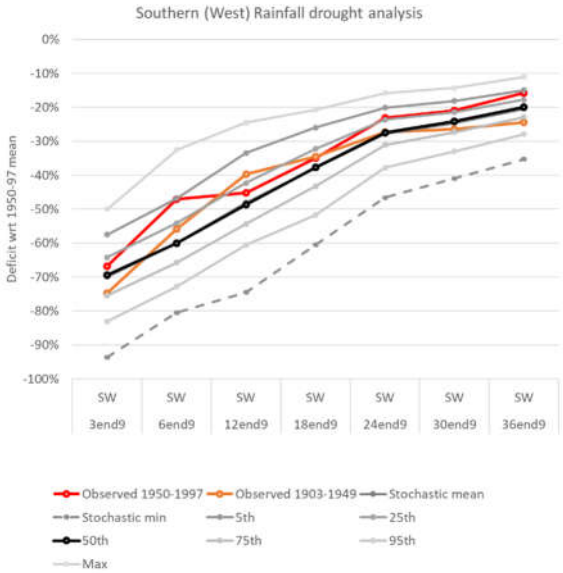
Correlation between regions

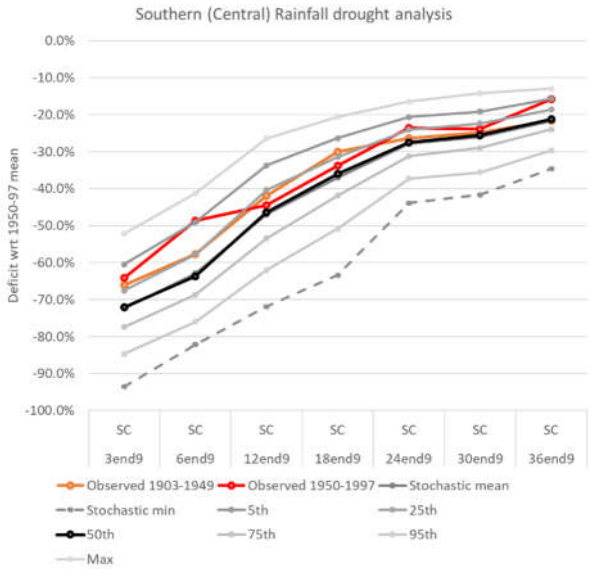
Figure 2-12 illustrates the correlation in low rainfall between sub-regions. While there is a positive correlation between sub-regions, it declines with distance. The black lines indicate the minimum sub-regional rainfalls for hydrological years. The plots highlight the much wider spread of the stochastic minima and the possibility of drier or wetter periods in both regions and the somewhat lower chance of drier periods in one region and wetter periods in the second region, i.e. more local severe drought conditions.

Along with an assessment of drought severity, the correlation between regions is an important consideration if the data are sampled to create drought scenarios. For example, it may be useful to stress test the regional water resources system against both severe regional droughts and more local droughts with extremely low rainfall in the east or west of the region. Understanding correlations is essential for the assessment of national transfers.









Notes:

Each region is represented by up to 10 rainfall locations. This model used 57 sites including large areas of the River Severn, which are not summarised here. This analysis is for the worst drought in each run only.

The red line is observed data from 1950-1997 from HadUK 1km; the orange line is 1903-1947 and provides an independent check on the model fit. The black line shows the median of the stochastic data Grey lines are percentiles and min/max of 400 stochastic runs. Deficits are calculated against 1950-97 mean rainfall for each metric.

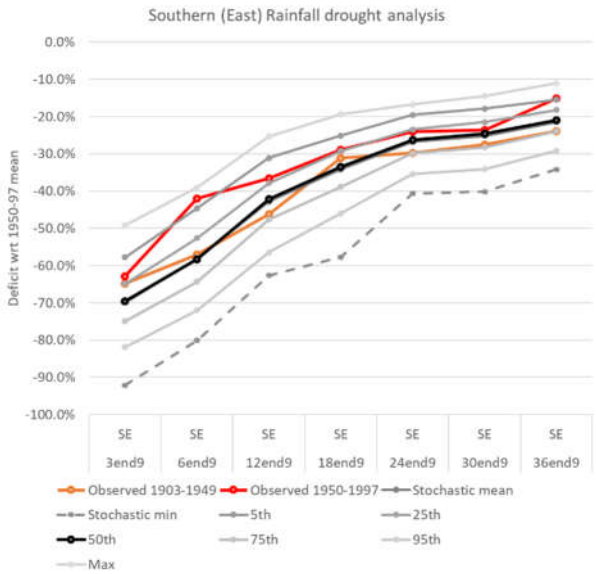
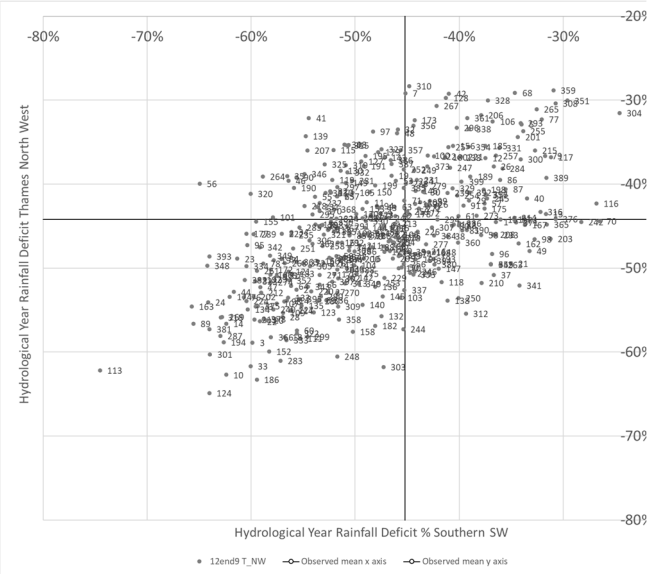
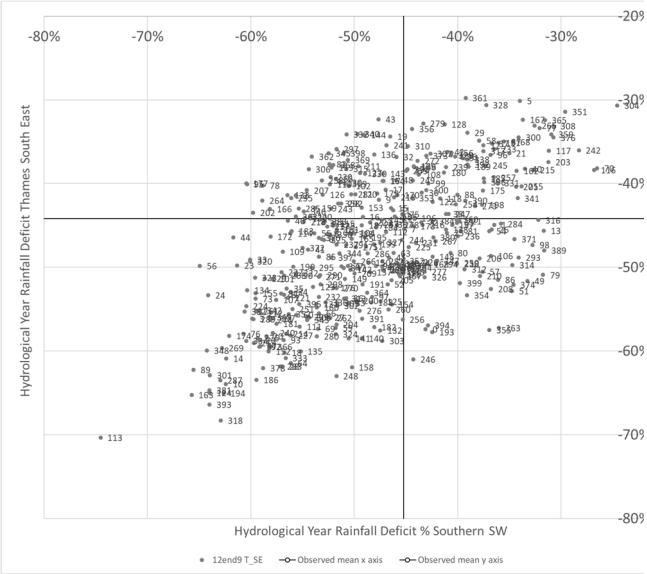


Figure 2-12 - The WRSE Stochastic Rainfall Data Summary: Rainfall droughts of between 3 and 36 months duration

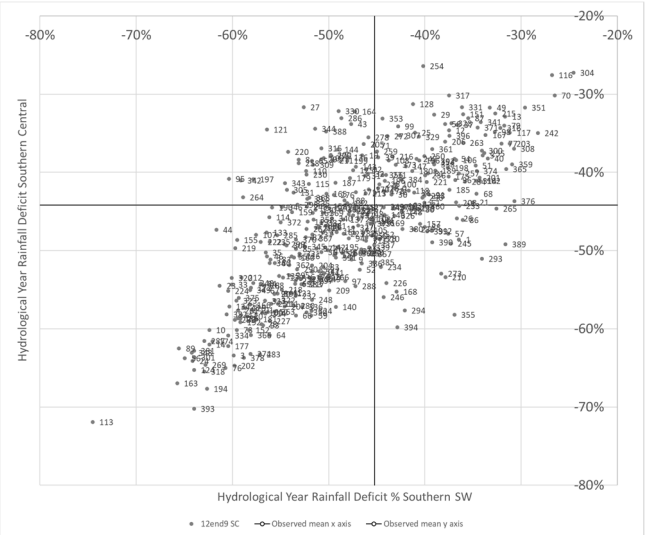
Southern South West versus Thames NW



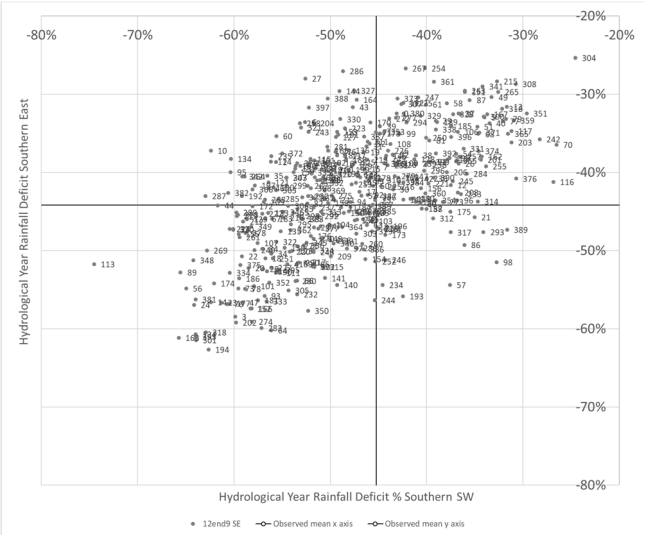
Southern South West versus Thames South East



West versus Central



West vs East



Correlation is strong between rainfall metrics of the same duration and neighbouring regions, but decays with distance

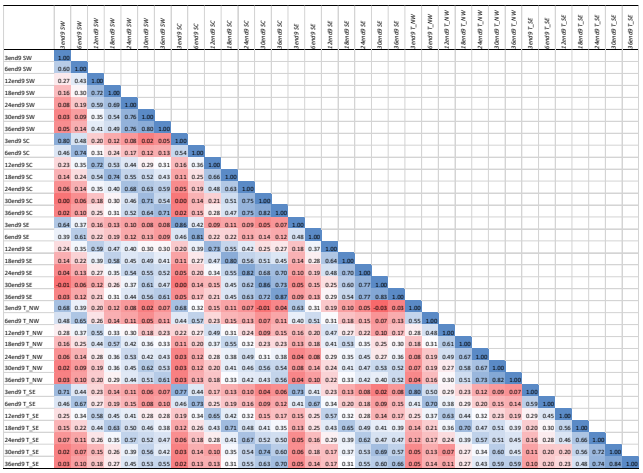


Figure 2-13 Correlations of minima between WRSE bias- regions

2.4.2 Analysis of single sites

The analysis of single sites provides a check on the model's performance and is useful to compare periods of low rainfall in the stochastics with the observed data, including an independent observed data set prior to 1950.

Time series

A standard Excel sheet was provided to assist in the analysis of single sites. Time series plots (such as Figure 2-14) show the observed data (red) compared to the median (black) and the 5th to 95th percentiles (grey) of the stochastic data. Figure 2-14 shows how the stochastics follow the observed pattern fitting closely where North Atlantic Oscillation (NAO) index and other teleconnections explain the rainfall pattern but deviate in some years. Overall the observed 1950-1997 series fits well with the stochastics and always within the min and max range. However, it's clear that the stochastics include many years with lower rainfall than observed during the 1950-1997 period.

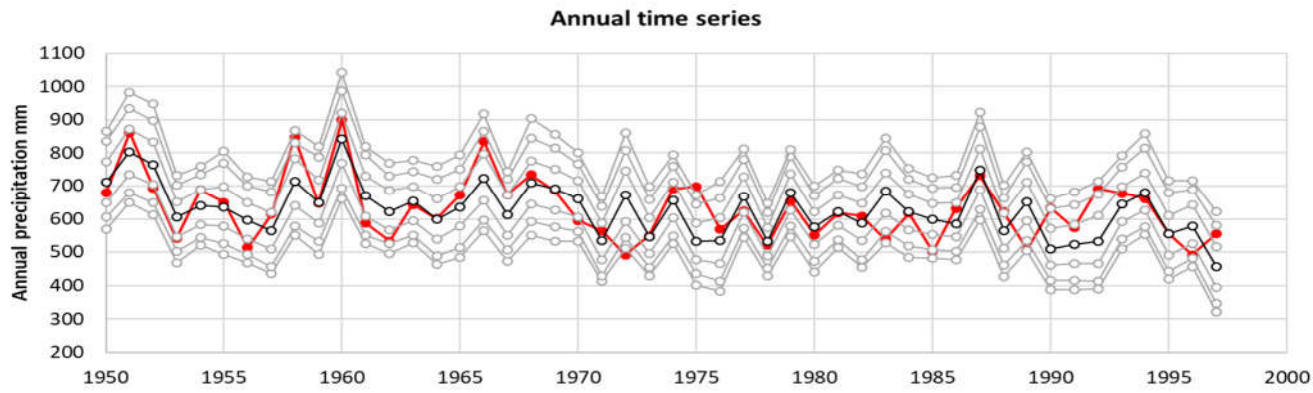


Figure 2-14 Annual rainfall time series for Canterbury showing observed HadUK data (red) and 400 stochastic series as percentiles

The series can be presented as a Drought Deficit by subtracting the mean and dividing by the standard deviation, then multiplying by minus one, so that droughts are positive in the range 1 to 3 as shown in Figure 2-15**.** Fairly normal conditions cover the range +1 to -1 and wetter conditions are less than -1.This particular series suggests a small increase in the magnitude of rainfall drought after 1970 but there were lower rainfall periods in the first half of the 21st century (see extreme value analysis in next section).

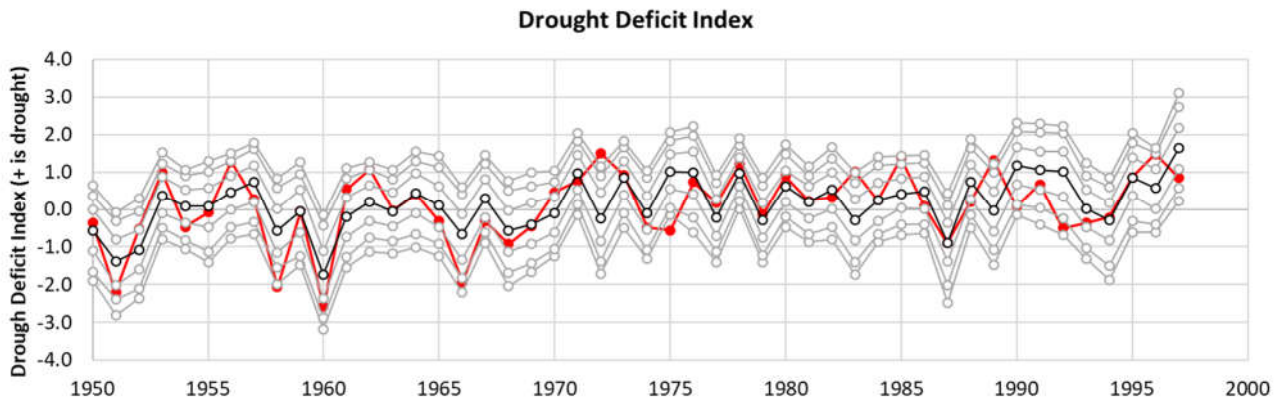


Figure 2-15 Annual Drought Deficit time series for Canterbury showing observed HadUK data (red) and 400 stochastic series as percentiles

2.4.3. Extreme Value Analysis

As part of the framework development we have undertaken a study looking at extreme value analysis of low rainfalls (see Figure 2-16). **This indicated that a Weibull distribution provides the best fit and most practical distribution for periods of low rainfall.** There are still many different ways that EVA can be

approached using the stochastic data; this section presents two simple approaches that can be implemented in Excel without the need for specialist statistical software.

Case study: WRSE (Western Rother, Hardham)

We used the Western Rother catchment, at Hardham to consider the impact of different approaches to Extreme Value Analysis (EVA) for calculating the return period (RT) of droughts. We explored the use of Weibull and other distributions instead of ranking, use of outputs as replicates rather than a single long time series and the use of more complex Bayesian methods.

We analysed the EVA method for calculating Return Periods (RP) from a Peaks Over Threshold (POT) or Summer Average rainfall deficit index (RDI) series. The EVA methods explored were:

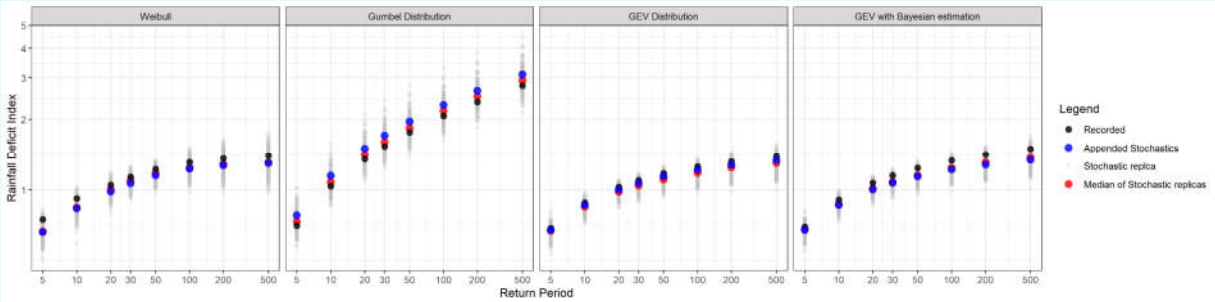
- Weibull method
- Fitting a Gumbell distribution
- Fitting a Generalized Extreme Value (GEV) distribution
- Fitting a GEV distribution with Bayesian estimation with prior assumptions taken from a similar Met Office analysis for Water Resources East

As shown in the plots below, the POT approach produces anomalous results (when compared to the baseline) for the appended stochastics data treatment, when the data are treated as one long time series. In the POT series stochastic case, lower return periods are notably over-estimated compared to the baseline and POT parallel stochastic case. This is to be expected, as the effect of appending stochastic timeseries shifts the frequency distribution such that frequent events (such as 1 in 5 year) become more frequent compared to low frequency events (such as 1 in 500 year).

While the appended stochastics generally over predict the RP compared to baseline, the series stochastics centre around the baseline more closely, with the median of these being the closest to the baseline RPs.

We found that the GEV method provides the most conservative estimation of RP, however, fitting can be problematic simply due to the finer-scale variability in stochastic frequency distributions. To avoid over complication, the Weibull approach is recommended as it is easy to understand, calculate and is the most robust (i.e. plotting positions are easily calculated and its less sensitive to assumptions around distribution fitting).

EVA comparison for Summer Average extreme event definition:



EVA comparison for POT extreme event definition:

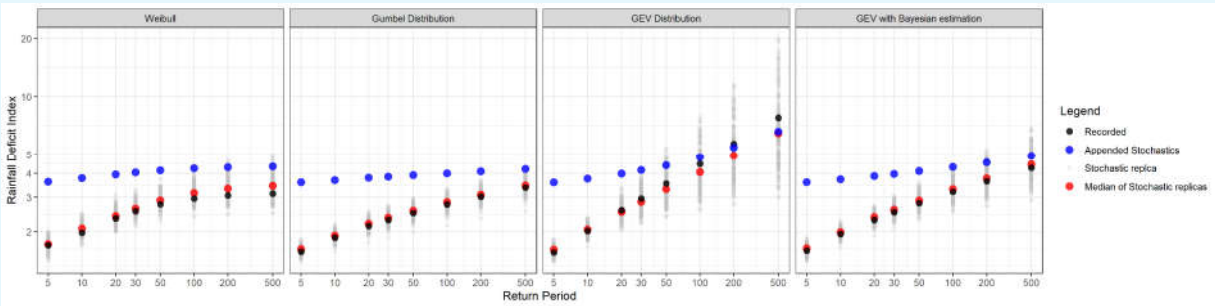


Figure 2-16 - Exploration of Extreme Value Analysis Methods using WRSE, Western Rother case study location

EVA of full stochastic time series

A key aspect of the stochastics is how to interpret the probability of periods of low rainfall, in particular whether to treat the stochastics as 400 runs or 'replicates' of 48 years or as a larger data set equivalent to 19,200 years. While the former approach is most appropriate because the model is driven by specific climate drivers for that period, at some stage the data need to be ranked and sorted to support the selection of particular runs or replicates. This is particularly the case where it is not possible to run 400 models (e.g. detailed groundwater modelling or rapid assessment in a low vulnerability zone).

The simplest estimate of average frequency is the rank order divided by the sample size and annual minima are typically plotted using rank divided by n + 1, which is the Weibull plotting position. In spreadsheets that accompany the results files, indicators of the rank and frequency of the minimum rainfall in each run are summarised so that the user can estimate drought magnitude and frequency across the full data set.

In addition to using a simple frequency estimate, a Weibull distribution can be fitted to the observed or any stochastic data using Maximum Likelihood Estimation; in this case the Excel Data Solver tool was used to optimise the fit of the parameters 'alpha' and 'beta' for the 1950-1997 and 1902-1949 periods. For simplicity, the parameters for 400 stochastic series can be estimated assuming a constant relationship between the mean and beta derived in the spreadsheet. Low rainfalls for any return period can then be estimated from:

$$Q = \beta\left(-\ln\left(1-\frac{1}{R}\right)^{\frac{1}{\alpha}}\right)$$

Q – Quantile (mm)
R – Return Period in Years
β – Beta parameter of Weibull distribution
α – Alpha parameter of Weibull distribution

Developing a satisfactory fit for an extreme value distribution is complex, particularly for events that last more than one year. In the project team's experience, the simple approach of ranking the stochastic data and estimating the annual probability and return period produces plausible results for low rainfall that tend to decline to an asymptote, whereas a standard EVA on a short record of 48 years can produce rather unrealistic results and be very sensitive to the choice of fitting method and the influence of outliers.

An important aspect of the analysis is that the same approach is applied to all data, so the relative magnitude is calculated in the same way. We also found that a lognormal distribution can provide an adequate fit beyond 1 in 20 years but can't be fitted easily to the full data set. More advanced statistical software, such as In-Extremes in R could be used for a more detailed assessment as shown in the above case study.

In

Figure 2-17, the rainfall droughts are shown following these approaches, including plotting the most extreme stochastic droughts as a range of values around a 1 in 48 year drought, as ranked and plotted according to the full data set of 19200 years. This highlights the large uncertainties around the estimation of 1 in 100, 200 and 500-year droughts and the sensitivity of the time period selected (for example 1902-1949 plots vary differently to 1950-1997). It also shows that the stochastic data minima from 400 series cover a range of probabilities (according to the fitted Weibull distributions) from annual probabilities of 10% to less than 0.01% providing a large library of drought events with different time series.

A Rapid Assessment Method for analysis of rainfall droughts based on "worst droughts" in each stochastic run

By introducing some simplifying assumptions, an understanding of drought magnitude and risk can be established through analysis of the "worst droughts" in each stochastic run, reducing the analysis load 50-fold.

The Rapid Assessment Method is based on the minimum rainfall for specific metrics in each stochastic run. If it is assumed that these minima span a range from say 1 in 25 years to 1 in 19200 years, with the same difference in annual probability between each run minima they can be converted from Type A to Type B without analysing all years, just focusing on the minimum of each 48 year period.

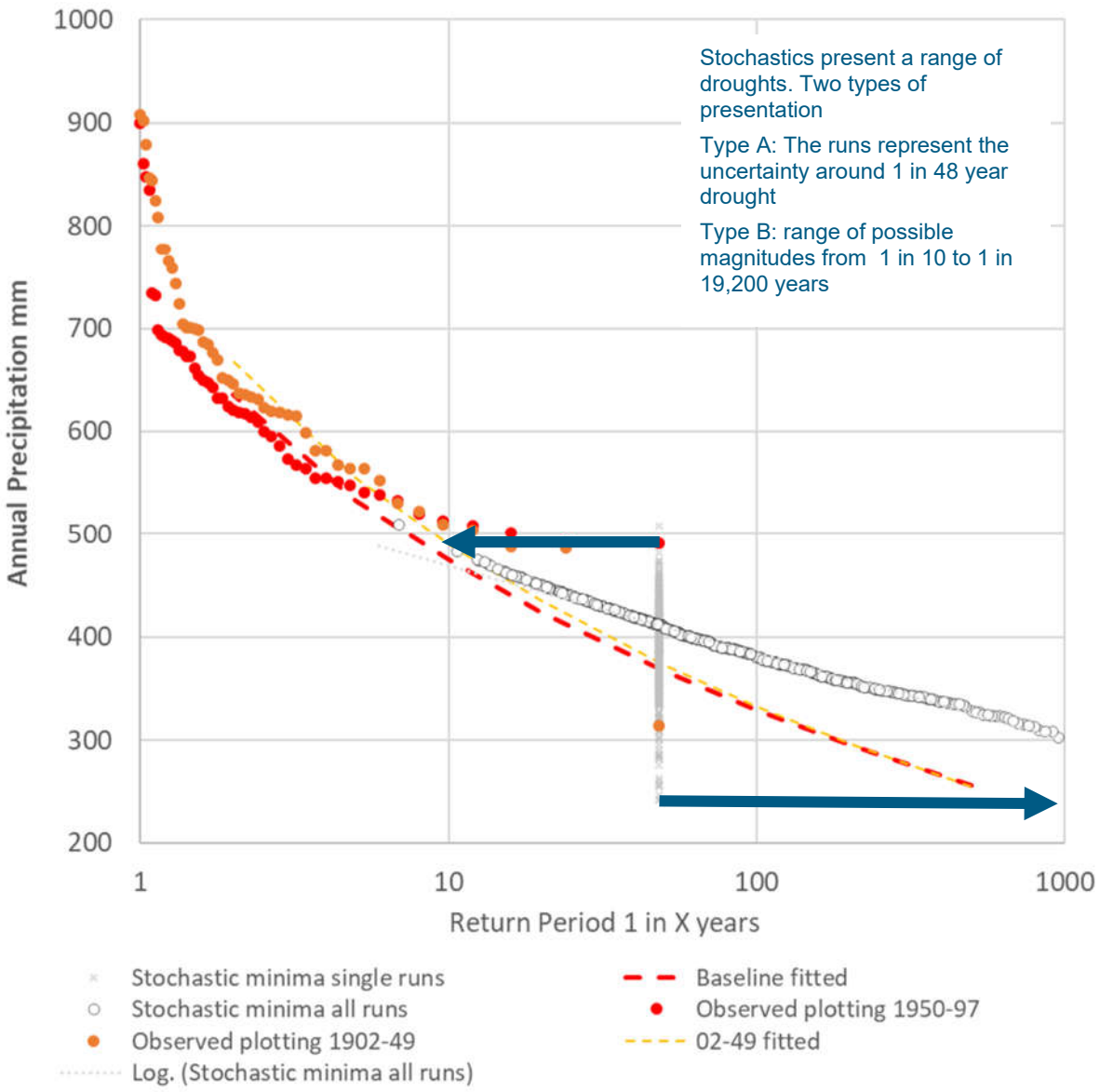
If RP bar is the estimated return period, R is the rank of run minima from 400 runs and 'c' is the difference in annual probability between each data point.

$$\overline{RP} = \frac{1}{\left(\frac{1}{19200}\right) + c.(R-1)}$$

The coefficient c is calculated by assuming the return period of the wettest stochastic run minimum rainfall. If we assume it is 1 in 25 years[17]:

$$c = \frac{\frac{1}{25} - \frac{1}{19200}}{400}$$

This gives the following relationship between rank of run minima and approximate return period and implies a range of ranks that are suitable for assessment of 500 year and other droughts (see Figure 2-18 and Figure 2-19). The median or 200th rank stochastic run minima will be interpreted as a 1:50-year event in this case. With these assumptions the 1:500-year drought will sit close to the 5th percentile of the Drought Vulnerability Framework (DVF) plots.



[17] The starting return period could be 1 in 10, or estimated more precisely, but 25 years assumption provides a neat solution and useful heuristic as the 200th rank run will equal a 50 year event.

Figure 2-17 - Extreme value analysis of low annual rainfall for Canterbury showing the observed data used for training the model (red), an independent observed data set (orange), Weibull distributions (dashed), stochastic data plotted for individual runs (grey crosses) and the rank 1 droughts from the full stochastic data set (grey circles), grey dashed line for lognormal fit to the full stochastic rank 1 series

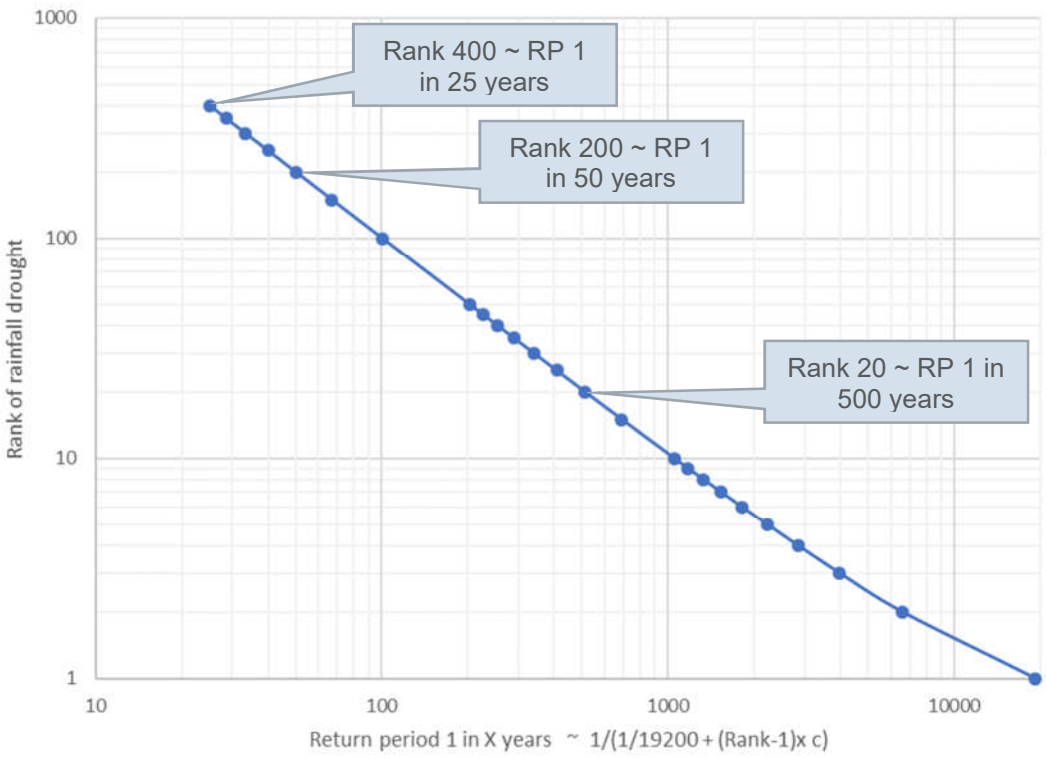
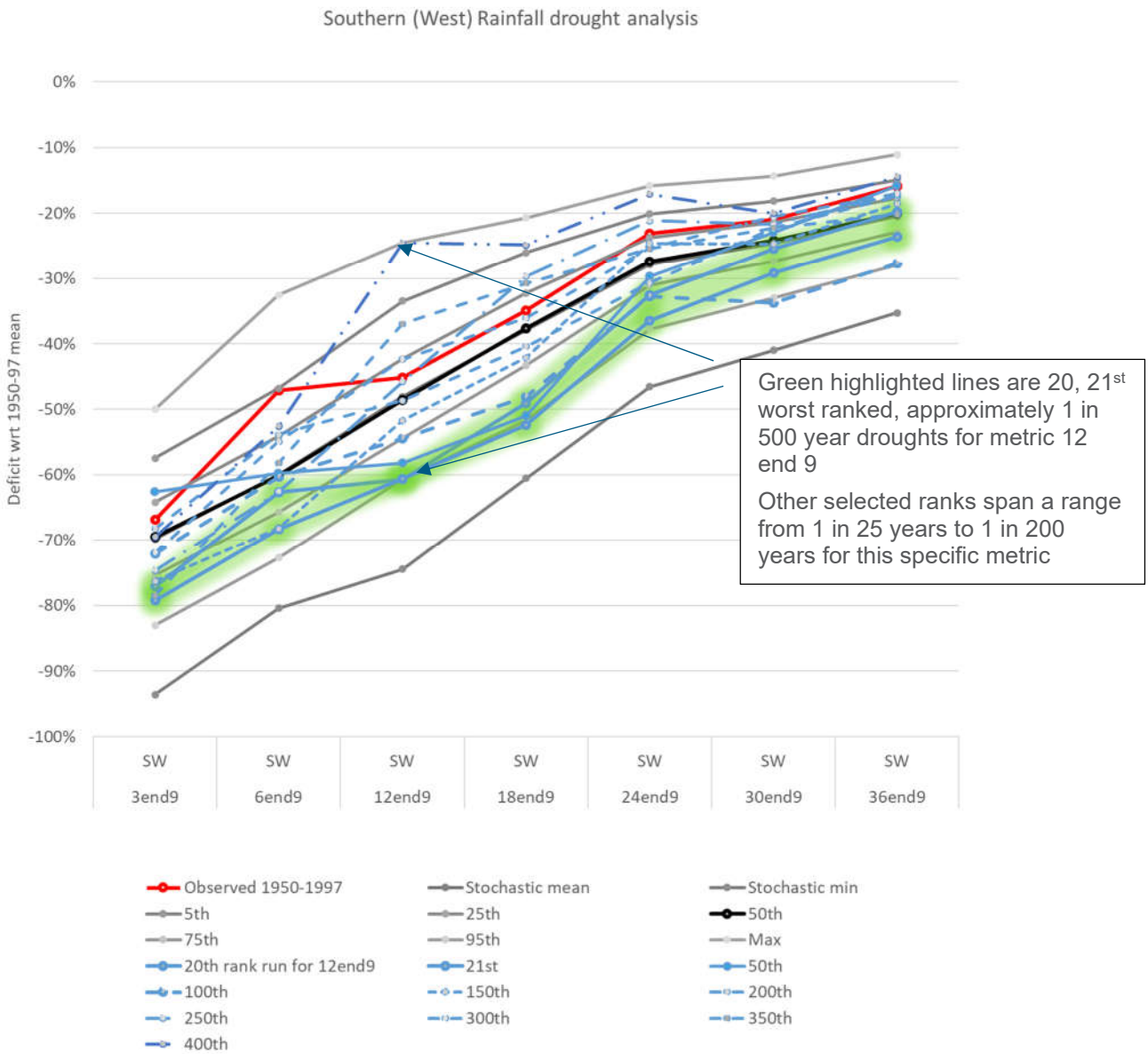


Figure 2-18 Estimated relationship between rank of run minima and average frequency of events over a longer time period

This approach can be used to select droughts using the most important rainfall metric, in cases where a smaller sample of stochastic data are required. Figure 2-18 provides an example of the west of southern England (centred on Hampshire) with a range of stochastic time series selected based on the probability of low rainfall in hydrological years ending September.



Notes: Grey lines are percentiles of 400 stochastic runs and the blue lines are ranks according to the hydrological year rainfall minima.

Figure 2-19 - Example for Hampshire (Metric – Hydrological Year rainfall 12 end 9)

If all 400 stochastic time series are input into hydrological models, a similar analysis is useful to understand the severity of rainfall droughts and how these may impact on river flows and groundwater availability.

2.4.4. Case studies of stochastic data applied to hydrological modelling

Several case studies were completed to test the workflow of hydrological modelling and different aspects of the development of the stochastics tools. The case studies are summarised in Appendix D.

The changes from the WRMP19 rainfall generator to the new rainfall generator was tested on 5 case studies. Figure 2-20 shows some results from the Ouse case study completed by WRE, summarising the impacts on median, 70th percentile and 95th percentile flow. The new stochastics were calibrated on 1950-97 and therefore the resulting flows are expected to be centred on the historic flows for this period, whereas the previous model used a longer time period for calibration from around 1918-1990. In this case study the new stochastic data

produced a wider range of possible flow conditions despite being fitted on a shorter period. It indicated marginally lower Q95 flows than the 1950-1997 period and the distribution sits between the different historical periods. This shows that the model provides a good coverage of a range of historical conditions as well as the possibility of wetter and much drier conditions than have been observed in the 1918-2015 period.

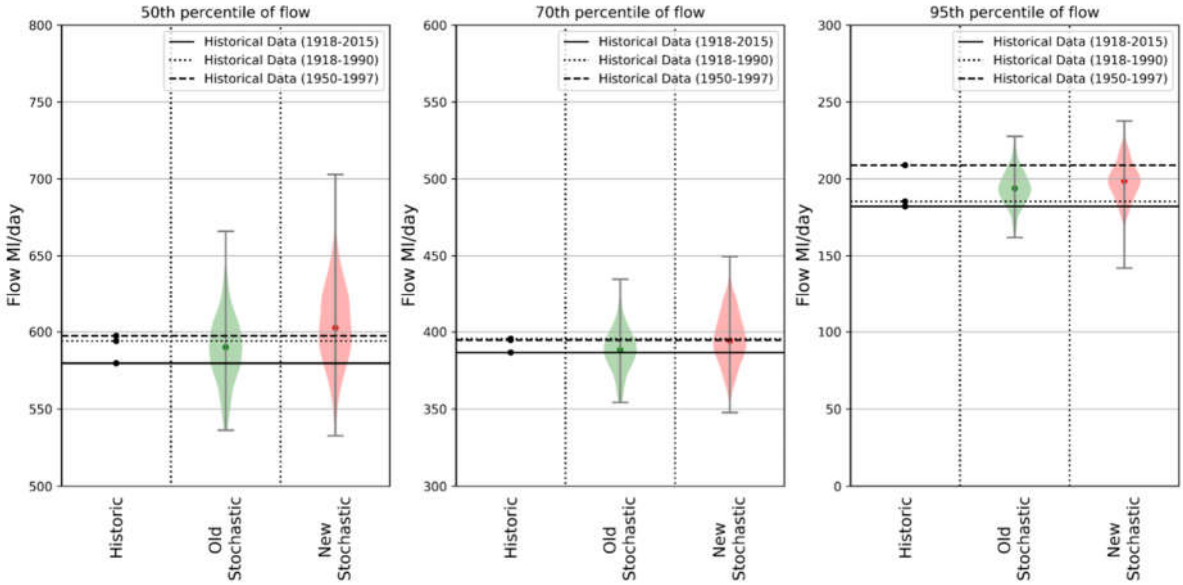


Figure 2-20 - Flow statistics for stochastic series compared against historical data (provided by the WRE team)

Similar results were found for Hardham with the median results from the new stochastic model providing a good fit to Q5 and Q95 flows, with a marginally higher flow at Q50 (Appendix D)

3. Climate change data sets

This section evaluates the strengths and weaknesses of UKCP18 and other climate data sets for regional water resources planning. The climate change outputs of this study were presented in March 2020 and this section provide a summary of the outputs with the remainder of the project's interim report included in Appendix C.

The Water UK Long Term Water Resources Planning Framework[18] (LTWRP) provided the first national assessment that included the use of stochastic rainfall generators and future climate scenarios to assess future drought risk. Many water companies made use of stochastic models in WRMP19 as well as the UK Climate Projections 2009 (UKCP09).

This project was undertaken in advance of the Environment Agency Water Resources Management Planning guidelines for drought and climate change risk assessment. However, it adopted some basic principles that should apply, based on the LTWRP and the water resources and climate risk assessment literature:

- Planning for the longer term
  - National and regional water resources infrastructures are significant long-term investments that should consider drought risks under the current climate as well as climate and socio-economic scenarios to the end of the century.
- Adaptive decision making
  - National and regional drought scenarios should consider a wide range of plausible drought conditions, including droughts of different magnitude, severity, duration and spatial extent.
  - Future climate scenarios should cover a range of possible future conditions to support decision making; planning for a single or narrow range of scenarios increases the chance of maladaptation (building too much, too soon or too little too late.

[18] https://www.water.org.uk/publication/water-resources-long-term-planning/

- Understanding risks and resilience
  - Future climate scenarios should include low probability but high consequence models to demonstrate their climate resilience and ability to maintain supplies during severe national/regional future drought scenarios.
- Line of sight between regional and company plans
  - Regional plans should inform company Water Resources Management Plans (WRMPs) and therefore provide higher level/broader scale drought/climate scenarios that can be investigated in more detail or at least be consistent with those used for WRMPs.

The project considered UKCP18 Global Climate Model (GCM), UKCP18 probabilistic, UKCP18 Regional Climate Model (RCM) and MaRIUS climate model data in terms of their technical quality, usability and above principles. Regional planning has specific requirements, such as the development of plausible regional and national drought scenarios that can be used to test proposed regional transfers and other significant national and regional supply/demand measures. In the context of climate change, these scenarios need to be 'spatially coherent' or in other words provide a credible representation of the spatial patterns of drought both in the past and under future climate change scenarios.

The advantages, disadvantages and potential use of each data set is summarised in Table 3-1 and Appendix B provides a detailed Strengths-Weaknesses-Opportunities-Threats (SWOT) assessment of each data source following a review of the data sets, particularly testing the RCM outputs against observed data sets.

The work undertaken in this project has shown that:

- The UKCP probabilistic projections headline findings are similar to UKCP09. The range of possible outcomes in UKCP18 RCP8.5 probabilistic data cover almost all of the other scenarios and A1B Medium Emissions scenario can be used for direct comparison with the UKCP09 Medium Emissions.
- The UKCP GCMs include both Met Office Hadley Centre (MOHC) and a filtered set of CMIP5 models for RCP8.5. The former models are hotter than CMIP5, which has implications for water resources planning; this issue has knock-on impacts to the RCMs that are driven only by the MOHC models.
- The UKCP RCM raw data provide a poor fit to monthly precipitation at the UKCP river basin scale and require correction for biases at the daily, monthly and annual time scales.

Different bias correction methods were reviewed and tested. An implementation of the Quantile Mapping method Equidistant CDF (EDCDF) mapping was the most promising approach because it can correct daily, monthly and seasonal bias in precipitation (Li, Sheffield and Wood, 2011). We have shown that this corrects for the bias in the observed period and illustrated the impact of this method at the regional scale.

Table 3-1 - Climate change data sets for regional planning (RAG credibility score)

Data set	Advantages	Disadvantages	Potential use for regional planning
UKCP18 Probabilistic Projections	Flexible User Interface (UI) and ease of use. Covers a large range of futures outcomes based on RCPs and the A1B(Medium) emissions scenario. Scenarios available for the end of 21st century and at many spatial scales.	3000 scenarios per time/period and RCP so sub-sampling is needed for most users. Lack of spatial coherence between catchments.	Supply forecasts or scenarios ~ climate change perturbation using RCP8.5 at the UKCP regional river basin or national scales. (A1B can be used to provide an audit trail to previous assessments based on UCKP09 Medium Emissions) Headroom assessment.
UKCP18 Regional Climate Models (raw data)	Flexible UI and ease of use. Spatially coherent change factors.	Only available for RCP8.5. Poor fit to observed precipitation in the baseline period (1981-2000). High rates of warming compared to CMIP5 models with implications for PET (particularly if derived using temperature based formulae).	None (poor fit to observed precipitation limits their credibility).
UKCP18 RCM (bias-corrected)	Bias correction deals with poor daily, seasonal and annual fit for precipitation. Provides transient time series as required by	Bias correction model introduces specific assumptions/caveats. Potential loss of spatial coherence. Only available for RCP8.5.	Stress testing of regional water resources plans.

Data set	Advantages	Disadvantages	Potential use for regional planning
	some decision-making methods. *To be made available for regional planning basins as part of this project.*	High rates of warming compared to CMIP5 models with implications for PET.	Relying on RCMs alone will not cover a sufficient range of possible outcomes.
UKCP18 GCM	Flexible UI and ease of use. Includes a filtered set of CMIP5 models. Will include information on weather types (yet to be released).	Coarser data set with lower confidence in precipitation modelling. Only available for RCP8.5.	Supply forecasts or scenarios ~ climate change perturbation using simplified scenarios (England and Wales or regional scale) Weather generator ~ use of weather types could improve the weather generator
MARIUS data set	Includes 100 time series representing the near term and longer term. Includes bias corrected precipitation, using a simple method. Includes two versions of PET for hydrological modelling.	Difficult to use data set (e.g. rotated grid and awkward file structure). Too warm and dry in the summer season. Only available for RCP8.5.	Unclear at this stage, expensive time investment required to roll out and known biases.

3.1 Project outputs

The outputs provided by the project are as follows:

- Twelve sets of RCM bias-corrected precipitation and PET climate change factors[19] for scenario RCP8.5 and the 2070s period for every river basin required for regional planning
- RCM Bias-corrected precipitation and temperature time series for scenario RCP8.5 and the 2070s for each basin
- UKCP18 probabilistic data for RCP8.5 and A1B and 'raw' Global Climate Model data for RCP8.5 for England and Wales to provide a broader context for the RCM based data above.

An example of the bias corrected average temperature data for the Anglian Region are shown in Figure 3-1.

Changes in future seasonal rainfall and average annual temperature for England and Wales are shown in Figure 3-2. The Met Office global models are shown as red squares and the RCMs as red diamonds; the CMIP5 models are shown as blue squares; the probabilistic data for RCP8.5; the same data are shown for scenario A1B, which is equivalent to the previous Medium emissions scenario.

It is anticipated that users will apply RCM RCP8.5 change factors to the stochastic data to assess the potential impacts of climate change. As outline in the draft WRMP guidance this will be a supplementary assessment, which will be combined with other evidence for a "Tier 2" assessment. For the most detailed "Tier 3" assessment, users may wish to add further scenarios to sample a broader range of possible climate change futures, which could be based on the Global CMIP5 models or a sub-sample of the UKCP18 probabilistic data.

Several case studies were completed on the impacts of stochastic data and climate change scenarios on river flows. These studies confirmed that the RCM data for RCP8.5 is significantly different to the other data sets and, as expected, produces larger reductions in river flow (Section 3.2; Appendix D).

[19] Change factors were based on the Oudin temperature based PET formula

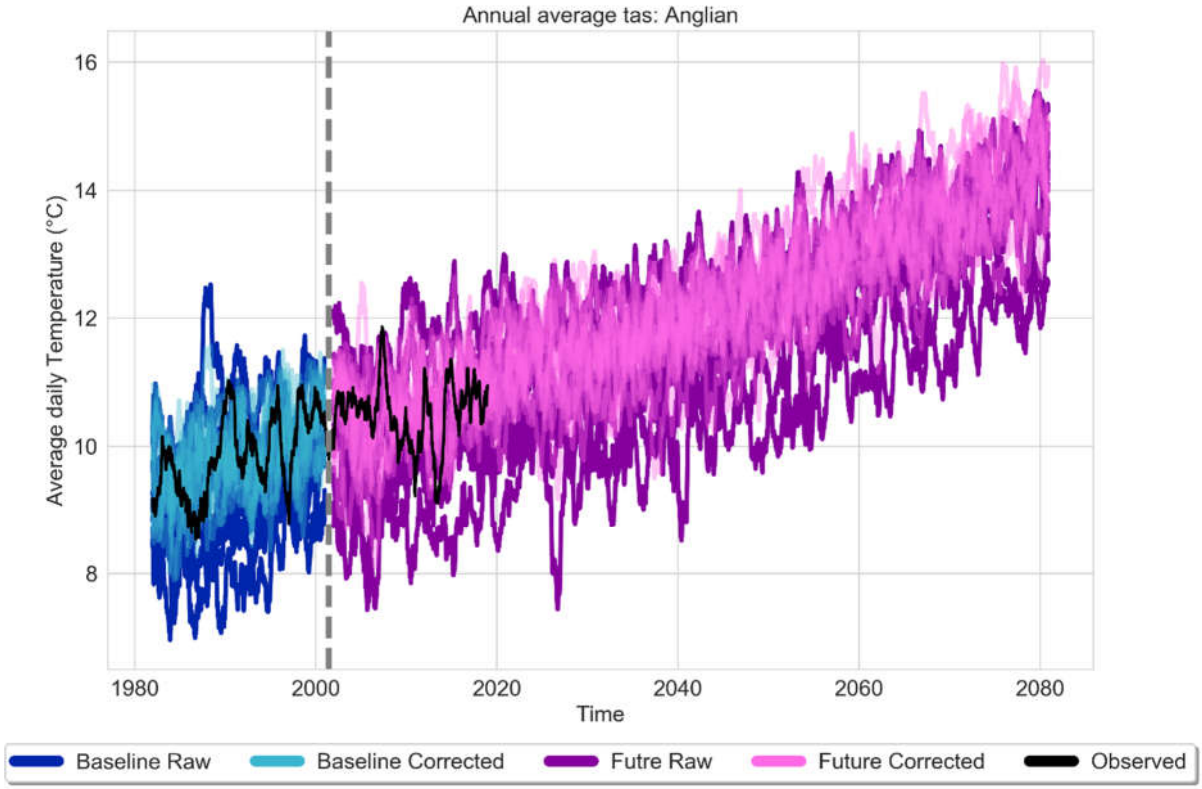


Figure 3-1 – Example of bias-corrected temperature time series

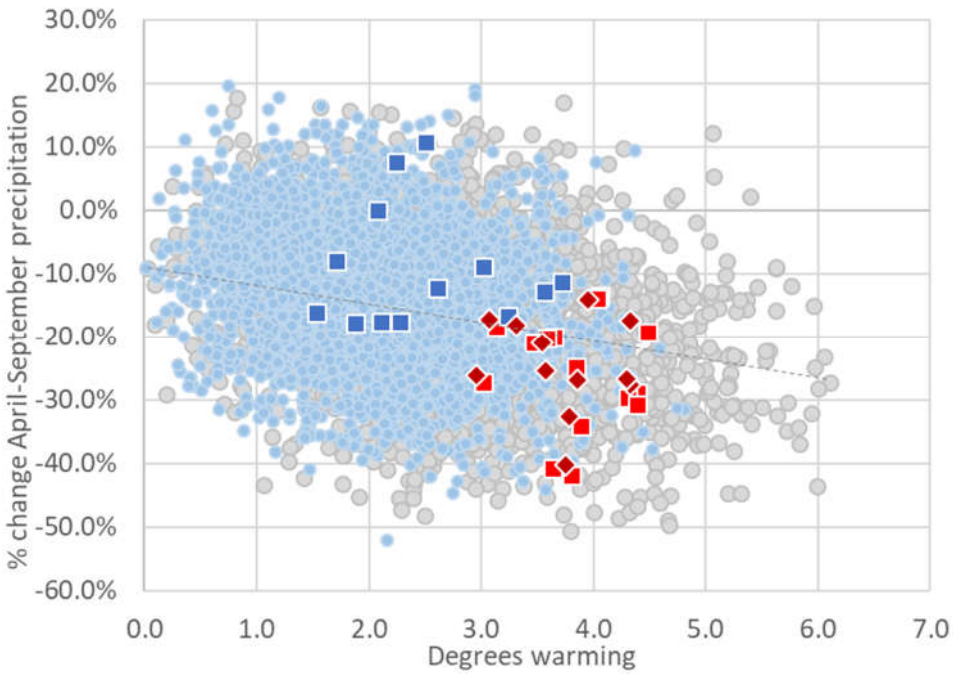


Figure 3-2 - Comparison of different climate model data for England and Wales in the 2070s (UKCP probabilistic A1B blue circles; RCP8.5 grey circles; CMIP5 blue squares; HadGEM red squares and RCM red diamonds)

3.2 Case studies of the impacts of climate change scenarios on low river flows

Several case studies have been undertaken to assess the impacts of climate change on flows, based perturbation of the full stochastic data set with different climate change factors for the 2070s. In the case of Hardham on the Western Rother the stochastic data produce a much wider range of flows than observed, ca. +10%/-5% on Q5 high flows. +/- 10% on median flows and +10%/-12% on Q95 low flows.

The impacts of climate change under RCP8.5 by the 2070s is greater with median impacts of around -10%, -22% and -12% for UKCP18 probabilistic, RCM and CMIP5 GCMs (Figure 3-3). Similar results were found for Wimbleball case study, with median changes to Q95 of around -35%, -50% and -30% for the same scenarios (Figure 3.4).

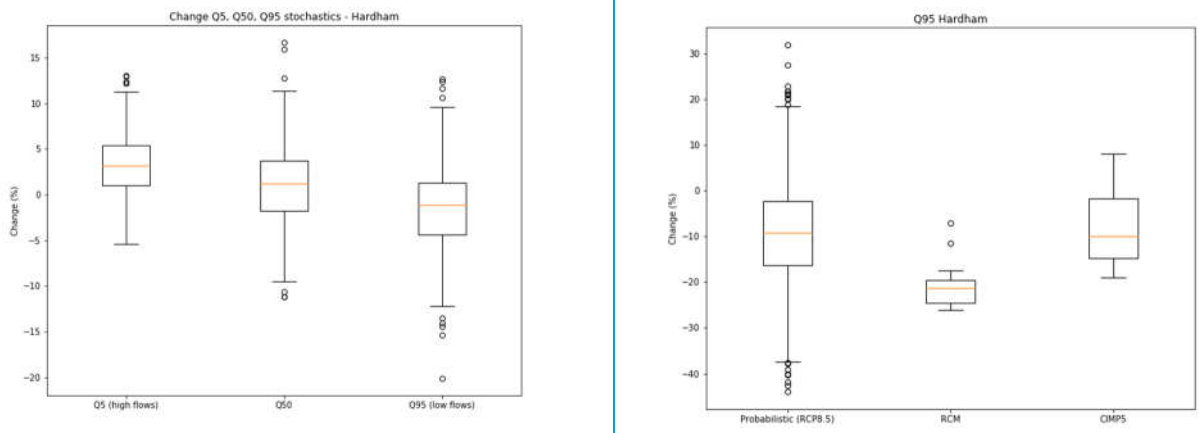


Figure 3-3 – A) Percentage differences between flows at Hardham calculated using observed HadUK 1961-1997 and those calculated using stochastic weather data (Q5: extreme high flows, Q50: median flows, Q95: extreme low flows). B) Percentage differences between baseline Q95 and Q95 in the 2070s based on UKCP18 RCP8.5 probabilistic data (3000 scenarios), bias corrected RCMs (12 scenarios) and CMIP5 global models (13 scenarios).

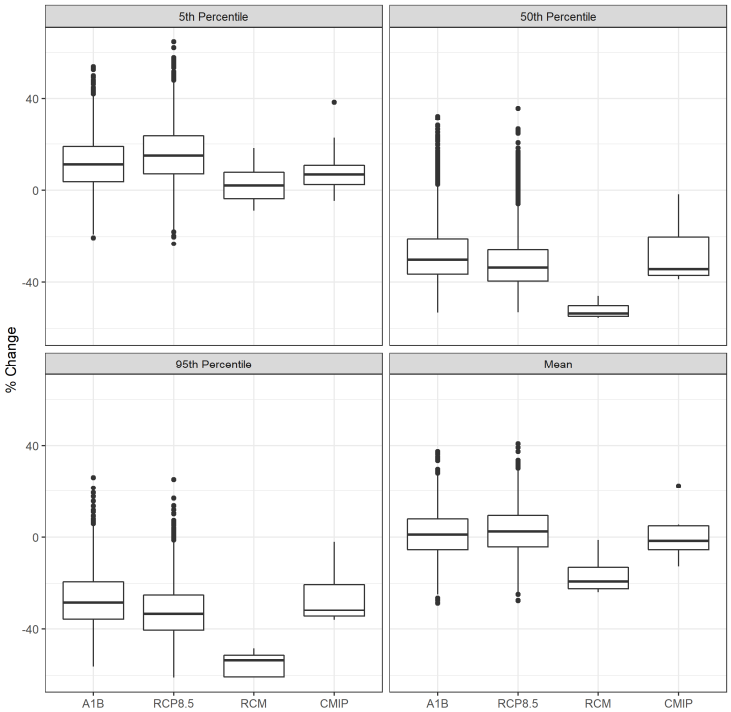


Figure 3-4 – Impacts of climate change in the 2070s on Wimbleball flows under A1B and RCP8.5 scenarios (A1B and RCP8.5 probabilistic based on 3000 runs, RCM, 12 runs and CMIP5, 13 runs)

4. Conclusions and recommendations

The project has provided two new national data sets to support regional water resources planning:

- Stochastic time series of precipitation and potential evapotranspiration for more than 200 locations in England and Wales, based on Met Office HadUK observation data for precipitation and several Potential Evapotranspiration (PET) data sets, required for water resources modelling
- Bias corrected future climate change factors and time series based on UK Climate Projections 2018 Regional Climate Models under Representative Concentration Pathway (RCP8.5) and HadUK precipitation and temperature at the catchment scale

The first data set provides a set of 400 time series for each location for the assessment of climatological drought risk across England and Wales for a baseline climate without climate change. The overall impact of improving the model fit to low rainfall by 25%[20]. Our analysis shows that model provides a wide range of drought conditions for drought risk assessment and testing of water resources systems models.

The second data set provides spatially coherent Regional Climate Model (RCM) change factors and accompanying time series to assess the impacts of climate change. These scenarios are based on bias-corrected UKCP18 Regional Climate Models under scenario Representative Concentration Pathway RCP8.5. Our analysis shows that this scenario has high rates of warming compared to other global models with a greater impact on river flows. Climate change assessments following EA WRMP guidelines may also use the England and Wales CMIP5 factors and other evidence to provide a comprehensive assessment of risks in water resources zones with a high vulnerability to climate change.

Both data sets can be used in a way that is fully compliant with the Environment Agency Water Resources Planning Guidelines and supplementary guidance on stochastics and climate change.

Based on this work we make the following recommendations:

- Update the stochastics assessment running at a national scale rather the regional scale and with the new EA PET data sets for all regions

[20] Based on the Mean Absolute Error of low rainfall in mm/month for three test regions and low rainfall metrics from 3 months to 36 months.

- Further development of post-processing tools to visualise, screen and select results
- Running stochastic models up to 2020 to explore the increased risk of low rainfall due to changes in climate drivers.
- Downscaling of the CMIP5 and new HadGEM RCP2.6 global climate models to the same 200 catchments to provide a spatially coherent climate change data sets, which provide future scenarios with less warming than UKCP RCM RCP8.5 models
- Application of the RCM bias-corrected time series to models from 1981-2080 to provide more information on the pace of hydrological change and potential onset of more extreme droughts due to climate change.
- Application of the bias corrected RCM data as stress-test to proposed water resources infrastructure but to combine these data with other assessments to consider a wider range of adaptation pathways.

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Appendices

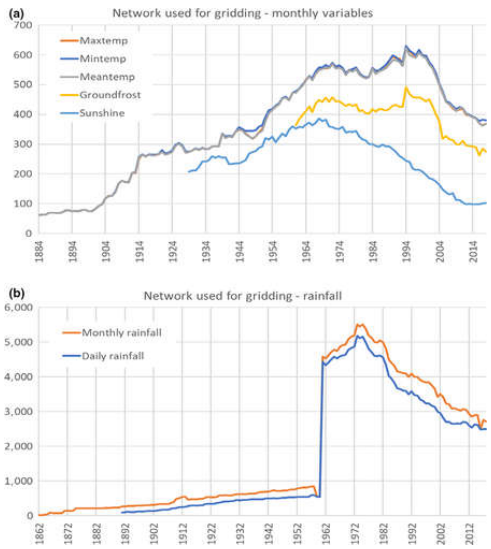
Appendix A. Background data sets

A.1. UK Observations Data

Meteorological and hydrological monitoring in England and Wales is undertaken by the Met Office, Environment Agency and Natural Resources Wales. The national meteorological network of synoptic stations, which measure a full range of weather variables[21], is supplemented by specialist networks and individual observer stations that collect precipitation and temperature data. These data are brought together in a number of national data sets curated by the Met Office[22], Centre for Ecology and Hydrology (CEH) and the Environment Agency and include gridded data products at resolution from 1km to 60km.

Water companies typically develop their own catchment data sets using local networks of station data collected by the Environment Agency and on their own sites. Increasingly, use is being made of national gridded data sets, such as CEH GEAR 1km precipitation data[23] (Tanguy et al., 2019) and the Met Office HadObs 1km precipitation data (Met Office, 2018a; Hollis et al;., 2019). This report has used the HadObs data sets to test the performance of the UKCP Regional Climate Models (Section 2.2.4). There are differences in these data sets depending on the level of checking and QA and the adopted interpolation methods, which rely on fewer observations further back in the historical record. Figure 2.1 highlights that large difference in the number of statins (Hollis et al., 2019). The strengths and weaknesses of these data sets are not discussed in this report but will be highlighted in the project's case study work and uncertainty analysis.

Figure 5 -1 - Number of observations stations used for Met Office gridded climate observations data sets



Source: Hollis et al., 2019 Geoscience Data Journal, Volume: 6, Issue: 2, Pages: 151-159, First published: 05 September 2019, DOI: (10.1002/gdj3.78)

[21] https://www.metoffice.gov.uk/weather/guides/observations/uk-observations-network
[22] https://www.metoffice.gov.uk/research/climate/maps-and-data/about/archives

Appendix B. Stochastic Modelling

B.1. Introduction

This Appendix includes further detailed information on the stochastic data for WRSE region and background research and generator development completed as part of the project.

B.2. Precipitation locations

OBJECTID	Alt ID	Nearby Station Name	x	y	Quality	Comments
25	411686	Lyneham	400600	178300	good	Original selection
26	336376	Boscombe Down	417200	140300	good	Original selection
27	329084	Houghton Lodge	434400	133200	OK	Original selection
28	325638	Otterbourne	446800	122500	OK	Original selection
29	334509	Wight: Cowes W Wks	449100	95200	good	Original selection
30	333785	Wight: Shanklin Victoria Avenue	458100	81200	OK	Original selection
31	280369	Rotherfield Park	469300	132400	good	Original selection
32	320345	Bognor Regis	493300	98800	good	Original selection, Y grid location round up to miss sea
33	285411	Dorking, Pixham Lane S Wks	517700	150500	good	Original selection
34	314073	Mile Oak P Sta	524300	107900	good	Original selection
35	311123	Balcombe W Wks	529000	131200	OK	Original selection
36	311001	Poverty Bottom W Wks	546700	102300	good	Original selection
37	293375	Falconhurst	547000	142600	OK	Original selection
63	453197	Blockley, Greenway Resr	416000	235100	OK	Original selection
64	97263	Whitacre New W Wks	421600	291100	good	Original selection
66	98543	Hartshill S Wks	433000	295100	OK	Original selection
71	256221	Oxford	450900	207200	OK	Original selection
72	448540	Rugby, Braunston	451200	274900	OK	Original selection
73	111947	Wigston S Wks	459300	296700	good	Original selection
74	161728	Wellingborough, Swanspool	489400	267500	OK	Original selection
75	172601	Woburn	496400	236000	OK	Original selection
80	182074	Odsey	529200	238000	OK	Original selection
84	181126	Saffron Walden, Co High School	553200	237800	OK	Original selection
96	281629	Hindhead W Wks	488900	135900	OK	Original selection
97	280037	Shepperton Lock	507300	165900	good	Original selection
98	247536	Heathrow	507700	176700	good	Original selection
99	277604	Watford, Aldenham Road P Sta	512000	195800	good	Original selection

100	284152	Hampton W Wks	513100	169500	good	Original selection
101	244569	Darnicle Hill P Sta	530900	204800	good	Original selection
102	242787	Moor Place	542200	218800	good	Original selection
103	290116	Betsoms Hill	543000	156300	OK	Original selection
104	290007	Cross Ness S Wks	548700	180600	good	Original selection
105	309730	Hailsham, Magham Down	560900	111600	OK	Original selection
106	310007	Eastbourne	561100	98000	good	Original selection
107	297880	East Malling	570800	157100	good	Original selection
109	295604	Goudhurst	572200	133300	OK	Original selection, also covers Bedgebury (X571900_Y134100) which closed in 1975
110	297347	Barming W Wks	573500	154900	OK	Original selection
111	309040	Hastings, Newgate	580700	110200	OK	Original selection
112	306947	Great Dixter	582000	125000	good	Original selection
113	301985	Ashford, Hythe Road	601800	142500	OK	Original selection
114	302770	Canterbury S Wks	616900	159700	good	Original selection
115	303401	Barham P Sta	619900	150900	good	Original selection
116	305050	Dover W Wks	632200	142100	good	Original selection
161	442927	Church Stretton S Wks No 2	343900	290900	good	Original selection, also covers Church Stretton gauge (X343800_Y291100) which closed in 1981
162	443216	Oakly Park	349100	276200	good	Original selection
163	432251	Newport (Salop)	371100	320300	good	Original selection
164	435528	Hatton Grange	376400	304300	good	Original selection
165	438993	Lincombe Lock	382100	269300	good	Original selection
166	440222	Worcester, Fort Royal Hill	385500	254300	OK	Original selection
167	459378	Witcombe Resr	390400	215100	OK	Original selection
168	458896	Cheltenham, Sandford Mead	395300	221600	OK	Original selection
169	96712	Highters Heath Resr	408600	279200	OK	Original selection
171	246695	Hampstead, Kidderpore Resr	525200	185900	OK	Original selection
173	346876	BRANKSOME, BOURNE VALLEY GAS WKS	406000	92500	OK	Added by SDW
174	344052	BRYANSTON	387200	106700	OK	Added by SDW
175	340765	MARTIN DOWN NO 2	405900	118800	OK	Added by SDW
178	Not in Met Office archive	South Kingston Deverill	384740	135179	OK	Suggested by CH

B.3. Analysis of teleconnections

B.3.1. Representation of seasonal and inter-annual variability

The current weather generator uses explanatory teleconnection data to model monthly observed rainfall. For the previously applied projects North Atlantic Oscillation (NAO) and Sea Surface Temperature (SST) were used with the WRE generated data also considering the East Atlantic Index (EAI).

As part of this project we have reviewed available teleconnection series with reference to data availability and an initial analysis of precipitation / teleconnection correlation across the country. Based on this initial analysis, we have analysed model outputs against various changes to the model explanatory factors for the three case study areas with existing stochastic data.

We analysed:

- Inclusion of additional explanatory factors (e.g. teleconnection series);
- Inclusion of interaction terms between the factors within the “gamlss” model which were not previously considered;
- Impact of the length of input data (due to the scarcity of teleconnection data prior to 1950).

The ‘success’ of a model variation has been judged against two areas:

- The model statistics including significance of factors within the model and overall model fit statistics. This has specifically been used to identify the significance of interaction terms within the gamlss model.
- The ability of the outputs to represent the observed rainfall record. This is evidenced with the use of rainfall duration plots against seasonal as well as longer inter-annual trends.

B.3.2. Teleconnection data

This section highlights the groups of teleconnections patterns analysed in the model.

North Atlantic Oscillation (NAO)

The NAO is one of the major modes of variability of the Northern Hemisphere atmosphere. Traditionally defined as the normalised pressure difference between a station on the Azores and one on Iceland, it combines parts of the East-Atlantic and West Atlantic patterns originally identified by Wallace and Gutzler (1981) for the winter season.

Strong positive phases in the NAO tend to be associated with above average temperatures and high winter precipitation across northern Europe and strong negative phases usually lead to drier conditions.

Two sources of NAO have been analysed:

- NAO (Jones): available between 1821 – 2019, series used in previous stochastic generation projects. From Climate Research Unit, University of East Anglia.
- NAO: available between 1950 – 2019. From the NOAA (National Oceanic and Atmospheric Administration)

Sea Surface Temperature (SST):

- Sea surface temperatures, particularly warmer temperatures due to the Gulf Stream, have a significant effect on the UK climate.
- The SST datasets are available as gridded data either in absolute values or anomaly form. The original Serinaldi and Kilsby (2012) study and previously applied stochastic projects used SST anomalies averaged across the gridded data corresponding to the three 5° x 5° boxes in the domain 50°N-55°N, 10°W-5°E. These gridded boxes were chosen to analyse the relationship between rainfall and a local climate index, as the grid boxes represent an area covering England, Wales and Ireland. For consistency this same gridded region was used for comparison between the other SST datasets.

Three sources of SST have been analysed:

- HadSST2: available between 1850 – 2011, series used in the previous stochastic generation projects. From UKMO Hadley Centre
- Kaplan SST V2: available between 1856 – 2019. From the NOAA
- COBE-SST2: available 1850 – 2018. Data provided by the *NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at https://www.esrl.noaa.gov/psd/*

East Atlantic Index (EA)

- The East Atlantic Index is structurally similar to the NAO consisting of a north-south dipole of anomaly centres spanning the North Atlantic from east to west. The anomaly centres of the EA pattern are displaced south-eastward to the approximate nodal lines of the NAO and for this reason the EA is often interpreted as a southward shifted NAO pattern. However, it contains a strong subtropical link which makes it distinct from the NAO.
- Positive phase EA values are associated with above average surface temperature in Europe in all months as well as above average precipitation over norther Europe.

Two sources of EA have been analysed:

- EAI: available between 1850 – 2016, series used in the Water Resource East analysis. Data was calculated by the Met Office for the purposes of the project.
- EA: available between 1950 – 2019. From the NOAA
- East Atlantic / Western Russia (EA/WR)
- The EAWR is one of the three prominent teleconnection patterns that affect Eurasia throughout the year. It consists of four main anomaly centres. The positive phase EAWR is associated with below average precipitation across central Europe.

One series has been analysed:

- EAWR: available between 1950 – 2019. From the NOAA

Scandinavia (SCA)

The Scandinavia pattern consists of a primary circulation centre over Scandinavia, with weaker centres of opposite sign over western Europe and eastern Russia. The positive phase of the SCA is associated with below average temperatures across western Europe, above average precipitation across central and southern Europe and below average precipitation across Scandinavia.

One series has been analysed:

- SCA: available 1950 – 2019. From the NOAA.

Atlantic Multidecadal Oscillation Index (AMO)

The AMO is an ongoing series of long duration changes in the sea surface temperature of the North Atlantic Ocean, with cool and warm phases that may last for 20-40 years at a time and a difference of about 1°F between extremes. The AMO affects air temperatures and rainfall over the Northern Hemisphere. It is associated with changes in the frequency of droughts and if reflected in the frequency of severe Atlantic hurricanes.

One series has been analysed:

- AMO: available between 1856 – 2019. Calculated from the Kaplan SST V2 dataset. From ESRL

B.3.3. Teleconnection correlations

This section summarises the initial exploratory analysis of precipitation and teleconnection correlations. Figure 5.2 shows that NAO is positive correlated with rainfall in the north and west of the country, particularly during the winter months. This supports existing understanding of the influence of NAO across the country (see Serinadli and Kilsby, 2012).

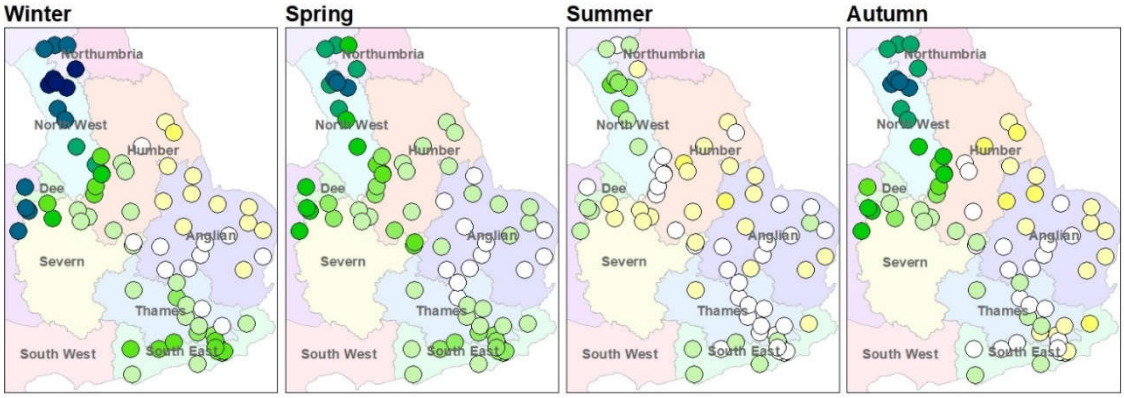


Figure 5-2 – NAO (1950 onwards) vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

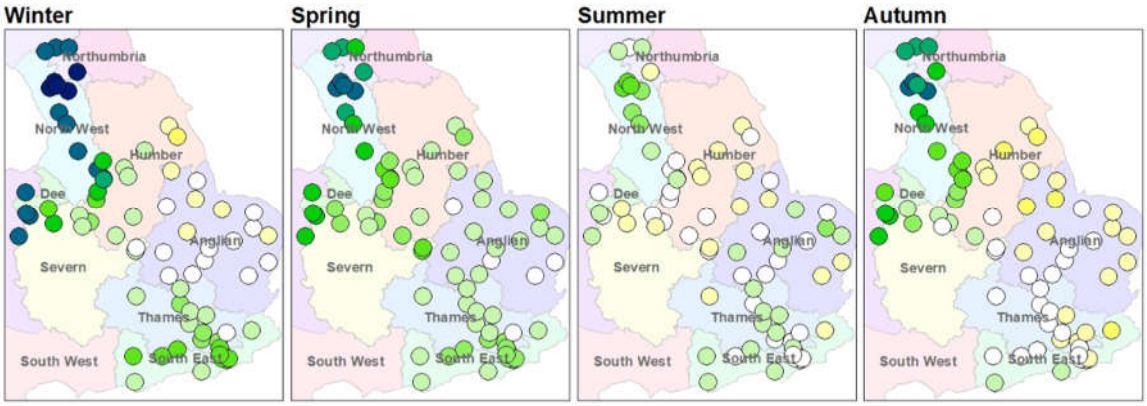


Figure 5-3 – NAO Jones vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

Figure 5-4 shows a weaker relationship between SST and precipitation as compared to NAO however some patterns can still be observed suggesting higher SST anomalies associated with wetter winter conditions and drier summer conditions, particularly in the north west. This analysis also suggests that the HadSST series used in the previous weather generation may not be the best sea surface temperature indicator to use.

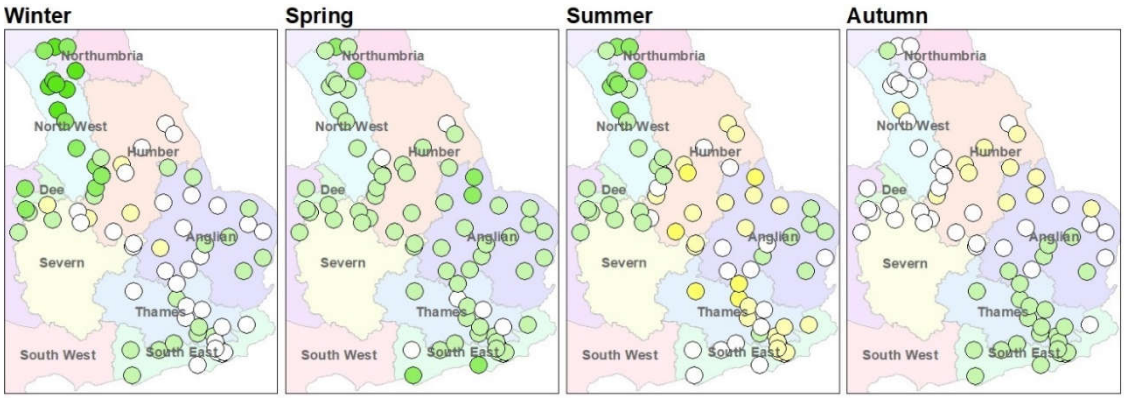


Figure 5-4 – SST vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

The East Atlantic (EA) pattern shows a strong positive correlation of precipitation across all water resource regions and all seasons as shown in Figure XX.

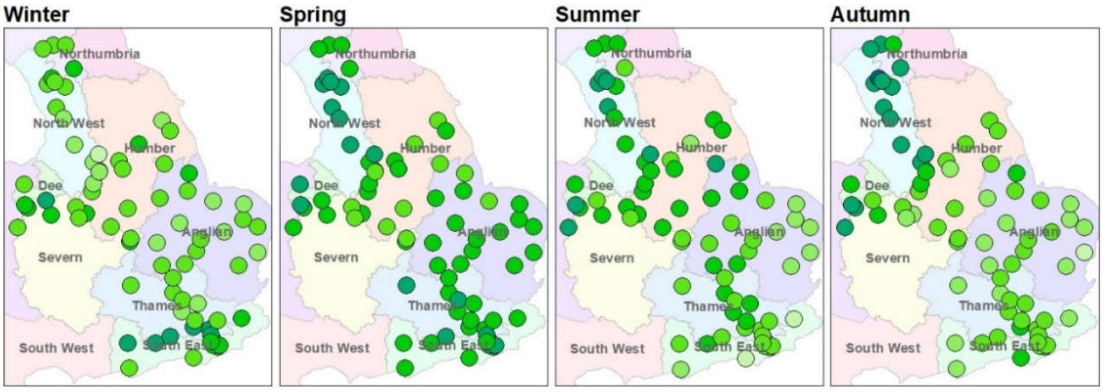


Figure 5-5 – EA vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

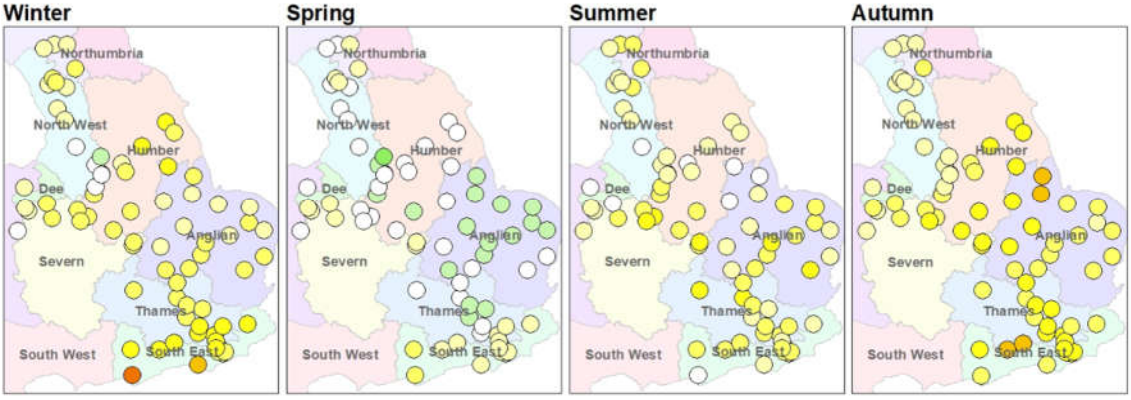


Figure 5-6 – EA Index (calculated by Met Office for WRE) vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

The East Atlantic / West Russian (EAWR) pattern provides a strong negative indicator of precipitation in the summer and autumn months across all regions. The relationship is weakened in the south of the country (WRSE region) during winter and spring, with the inverse observed in the north west (WRW region) in winter and spring.

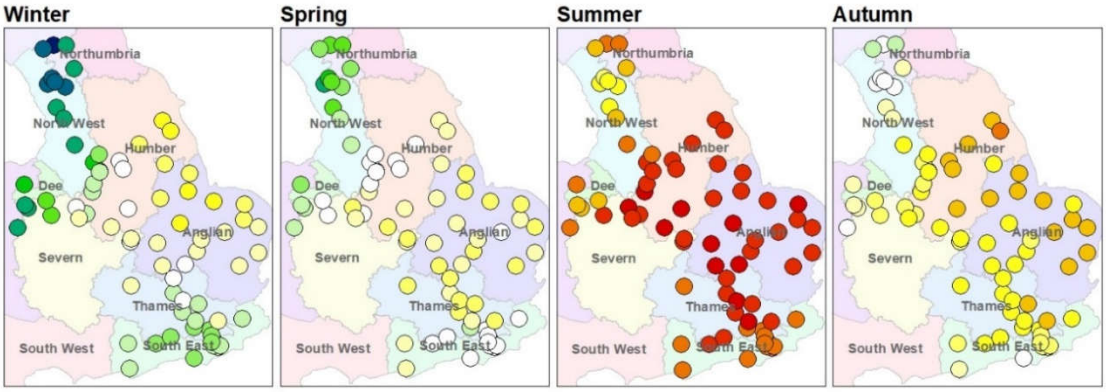


Figure 5-7 – EA/WR vs precipitation correlations across the UK. Darker blue/green shades indicating stronger positive correlations and red strong negative correlations.

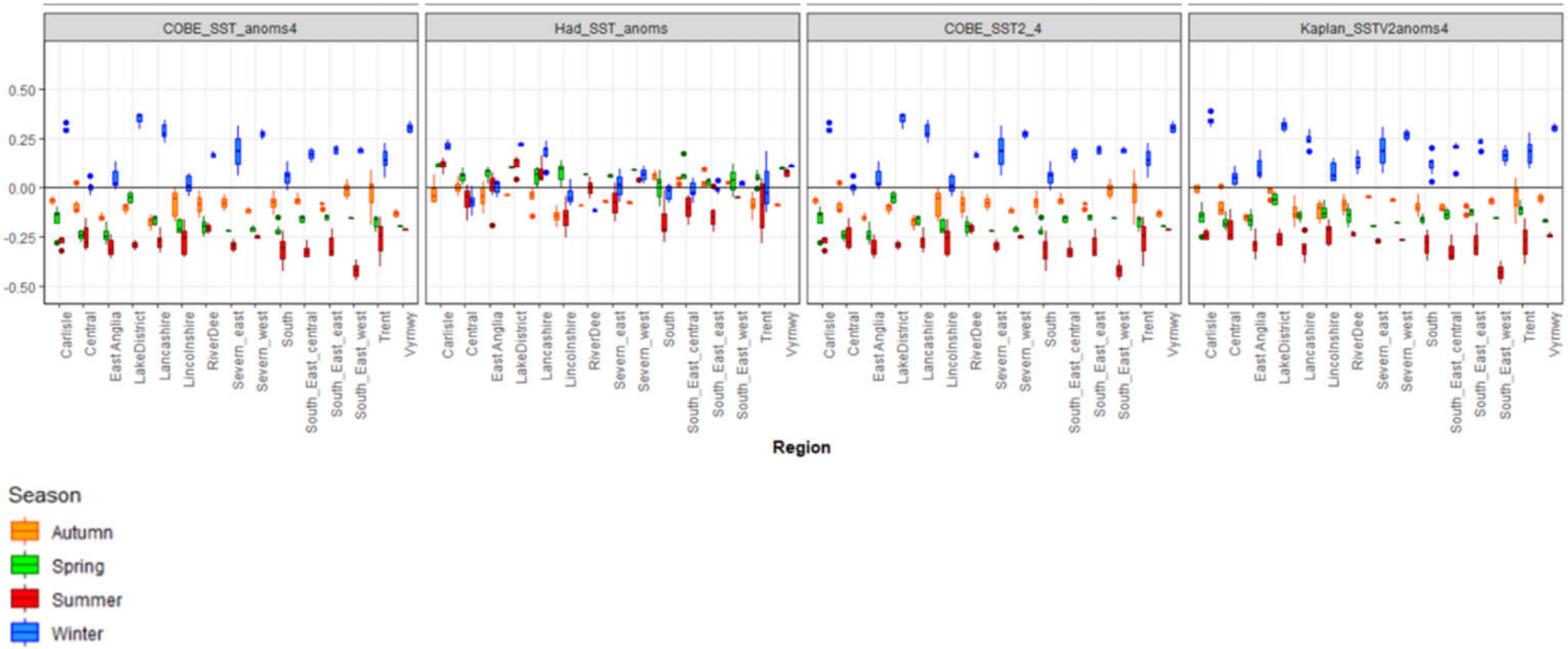


Figure 5-8 – SST vs precipitation correlations across the UK for each season.

The SCA pattern indicates increased precipitation totals in during winter and autumn in the south and east of the country as shown in Figure XX.

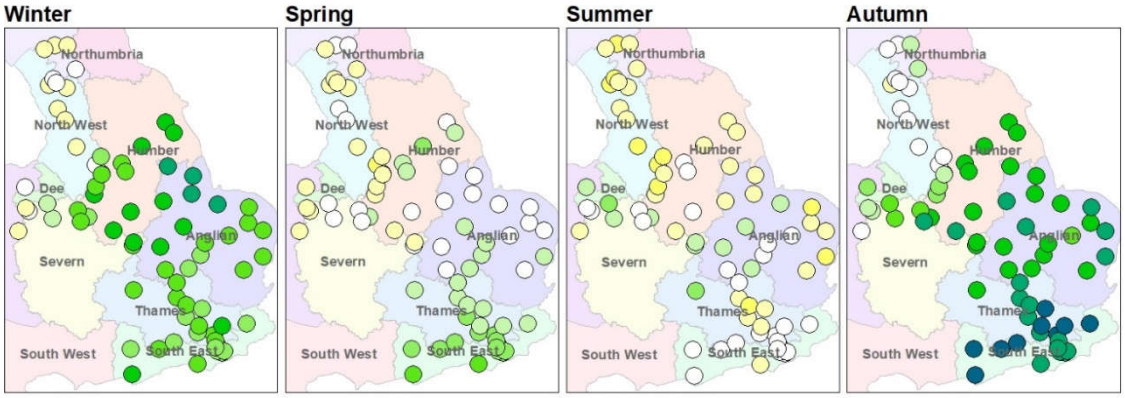


Figure 5-9 – SCA vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

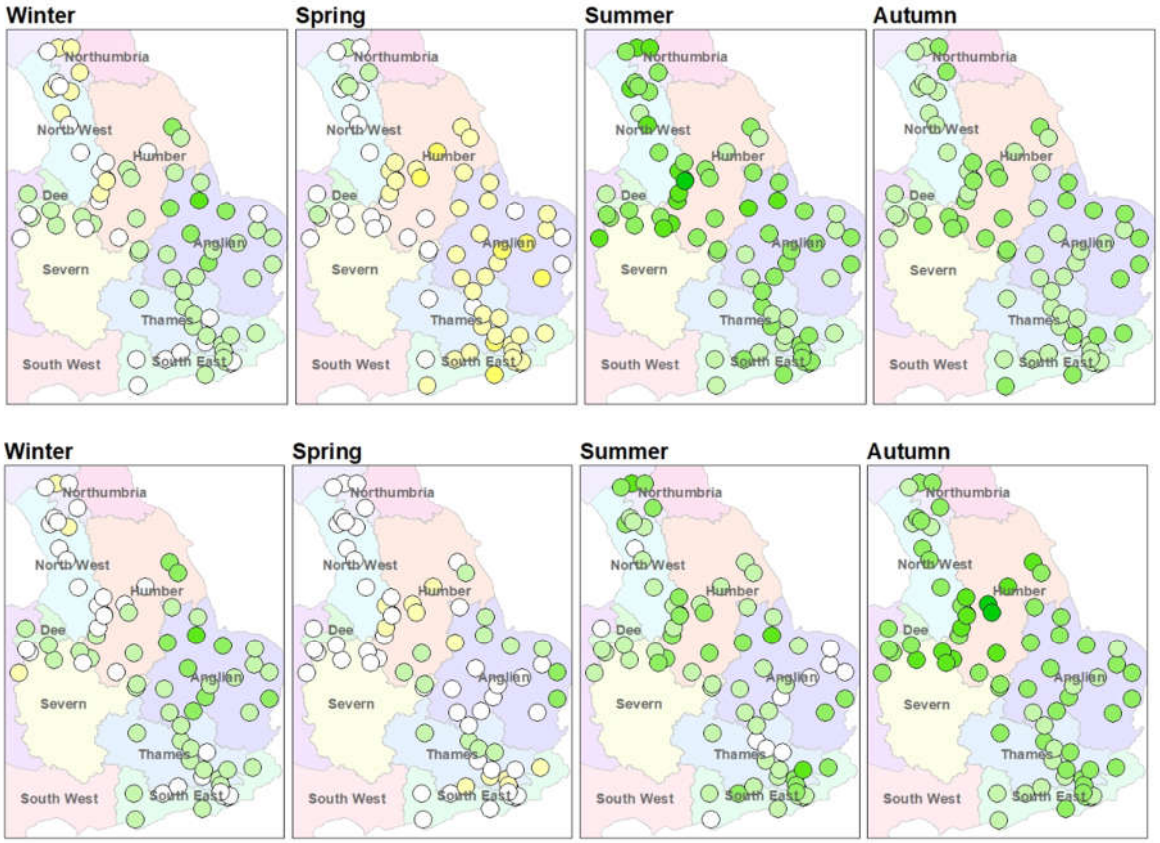


Figure 5-10 – AMO smoothed (top) unsmoothed (bottom) vs precipitation correlations across the UK. Darker shades indicating stronger positive correlations.

B.4. Demonstrating the improved fit of the 1950s model over the 20th century model

B.4.1. Models

All the models have been run with historical rainfall data from the HadUK 1km gridded dataset using observed data as outlined in the table below[24]. To maintain a sizeable quantity of stochastic data 400 replications of the 1950's models have been generated as opposed to 200 previously adopted for the stochastic work.

Model	Region	Historical years	Teleconnections
20th Century	WRSE	1920 – 1997	Main effects and interactions between: • Month factor • North Atlantic Oscillation • Sea Surface Temperature • Atlantic Multi-decadal Oscillation • East Atlantic Index
	WRE	1900 – 1997	
	UUW	1911 – 1997	
1950's	WRSE	1950 – 1997	Main effects and interactions between: • Month factor • North Atlantic Oscillation • Sea Surface Temperature • Atlantic Multidecadal Oscillation • East Atlantic • East Atlantic West Russia • Scandinavia
	WRE		
	UUW		

B.4.2. Comparison of outputs

Several approaches have been used to compare the outputs of the models[25]:

- QQ plots of the range of stochastic replications against the observed rainfall values at multiple rainfall total metrics;
- Cumulative plots of each of the stochastic series' against observed rainfall at multiple rainfall total metrics;
- Comparison of the two models in terms of estimated rainfall return periods at multiple metrics after fitting GEV distributions to the generated stochastic data.

A detailed Atkins internal memo describes the changes and selected extremes statistic for all trial regions are summarised below.

For WRSE WRE and UU the Mean Absolute Errors of extremely low rainfall between 1:50 year and 1:500 year metrics have been reduced from -3.83 mm/month in the previous model to -2.9 mm/month in the new model (25% reduction in average errors).

For WRSE the Mean Absolute Errors have been reduced from -6.05 mm/month to -5.74 mm/month (5% reduction in average errors)

This shows a marginal improvement in the model fit even though the 1950s models were trained on a much shorter period of observed data.

The differences at individual sites can be larger and some bias correction is still required. In general, the stochastic model produces slightly higher rainfall/wetter conditions that observed.

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[24] The 20th Century models have been run from the historical year used for the original generation of these datasets ranging between 1900 and 1920.
[25] Note: this comparison has been undertaken on the 'raw' outputs before any bias correction or adjustments have been applied.

B.4.3. Summary of return period analysis to check model fits

This analysis was completed to compare the old model to the new model for sites used in the WRMP19 plans. Note that any EVA is highly sensitive to the methods chosen and in this case an automated method was use for comparison purposes only. These data should not be used for planning purposes that may require more detailed analysis.

Metric	Region	RP	Obs	20th Century model	1950s model	Diff 20thC – 1950s (per month)	Diff Obs – 20thC (per month)	Diff Obs – 1950s (per month)
April - August	UUW	50	261.8	276.5	267.9	1.7	-2.9	-1.2
	UUW	100	221.4	257.4	248.0	1.9	-7.2	-5.3
	UUW	200	180.1	240.8	230.6	2.0	-12.1	-10.1
	UUW	500	123.7	221.7	210.2	2.3	-19.6	-17.3
	WRSE	50	116.3	158.4	147.4	2.2	-8.4	-6.2
	WRSE	100	81.6	144.5	132.4	2.4	-12.6	-10.2
	WRSE	200	47.2	132.3	119.4	2.6	-17.0	-14.4
	WRSE	500	1.6	118.2	104.3	2.8	-23.3	-20.5
	WRE	50	144.0	159.1	153.2	1.2	-3.0	-1.8
	WRE	100	121.2	146.3	139.9	1.3	-5.0	-3.7
	WRE	200	99.1	135.2	128.3	1.4	-7.2	-5.8
	WRE	500	70.3	122.4	114.7	1.5	-10.4	-8.9
April - September	UUW	50	365.1	354.5	340.3	2.4	1.8	4.1
	UUW	100	337.8	331.0	314.1	2.8	1.1	4.0
	UUW	200	311.7	310.4	291.2	3.2	0.2	3.4
	UUW	500	278.4	286.7	264.5	3.7	-1.4	2.3
	WRSE	50	195.5	207.0	190.3	2.8	-1.9	0.9
	WRSE	100	176.8	191.1	171.0	3.4	-2.4	1.0
	WRSE	200	160.5	177.3	154.1	3.9	-2.8	1.1
	WRSE	500	141.4	161.3	134.5	4.5	-3.3	1.2
	WRE	50	199.6	199.1	193.9	0.9	0.1	1.0
	WRE	100	186.9	184.4	177.4	1.2	0.4	1.6
	WRE	200	176.0	171.6	162.9	1.5	0.7	2.2
	WRE	500	163.6	156.8	145.9	1.8	1.1	3.0
January - August	UUW	50	573.1	540.3	543.1	-0.3	4.1	3.7
	UUW	100	549.7	513.2	513.5	0.0	4.6	4.5
	UUW	200	529.5	489.6	486.2	0.4	5.0	5.4
	UUW	500	506.0	462.5	452.5	1.3	5.4	6.7
	WRSE	50	243.2	309.3	304.2	0.6	-8.3	-7.6
	WRSE	100	184.3	289.5	283.2	0.8	-13.2	-12.4
	WRSE	200	124.4	272.3	265.0	0.9	-18.5	-17.6

Metric	Region	RP	Obs	20th Century model	1950s model	Diff 20thC – 1950s (per month)	Diff Obs – 20thC (per month)	Diff Obs – 1950s (per month)
	WRSE	500	43.1	252.4	243.7	1.1	-26.2	-25.1
	WRE	50	265.3	n/a	285.3	n/a	n/a	-2.5
	WRE	100	237.7	n/a	268.4	n/a	n/a	-3.8
	WRE	200	212.2	n/a	253.4	n/a	n/a	-5.2
	WRE	500	180.6	n/a	235.9	n/a	n/a	-6.9
October - September	UUW	50	967.5	972.3	n/a	n/a	-0.4	n/a
	UUW	100	924.9	931.0	n/a	n/a	-0.5	n/a
	UUW	200	888.0	895.1	n/a	n/a	-0.6	n/a
	UUW	500	845.3	854.1	n/a	n/a	-0.7	n/a
	WRSE	50	501.7	551.8	n/a	n/a	-4.2	n/a
	WRSE	100	459.8	516.6	n/a	n/a	-4.7	n/a
	WRSE	200	423.6	485.5	n/a	n/a	-5.2	n/a
	WRSE	500	381.6	448.9	n/a	n/a	-5.6	n/a
	WRE	50	460.7	498.8	480.9	1.5	-3.2	-1.7
	WRE	100	426.0	474.0	455.4	1.5	-4.0	-2.5
	WRE	200	394.3	451.3	433.2	1.5	-4.7	-3.2
	WRE	500	355.6	423.6	407.2	1.4	-5.7	-4.3
January - December	UUW	50	988.2	969.8	962.8	0.6	1.5	2.1
	UUW	100	932.7	929.8	920.9	0.7	0.2	1.0
	UUW	200	878.2	894.9	884.5	0.9	-1.4	-0.5
	UUW	500	806.7	854.9	842.1	1.1	-4.0	-3.0
	WRSE	50	565.7	559.1	n/a	n/a	0.6	n/a
	WRSE	100	514.3	528.9	n/a	n/a	-1.2	n/a
	WRSE	200	463.4	502.7	n/a	n/a	-3.3	n/a
	WRSE	500	396.3	472.3	n/a	n/a	-6.3	n/a
	WRE	50	516.2	496.2	490.3	0.5	1.7	2.2
	WRE	100	495.7	475.6	466.5	0.8	1.7	2.4
	WRE	200	476.8	458.0	445.9	1.0	1.6	2.6
	WRE	500	453.5	437.9	421.8	1.3	1.3	2.6
October - March	UUW	50	471.9	478.6	472.5	1.0	-1.1	-0.1
	UUW	100	432.1	448.8	442.4	1.1	-2.8	-1.7
	UUW	200	394.8	422.9	416.2	1.1	-4.7	-3.6
	UUW	500	348.1	393.2	385.9	1.2	-7.5	-6.3
	WRSE	50	260.1	273.9	280.8	-1.1	-2.3	-3.4
	WRSE	100	237.7	254.5	262.3	-1.3	-2.8	-4.1

Metric	Region	RP	Obs	20th Century model	1950s model	Diff 20thC – 1950s (per month)	Diff Obs – 20thC (per month)	Diff Obs – 1950s (per month)
	WRSE	200	218.2	237.6	246.3	-1.5	-3.2	-4.7
	WRSE	500	195.5	218.1	227.7	-1.6	-3.8	-5.4
	WRE	50	218.0	223.3	223.1	0.0	-0.9	-0.8
	WRE	100	205.1	208.4	208.7	0.0	-0.5	-0.6
	WRE	200	194.3	195.5	196.2	-0.1	-0.2	-0.3
	WRE	500	182.1	180.6	181.7	-0.2	0.3	0.1
November - February	UUW	50	268.6	285.9	274.2	2.9	-4.3	-1.4
	UUW	100	220.3	262.0	253.8	2.0	-10.4	-8.4
	UUW	200	171.4	241.4	237.1	1.1	-17.5	-16.4
	UUW	500	105.3	217.9	218.6	-0.2	-28.1	-28.3
	WRSE	50	152.4	170.6	167.1	0.9	-4.5	-3.7
	WRSE	100	132.7	155.2	151.8	0.9	-5.6	-4.8
	WRSE	200	115.1	141.8	138.3	0.9	-6.7	-5.8
	WRSE	500	94.1	126.5	122.5	1.0	-8.1	-7.1
	WRE	50	132.4	142.1	142.6	-0.1	-2.4	-2.6
	WRE	100	122.4	132.4	131.6	0.2	-2.5	-2.3
	WRE	200	114.0	124.2	121.6	0.7	-2.6	-1.9
	WRE	500	104.4	115.1	109.5	1.4	-2.7	-1.3
18 months to September	UUW	50	1431.2	1449.8	n/a	n/a	-1.0	n/a
	UUW	100	1356.5	1394.9	n/a	n/a	-2.1	n/a
	UUW	200	1286.7	1347.0	n/a	n/a	-3.3	n/a
	UUW	500	1199.7	1292.0	n/a	n/a	-5.1	n/a
	WRSE	50	823.5	865.2	859.1	0.3	-2.3	-2.0
	WRSE	100	774.1	828.2	820.5	0.4	-3.0	-2.6
	WRSE	200	728.8	796.2	787.0	0.5	-3.7	-3.2
	WRSE	500	673.2	759.1	748.0	0.6	-4.8	-4.2
	WRE	50	744.5	769.8	760.2	0.5	-1.4	-0.9
	WRE	100	691.4	739.0	727.3	0.7	-2.6	-2.0
	WRE	200	638.0	712.3	698.7	0.8	-4.1	-3.4
	WRE	500	566.4	681.4	665.4	0.9	-6.4	-5.5
24 months to September	UUW	50	2199.9	2100.2	2099.5	0.0	4.2	4.2
	UUW	100	2127.7	2026.9	2033.1	-0.3	4.2	3.9
	UUW	200	2054.3	1962.0	1974.8	-0.5	3.8	3.3
	UUW	500	1954.4	1886.7	1906.5	-0.8	2.8	2.0
	WRSE	50	1270.3	1258.8	1263.6	-0.2	0.5	0.3

Metric	Region	RP	Obs	20th Century model	1950s model	Diff 20thC – 1950s (per month)	Diff Obs – 20thC (per month)	Diff Obs – 1950s (per month)
	WRSE	100	1205.9	1212.3	1217.5	-0.2	-0.3	-0.5
	WRSE	200	1142.2	1172.0	1177.4	-0.2	-1.2	-1.5
	WRSE	500	1058.2	1125.3	1130.9	-0.2	-2.8	-3.0
	WRE	50	1108.4	n/a	1087.5	n/a	n/a	0.9
	WRE	100	1071.3	n/a	1052.9	n/a	n/a	0.8
	WRE	200	1035.3	n/a	1022.5	n/a	n/a	0.5
	WRE	500	988.6	n/a	986.6	n/a	n/a	0.1

Note: This analysis takes a specific approach of automated fitting of extreme value distributions to the driest years only. It is not a traditional AMAX or POT style analysis.

B.5. Data delivery

B.5.1. Data checking and review

At each stage of the weather generation process the outputs are validated using a range of visualisations and at least 15 total rainfall metrics over different durations. In addition, Q-Q ranked rainfall plots and percentile plots are used to compare the stochastic data to the observed data for the calibration period and an independent data set (1902-1949) to demonstrate that the contemporary stochastic model can fit an historic period of low rainfall from the beginning of the 20th century.

A large amount of the checking process is done automatically but final checks are completed manually. This includes some Extreme Value Analysis (EVA), annual time series checks and independent checks against rainfall from 1902-1949. As well the rainfall generator Python code, additional checking tools in R and Excel are being made available to the WRSE modelling team. Some further details are provided in Appendix A.

When reviewing individual sites, it is important to consider that the data are calibrated to get good results across the whole region and retain coherence between sites. Any bias corrections made to improve the fits are completed on groups of sites called “bias regions” (Fig. 1) and are generally very small. Some individual sites may appear wetter or drier than observed for different metrics. The transposition of data to catchments provides an opportunity to align the stochastics with the baseline climatology of each river basin.

B.6. Files provided

The **inputs folder** contains the baseline daily and monthly rainfall and PET data sets from which the 1950 to 1997 rainfall was used to train the stochastic weather generator.

In addition, the **teleconnection data** are provided and file containing **bias regions**, which are used in the bias correction process (see Appendix A).

The main outputs are in the **daily folder**, include all generated precipitation and PET series. A figures sub-folder provides a large amount of percentile plots for visual checking of results. The precipitation sites have an ID number that is linked to each location (see Appendix B).

Finally, additional outputs are provided at the monthly scale in the **monthly_rain** folder

The **config.yaml** file details the stochastic weather generator parameters.

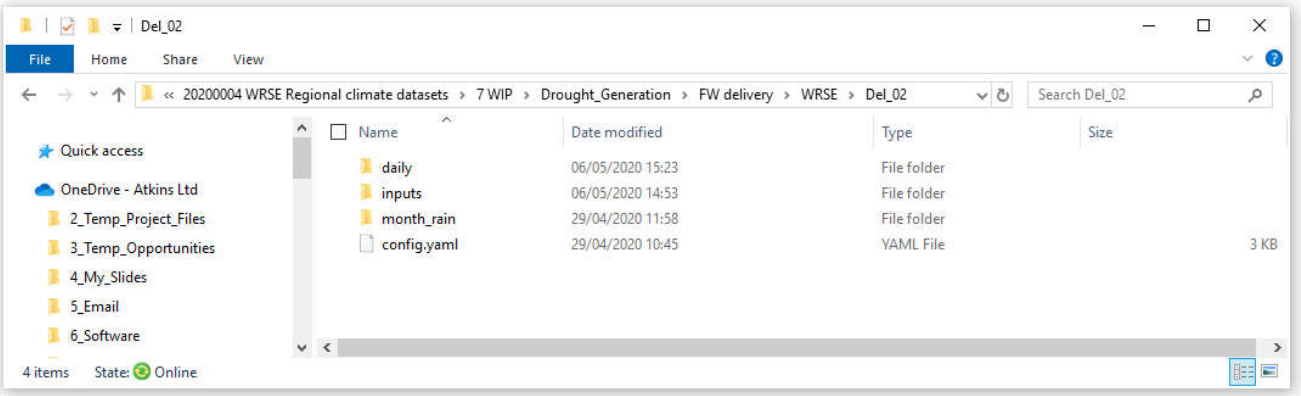


Figure 2. Screenshot of files provided

B.6.1. License for data use

Atkins licenses use of these data to the Client free of charge and on a non-exclusive, worldwide basis to such extent as is necessary to enable WRSE to make reasonable use of the Deliverables and the Services in relation to the Project[26].

The stochastic data are based on Had UK 1km data, which should be cited as follows:

Met Office; Hollis, D.; McCarthy, M.; Kendon, M.; Legg, T.; Simpson, I. (2019): HadUK-Grid Gridded Climate Observations on a 1km grid over the UK, v1.0.1.0 (1862-2018). Centre for Environmental Data Analysis, 14 November 2019. doi:10.5285/d134335808894b2bb249e9f222e2eca8.

http://dx.doi.org/10.5285/d134335808894b2bb249e9f222e2eca8

B.7. WRSE Drought Scorecards

The data were summarised in a series of scorecards, an example is shown below.

Table 3 Characteristics of annual rainfall droughts from 400 stochastic series, sorted based on proportion of sites in extreme droughts (Flags indicate relative magnitude and bars indicate the proportion of 43 sites in categories based on frequency, >2000 years, 200-2000 years, < 200 years)

[26] This includes providing access to the Environment Agency and other regional groups, which will fund their own climate data set development.

		Deficit (% of LTA)					Whole Region Drought Status		
Order	Replicate	SW	SC	SE	Thames NW	Thames SE	Extreme	Severe	Moderate
1	123	41%	38%	40%	44%	41%	91%	9%	0%
2	177	42%	38%	46%	59%	71%	60%	14%	26%
3	393	46%	40%	51%	61%	45%	47%	49%	5%
4	204	45%	47%	63%	64%	39%	47%	26%	28%
5	66	50%	42%	47%	56%	49%	42%	51%	7%
6	305	49%	53%	41%	53%	38%	42%	58%	0%
7	94	57%	44%	49%	50%	44%	40%	51%	9%
8	337	38%	57%	64%	43%	48%	30%	37%	33%
9	379	46%	47%	50%	52%	48%	30%	70%	0%
10	292	51%	45%	48%	56%	48%	28%	67%	5%
11	141	54%	47%	48%	55%	46%	26%	72%	2%
12	231	52%	57%	55%	48%	37%	26%	56%	19%
13	399	60%	45%	60%	63%	43%	23%	42%	35%
14	57	58%	50%	47%	54%	43%	23%	63%	14%
15	37	58%	54%	43%	56%	54%	23%	47%	30%
16	131	62%	54%	55%	62%	42%	21%	35%	44%
17	143	61%	46%	48%	66%	64%	21%	28%	51%
18	230	44%	56%	54%	62%	52%	19%	60%	21%
19	49	59%	62%	63%	62%	42%	16%	26%	58%
20	113	49%	49%	61%	51%	46%	14%	70%	16%
21	47	53%	51%	51%	52%	46%	14%	84%	2%
22	386	60%	50%	47%	66%	51%	14%	63%	23%
23	185	62%	64%	52%	53%	44%	14%	40%	47%
24	22	49%	47%	53%	48%	50%	12%	86%	2%
25	80	47%	65%	64%	57%	56%	12%	28%	60%
26	320	61%	51%	47%	66%	50%	12%	63%	26%
27	264	47%	60%	63%	63%	62%	12%	9%	79%
28	378	54%	50%	64%	53%	50%	9%	56%	35%
29	391	53%	50%	52%	55%	45%	9%	91%	0%
30	28	56%	51%	50%	50%	47%	9%	84%	7%
31	193	62%	55%	57%	51%	43%	9%	56%	35%
32	112	50%	63%	63%	47%	52%	9%	42%	49%
33	384	62%	58%	60%	46%	59%	7%	12%	81%
34	56	53%	49%	53%	61%	50%	7%	81%	12%
35	64	64%	59%	63%	53%	46%	7%	40%	53%
36	24	49%	55%	66%	62%	63%	7%	30%	63%
37	50	56%	54%	58%	48%	61%	5%	49%	47%
38	244	50%	54%	57%	63%	55%	5%	53%	42%
39	155	63%	53%	51%	60%	45%	5%	60%	35%
40	302	51%	55%	55%	59%	52%	5%	81%	14%
41	34	58%	57%	52%	66%	48%	5%	58%	37%
42	132	55%	49%	61%	63%	61%	5%	47%	49%
43	191	53%	55%	54%	53%	53%	2%	79%	19%
44	145	53%	52%	52%	58%	48%	2%	88%	9%
45	124	57%	55%	56%	52%	51%	2%	74%	23%
46	227	54%	50%	54%	56%	51%	2%	88%	9%
47	139	54%	47%	52%	61%	54%	2%	81%	16%
48	93	56%	55%	55%	54%	48%	2%	79%	19%
49	363	49%	50%	66%	57%	62%	2%	53%	44%
50	59	54%	52%	55%	61%	56%	2%	63%	35%

Run 141: Extreme drought in Thames SE and South Central/East

Run 131: Extreme drought in Thames SE and Severe across the region

Run 230: Extreme drought in Hampshire and Severe across the region

Run 124, 59: Severe across the region

Files provided

The following files are provided:

Excel template for ranking and sorting stochastic data for all sites

CSV files for stochastic data summarised by site and by metric

Appendix C. SWOT analysis of climate change products

This appendix includes a full review of UKCP data sets and example UKCP outputs for regions in England and Wales.

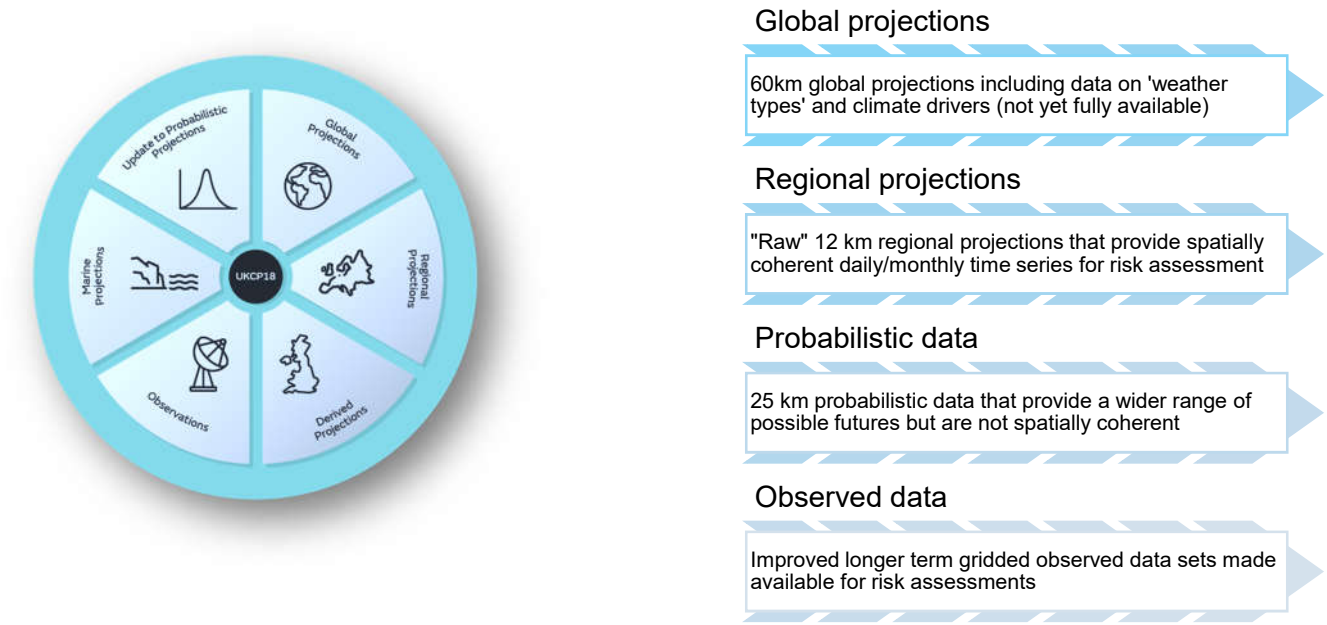
C.1. UK Climate Projections 2018 (UKCP18)

In November 2018 the UK Met Office released a new set of climate change projections for the UK (UKCP18) which are based on the latest versions of the Met Office Hadley Centre climate models and provide an update to the previous set of projections. The new UKCP18 projections are broadly consistent with earlier projections (UKCP09) showing an increased chance of warmer, wetter winters and hotter, drier summers along with an increase in the frequency and intensity of extreme climatic events[27]. UKCP18 provides a larger range of data sets, tools and capabilities introducing further options and choices for risk assessments, including the application to regional water resources planning. The key data products are summarised in Figure 2.1; the Derived Projections and new UKCP Local data are of less relevance for regional water resources planning and are not considered in this report.

C.1.1. Overview of UKCP data sets

Detailed background information on UKCP including guidance and caveats[28] are provided on the Met Office web pages. This section reviews some of the main data sets drawing our relevant points **for regional water resources planning.** The projections were published in late 2018, but some products are yet to be delivered including data sets of North Atlantic Oscillation (NAO) indices and weather types, which are of interest for the stochastic generation of droughts. The "UKCP Local" 2.2km are a higher resolution version of the RCMs, which have been promoted for assessment of heavy rainfall and other extremes. These are relevant for water resources planning at the more local scale but were out of scope for this study. There are no new H++ scenarios[29], which were used by some companies in the last round of plans (Wade et al., 2015).

Figure 5-11 - An overview of Met Office UKCP Products and their relevance to water resources planning



[27] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp-headline-findings-v2.pdf and https://www.metoffice.gov.uk/research/approach/collaboration/ukcp/
[28] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---caveats-and-limitations.pdf
[29] https://www.theccc.org.uk/publication/met-office-for-the-asc-developing-h-climate-change-scenarios/

C.1.2. Global Climate Models

A new set of GCM experiments have been developed for UKCP which combines the latest Met Office modelling with models from other research centres that have passed some screening tests to be included in the UKCP product. The data set includes 'GC3.05-PPE' – a new 15-member simulation of the global system at 60km resolution and a further 13 Coupled Model Inter-comparison Project (CMIP5) models (CMIP5-13). The former models were used to drive the 12km RCM simulations for the UK and Europe.

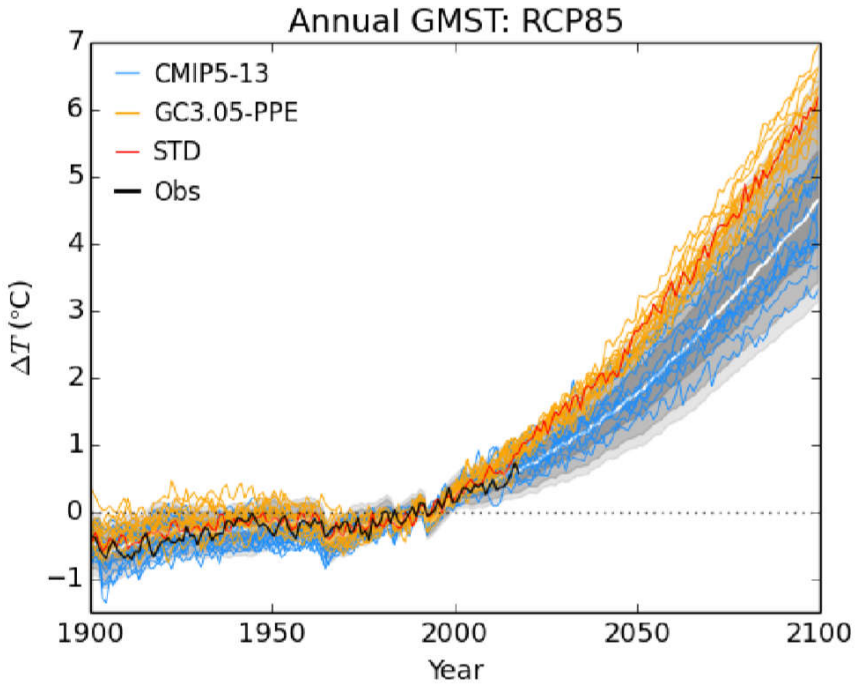
It is unlikely that global models would be downscaled for use in UK water resources planning because several other products have been made available by the Met Office (Figure 2.1). However, they are relevant because they provide a broader context for UKCP RCMs, highlight some weaknesses in the Hadley Centre model that carry through to the RCMs and include some data that could be applied in future water resources projects (e.g. a filtered set of CMIP5 models and UKCP Weather Types). The global data could be used to provide a simple set of change factors for England and Wales using downscaling and bias correction methods (Section 3.1), but most companies are expected to use the probabilistic data.

The Met Office UKCP Science Report provides detailed information on the evidence used for UKCP including the global models and how the Met Office models compare to the results from other modelling centres (Lowe *et al.,* 2018). The Met Office models sit at the "hot end" of the global ensemble (Figure 2.2) and as these models are used to drive the RCMs the high temperature uplifts will carry through to all RCM time series. The research literature has highlighted that the Met Office models are particularly hot and dry, offered some explanations behind this and suggested that these "hot and dry" models should be excluded from ensembles (e.g. Vogel, et al 2018). This has implications for the UK water industry because if plans are based *only on* these models, their validity could be challenged. This issue is discussed further in Section 4.

Table 5-1 - SWOT of UKCP Global Climate Models

Strengths	Weaknesses
Provides an ensemble of baseline conditions (28 models), with a greater range than the observed data. Includes a filtered set of the "best" 13 CMIP models as well as the Met Office Perturbed Physics Ensemble (PPE) models. The CMIP5 models in the ensemble cover a reasonable range of the changes reported in UKCP probabilistic data. Changes are spatially and temporally coherent across the UK. Available for a wider set of variables (that are physically consistent) than are available from the probabilistic projections. Will include Weather Types and other indicators that could be used for stochastic weather generation.	Relatively coarse resolution compared to other UKCP products. Only available for RCP8.5, a scenario with relatively high rates of warming. The Met Office PPE (15 models) is substantially warmer and drier than CMIP5 global projections, which is probably linked to the land-surface scheme used (Vogel et al., 2018). Application of the CMIP5 models would require spatial downscaling as well as bias correction.
Opportunities	**Threats**
Provides a 28 member time series, which can be used to explore changes in climate over the next 80 years. The Met office models could be used for stress testing extreme climate change at the margins of the global RCP8.5 ensemble.	Met Office PPE models simulate much higher rates of warming than the CMIP5 ensemble, which may undermine credibility of GCM and RCM outputs. See Figure 5-12and further discussion in Section 4.
Evidence	**References**
The Met Office UKCP Land Projections: Science Report (Murphy *et al*., 2018)	Lowe *et al.* (2018) Vogel *et al.* (2018)

Figure 5-12 - Historical and future changes in annual Global Mean Surface Temperature (GMST) from 1990-2100, relative to 1981-2000, from Strands 1 (probabilistic) and 2 (GCMs) of UKCP18, with future changes for the RCP8.5 emissions scenario



Notes: STD ~ Standard Perturbed Physics Ensemble (PPE) Variant; the grey shaded areas are the equivalent probabilistic data, with white line indicating the median.

C.1.3. Probabilistic data

The future probabilistic projections in UKCP18 are an update to those produced for UKCP09. The probabilities indicate how much the evidence from models and observations taken together support a particular future climate outcome. The projections are available for four different RCPs – 2.6, 4.5, 6.0 and 8.5 as well the scenario A1B, which was the Medium emissions scenario in UKCP09.

In the previous round of WRMPs most companies used the Medium emissions scenario for water resources planning but some also considered the UKCP09 High emissions scenario[30]. In UKCP18 there are 3000 possible climate outcomes for each RCP and future time period, whereas there were 10000 possible outcomes for each UKCP09 emissions scenario. Typically, a sub-sample of probabilistic data (e.g. 20 or 100 scenarios) are used for hydrological and water resources systems modelling (Thames Water, 2019).

The UKCP18 headline findings are similar to UKCP09 (Figure 2.3) but the move to RCPs means that the industry will need to consider different scenarios in order to understand the full range of possible climate outcomes. RCP6.0 is the closest to A1B (Medium emissions) but RCP8.5 is often used for risk assessment purposes. Some authors argue that the likelihood of RCP8.5 is reducing due to our efforts to reduce emissions[31] but observed carbon concentrations in the atmosphere continue to rise at a rate consistent with this scenario[32]. The range of possible outcomes in UKCP18 RCP8.5 probabilistic data cover almost all of the other scenarios.

The strengths and weaknesses of the available probabilistic data are summarised in Table 2-2.

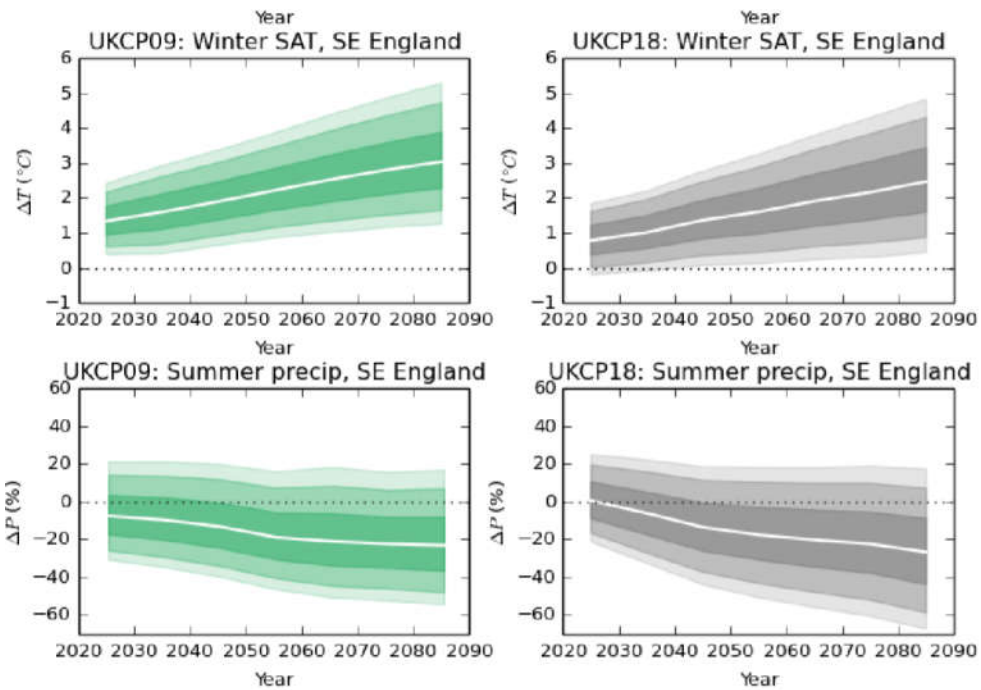
Table 5-2 - SWOT of UKCP probabilistic data

Strengths	Weaknesses

[30] Water Resources East and Anglian Water Services considered High Emissions and WRE also applied the UKCP09 Spatially Coherent Projections (SCPs), an 11-member ensemble, for regional planning rather than the probabilistic data.
[31] https://www.nature.com/magazine-assets/d41586-020-00177-3/d41586-020-00177-3.pdf
[32] https://www.esrl.noaa.gov/gmd/ccgg/trends/

Data are available for all RCP scenarios and for different future time periods. Provides a wider range of possible future changes in climate, including limiting warming to below 2°C and rising well above 4°C. The most widely used data set in WRMP19, so companies are familiar with these data.	Lack of spatial coherence between climate change factors in different regions, so risks that national drought could be overestimated. With 3000 scenarios for every RCP and time period, a sampling approach is needed to derive a practical set of future scenarios. No daily averages provided, only available as monthly, seasonal or annual projections for future time periods.
Opportunities	**Threats**
Clear audit trails: Updates the widely used UKCP09 probabilistic data, which formed the basis of most companies Price Review 2019 (PR19) assessments. The wider range of scenarios could be valuable for some specific risk assessments, which require a lower warming scenario, e.g. Task Force on Climate-related Financial Disclosures (TCFD) reporting. The wide range of possible futures is useful to specific decision-making methods such as robust decision making (RDM).	Lack of spatial coherence could lead to overestimation of risk and underestimation in yields of regional schemes (only if multiple sets of local factors are used). Application of different baseline periods between UKCP09 and UKCP18 – potential for errors and a communications challenge. Headlines of wetter winters and drier summers may underplay the likelihood of dry winters and wet summers.
Evidence	**References**
UKCP Science Overview and Science Reports Met Office (2018b) Summary plots are provided for UKCP river basin areas in Appendix A.	Lowe et al (2018); Atkins for Severn Trent Water (2019); Atkins for South West Water (2019).

Figure 5-13 - Probabilistic projections from UKCP09 (left) compared with those of UKCP18 (right), for the A1B emissions scenario for the South-East England administrative region



As part of a previous project, we assessed the impacts of UKCP18 probabilistic data using the same approaches to those used for UKCP09 projections for selected catchments in the Midlands and found that:

The overall impacts of climate change on river flows are very similar between UKCP18 and UKCP09 under a Medium emissions scenario and in the short term (2030s).

In the context of UKCP18 and improvements in underpinning climate science, UKCP09 appears to be too warm and marginally too dry; the extremely dry scenarios under UKCP18 A1B are less likely than in UKCP09 and were not selected when a “like for like” sampling methodology was adopted.

The UKCP18 RCP8.5 scenario has higher rates of warming than the UKCP09 Medium emissions scenario and is likely to have a greater impact on river flows and Deployable Outputs.

The choice of future emissions scenario (RCP4.5, RCP6.0, A1B or RCP8.5), the sampling method applied to UKCP18 probabilistic data and choice of time period (and any scaling method) were more important than the move to UKCP18 climate models *per se*.

The UKCP probabilistic data for all river basins, RCPs and SRE1AB have been downloaded and are summarised in Appendix A.

C.1.4. UKCP Regional Climate Models (raw data)

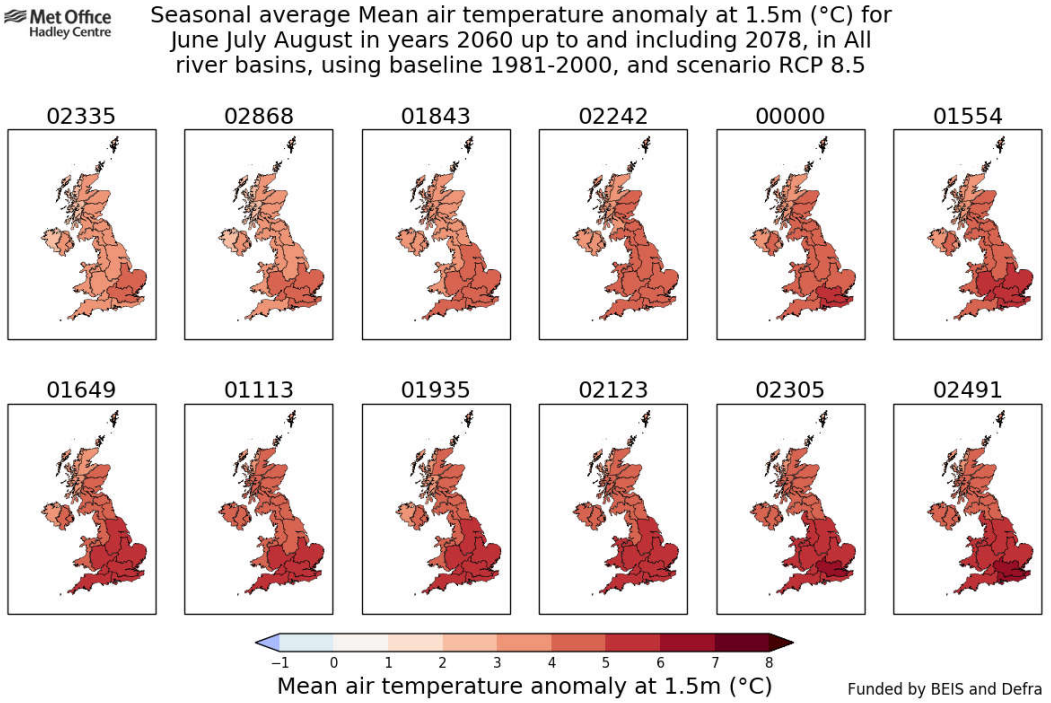
The UKCP18 Regional Climate Models are 12 projections for the RCP8.5 scenario at 12km grid scale. The headline findings are similar to the UKCP probabilistic data. The rates of warming are relatively high because the Met Office model projects greater rates of warming than most other CMIP5 global climate models. The RCMs cover a narrower range of possible outcomes than the UKCP18 probabilistic data.

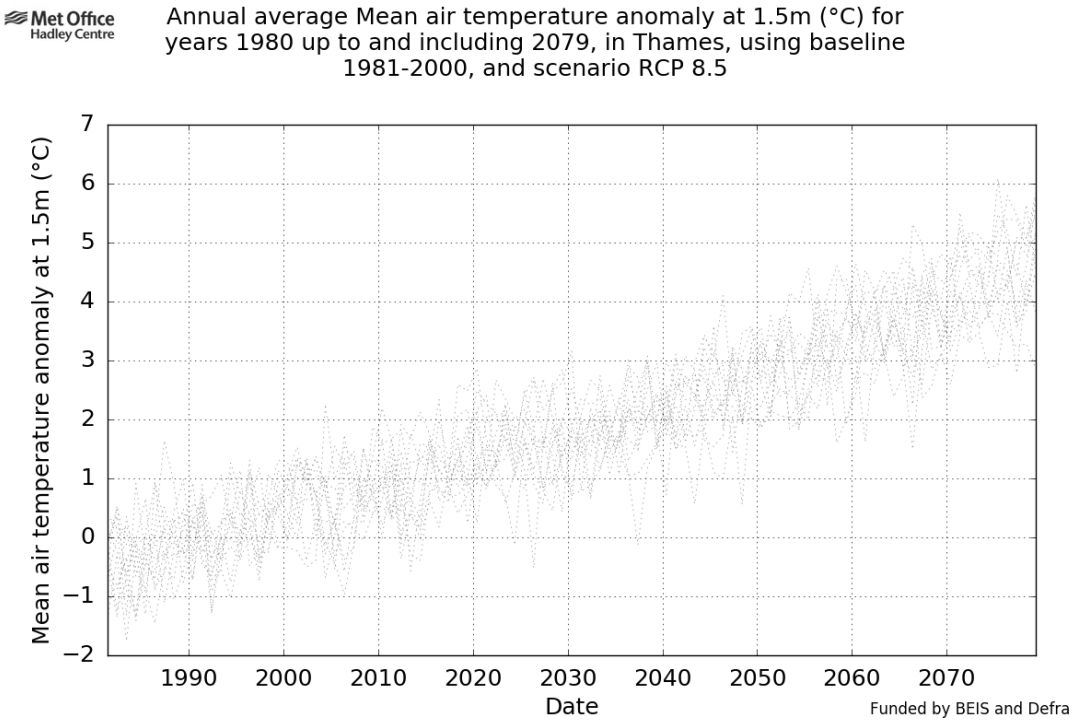
The most significant problem with the raw climate model data is the poor representation of precipitation at the grid and regional scales. For this reason, the data are bias corrected as outlined in Section 3. The strengths and weaknesses of the RCMs are summarised in Table 2-3. Comparisons of raw RCM data and HadObs observed data are shown in Appendix B.

Table 5-3 - SWOT of UKCP Regional Climate Models

Strengths	Weaknesses
Provides an ensemble of baseline conditions, with a greater range than the observed data. The 12km model is better at simulating heavy rainfall events in winter than the previous models. Finer spatial resolution than the 60km global model, with better representation of regional patterns. Changes are spatially and temporally coherent across the UK. Available for a wider set of variables than is available from the probabilistic projections.	Only downscales the Met Office atmospheric model. Systematic bias in the models means that they do not reproduce baseline rainfall very well. Do not cover the full range of the CMIP5 global projections, reported in the research literature. Indicates a smaller range of future changes than presented in the probabilistic scenarios. Only available for RCP8.5, a scenario with relatively high rates of warming. Projections only available from 1980 to 2080. Regional studies tend to consider impacts to 2100.
Opportunities	**Threats**
Provides a 12 member time series, which can be used to explore changes in climate over the next 60 years The Met Office promote the use of RCMs over and above weather generator methods (because they rely on atmospheric physics rather than statistics), but they may be more appropriate for stress testing rather than planning (Section 4).	Systematic bias in the precipitation baseline may undermine model credibility. Simulates much higher rates of warming than the CMIP5 ensemble, which may undermine credibility.
Evidence	**References**
Plots in Appendix B. Met Office (2018c)	Lowe *et al.* (2018).

Figure 5-14 - Example outputs of the Regional Climate Model: Increases in summer temperatures with implications for PET and soil drying (numbers indicate RCM run)





C.1.5. UKCP Regional climate model data (bias-corrected data)

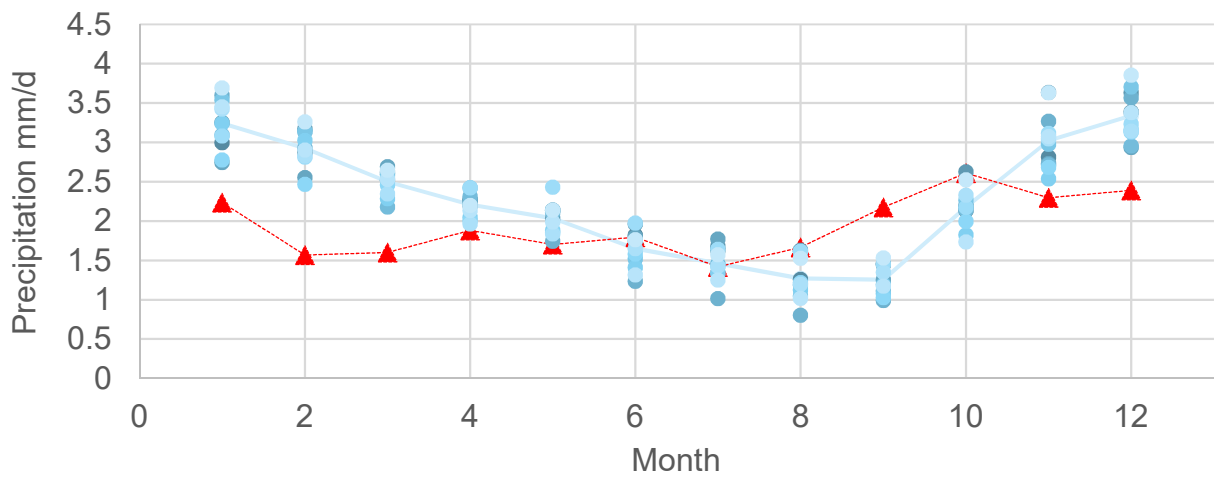
The UKCP18 Regional Climate Models bias corrected models are being developed by this project, based on published ‘quantile mapping’ bias correction methods (e.g. Li *et al.*, 2010). The specific method developed is referred to as Equidistant CDF mapping (EDCDF) in the scientific literature and involves correcting daily, seasonal and annual bias using 31 day moving window on daily RCM data independently for each variable and ensemble member. This method was chosen following a review of the RCM raw data at the river basin scale, which indicated clear problems with data at multiple time-scales (Figure 2.5).

There are 12 projections for the RCP8.5 scenario at the 12km grid scale. The strengths and weaknesses of the bias-corrected RCMs are summarised in Table 2-4. Section 3 provides a full description of the bias correction methodology and the impacts of bias correction are illustrated in Appendix B.

Table 5-4 - SWOT of UKCP bias corrected Regional Climate Models

Strengths	Weaknesses
The 12km model is better at simulating heavy rainfall events in winter than the previous models. Finer spatial resolution than the 60km global model, with better representation of regional patterns. Changes are spatially coherent across the UK. Systematic bias in the models are removed using bias correction methods, which ensure more realistic seasonal and daily variations in rainfall.	Only downscales the Met Office atmospheric model. Does not cover the full range of the CMIP5 global projections, reported in the research literature. Indicates a smaller range of future changes than presented in the probabilistic scenarios. Only available for RCP8.5, a scenario with relatively high rates of warming. Bias correction may have an impact on correlation between variables and also auto-correlation of time series; model may be "overfitted" to the baseline; variance could reduce.
Opportunities	**Threats**
Provides a 12-member time series, which can be used to explore changes in climate over the next 60 years. Baseline scenarios once corrected still provide a slightly wider range of conditions than the observed data.	Simulates much higher rates of warming than the CMIP5 ensemble, which may undermine credibility Many different bias correction methods can be applied, which will produce different results.
Evidence	**References**
Plots in Appendix B.	Lowe *et al*. (2018); Fung (2018)[33].

Figure 5-15 - An example of poor RCM model fit (blue) for catchment rainfall for the Thames Basin based on HadObs 1km data (red)



C.2. Other climate model data sets

C.2.1. MaRIUS Regional climate model data (raw and bias-corrected data)

The NERC MaRIUS project[34] included climate change modelling using data generated by weather@home2 project (Guillod *et al*., 2017a and Guillod *et al*., 2017b), which consists of a global and an embedded regional climate model (known as HadAM3P and HadRM3P respectively).

The main climate data generated within MaRIUS comprise 100 time series for the recent past and five plausible near and far future periods at a resolution of 25km. These timeseries represent a range of plausible continuous sequences of weather events. The most interesting features of MaRIUS are its larger ensemble of time series

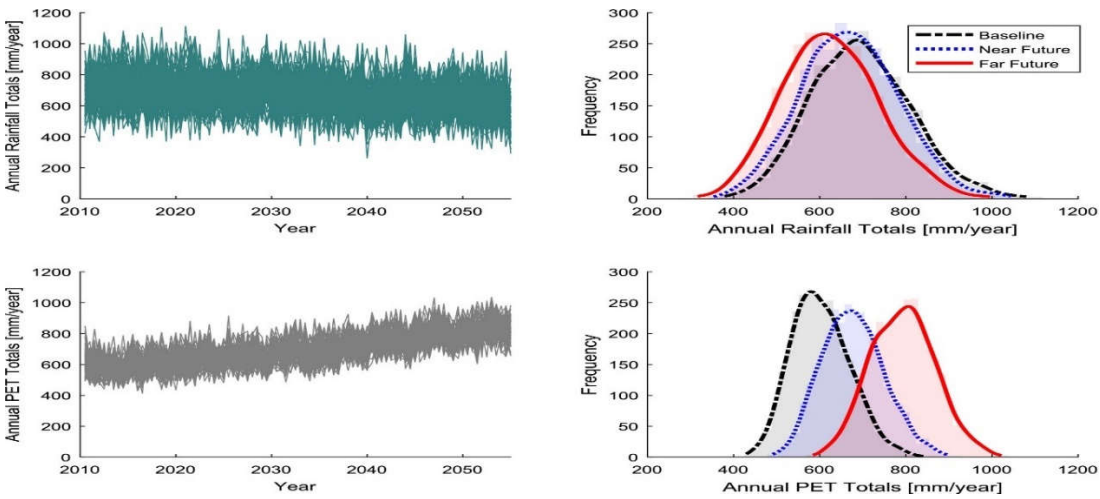
[33] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---how-to-bias-correct.pdf
[34] http://www.mariusdroughtproject.org/

compared to UKCP and its development of two potential evaporation data sets, which are not provided by the Met Office as part of UKCP. The main strengths and weaknesses of MaRIUS data are summarised in Table 2.5 and example outputs presented in Figure 2-6.

Table 5-5 - SWOT of MARIUS Regional Climate Models

Strengths	Weaknesses
Provides an ensemble of baseline conditions (n=100), with a greater range than the observed data. Finer 25km spatial resolution than the 60km global model, with better representation of regional patterns. Changes are spatially coherent across the UK.	Systematic bias in the models underestimates rainfall and over-estimates temperature in summer. A simple bias-corrected data set only adjusts for the mean change in monthly precipitation. Only available for RCP8.5, a scenario with relatively high rates of warming. The models were run one year at a time and then stitched together; a weakness for long droughts.
Opportunities	**Threats**
Provides a 100 member time series, which can be used to explore changes in climate for two periods in the next 80 years. Provides two PET data sets with different assumptions related to stomatal resistance.	Arguably replaced by UKCP18 RCMs, which may be regarded as a superior version of the Hadley Centre model. Both data sets appear to suffer from hot and dry bias in future compared to other CMIP5 models Data formats and structure are not easy to work with.
Evidence	**References**
Plots in Appendix B.	Guillod *et al*., 2017; Hall *et al*., 2019.

Figure 5-16 - Example outputs for the Thames basin (Hall et al., 2019)



C.3. Bias correction methods

Regional climate models can have systematic biases, which mean they have limited skill in reproducing important hydrological characteristics, such as the magnitude and frequency of very wet days and the length of dry periods. In addition, some models may be too warm/dry and/or too wet in specific months or seasons to accurately reproduce catchment water balances. For these reasons climate model outputs have typically been used to understand changes rather than absolute values of future rainfall and other climate variables.

Some water companies have an interest in using RCM data directly in their modelling, which requires the application of bias correction methods to correct the baseline period and future scenarios based on the assumption these biases carry through to the future modelling periods.

There are a range of possible applications and “use cases”:

Use of monthly change factors: Bias correction is not absolutely necessary if water companies or regional groups want to apply change factors. UKCP probabilistic data or RCM data can be applied to observed data or

stochastically generated baseline data. The use of change factors is very similar to linear scaling, which is the simplest form of bias correction of RCM time series data (Fung, 2018).

Use of monthly RCM time series. Bias correction is advisable if users want to use monthly time series. There are a number of possible methods that could be used to implement bias correction at a monthly scale (e.g. Vidal and Wade, 2008). These data could be combined with observed or stochastically generated patterns of precipitation, temperature and PET. However, bias correction may have an impact on correlation between variables and also auto-correlation of time series.

Use of daily RCM time series: Bias correction is essential if users want to use daily precipitation and other variables. There are a large range of possible methods for bias correction of daily data, which correct for specific issues, such as too many days of drizzle at a daily scale, through to correcting monthly statistics (Maraun, 2016). In general, basic methods change some aspects of the data, such as the change factors or long-term trends and should be used with caution and in the context of the objectives of the proposed study.

C.4. Previous UK water industry approaches

The traditional 'delta change' approach to applying climate change factors (based on future modelled versus historic modelled data) is akin to the simplest form of bias correction (based on the differences between historic modelled and historic observed data) (Navarro-Racines et al., 2015). In effect, climate models are used to understand potential future changes in monthly average climate and the observed baseline climate is regarded as the best data set for quantifying natural variability, including daily extremes.

The UKWIR CL-04 project (2004) applied bias-correction methods to 6 GCMs to produce national climate scenarios that were used by the water industry (Vidal and Wade, 2008). The method fitted statistical distributions to monthly temperature (normal) and precipitation (gamma), corrected the raw climate model data to match the observed data for the baseline period and assumed that future biases were the same as those seen in the model baseline period.

C.5. Future Flows

The Future Flows project took a different approach, most importantly precipitation was bias corrected using a gamma distribution at a daily scale rather than monthly scale and one transformation was applied to all the rainfall data, irrespective of the month or season (Prudhomme *et al*., 2012; Piani *et al*., 2010). Temperature was shifted using a linear transfer function for each month (Prudhomme *et al*., 2012). The main impact of this approach is removing the "drizzle" effect where climate models produce too many rain days with low intensities. The simple method has been shown to be effective in improving model skill at both wet extremes and for dry periods (Piani *et al*., 2010), however it would not be sufficient on its own to correct UKCP18 data due to the larger seasonal bias in modelled versus observed data.

C.6. UKCP guidance note

The Met Office presented a short summary of bias correction methods in the format of a UKCP Guidance Note[35].

Key assumptions include:

The causes of the biases do not change in the future.

Sufficient observational data are available to characterize the reference climatology.

The physical consistency of the different climate variables remains valid.

The original biases are not large and if they are, such models should be disregarded from the assessment.

In addition, the note explains that "[t]he most common application of the methods presented use station data as reference and are not suitable in a multi-site context, as the temporal correlation between neighbouring stations does not enter the method". On the contrary, it could be argued that the spatial correlation problem is trivial compared to original poor fit of the modelled data, which already exhibit unrealistic spatial patterns compared to what is observed.

The UKCP note highlights four methods. However, these are broad groups with many variants within each methodology: linear scaling, variance scaling, quantile mapping, trend-preserving quantile-mapping. For

[35] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---how-to-bias-correct.pdf

example, so called quantile mapping methods can be implemented on daily data or monthly data using fitted statistical distributions or empirical distributions (ranked data/percentiles).

C.7. Summary of methods

The different groups of bias correction methods are summarised in Table 3.1 based on UKCP guidance and methods implemented by this project are discussed in Section 3.5. There is a very large literature base on bias correction methods, which are likely to be reviewed as part of the larger Met Office Strategic Priorities Fund (SPF) research project.

Table 5-6 - Alternative bias correction methods including those tested on this project (grey shaded)

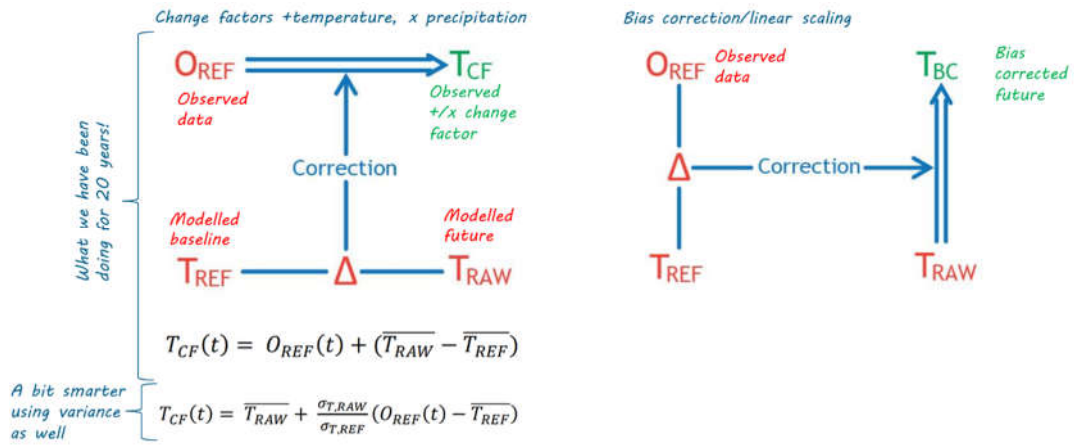
Method	Summary	References	Code	Tested
Linear scaling	Simple method that only adjusts for mean bias. Akin to the simple delta change methods used in the water industry but can be applied at any time-step, not just monthly.	UKCP Note (Fung, 2018) CCAFS website http://ccafs-climate.org/bias_correction/	Simple to code	Yes Useful comparator to other methods
Variance scaling	A popular method that adjusts mean and variance bias.	UKCP Note (Fung, 2018) CCAFS website http://ccafs-climate.org/bias_correction/	Simple to code	No
Quantile mapping	A method often used for precipitation as it preserves the distribution (of daily or monthly data) and can inform extreme values; a large family of methods with different variants.	UKCP Note (Fung, 2018) CCAFS website http://ccafs-climate.org/bias_correction/ Lafon *et al.* (2013), Li, Sheffield and Wood (2010), Maraun (2016),	Yes (QMAP in R[36]). Atkins Python code	Yes Two variants - a basic form and more advanced form
CDF transform	Method implemented by the 'Climate Data Factory'. This method does not rely on the stationarity hypothesis: model and observational distributions can evolve and be different. The assumption is that the model and observational distributions can be inferred by a mathematical function (the "transform") which remains the same for past and future distributions.	Michelangeli *et al*. (2009). Kallache *et al*. (2011)	R Code available[37]	No But this is similar to the method of Li et al 2010, which has been implemented.
Scaled Distribution Mapping	A bias correction method that preserves raw climate model projected changes.	Switanek *et al* (2017)	Yes (python)[38]	No

[36] https://cran.r-project.org/web/packages/qmap/qmap.pdf
[37] R Code available on rdocumention.com by M. Vrac
[38] https://pycat.readthedocs.io/en/latest/intro.html

C.8. Principles of change factors and bias correction using linear scaling

The simplest form of bias correction is using linear scaling and this approach is similar to the traditional use of change factors, which has been an industry standard approach for more than 20 years (see Fung, 2018; Navarro-Racines, 2015 and Appendix D). Change factors consider the long-term average differences between a modelled future period and a modelled reference or control period (for 20-30 year periods) and then apply this correction to the observed data using the same reference period or, in the case of UK water resources, longer observed records. Temperatures changes are additive (+ degrees centigrade) and precipitation changes are multiplicative (expressed % change or factors, e.g. +20% or x 1.2). The corrections are normally applied on a monthly basis. Linear scaling is very similar but uses the differences between modelled and observed data for the reference period and then applies this correction to the future modelled time series (Figure 3-1).

Figure 5-17 - Schematic representation of change factors and linear scaling



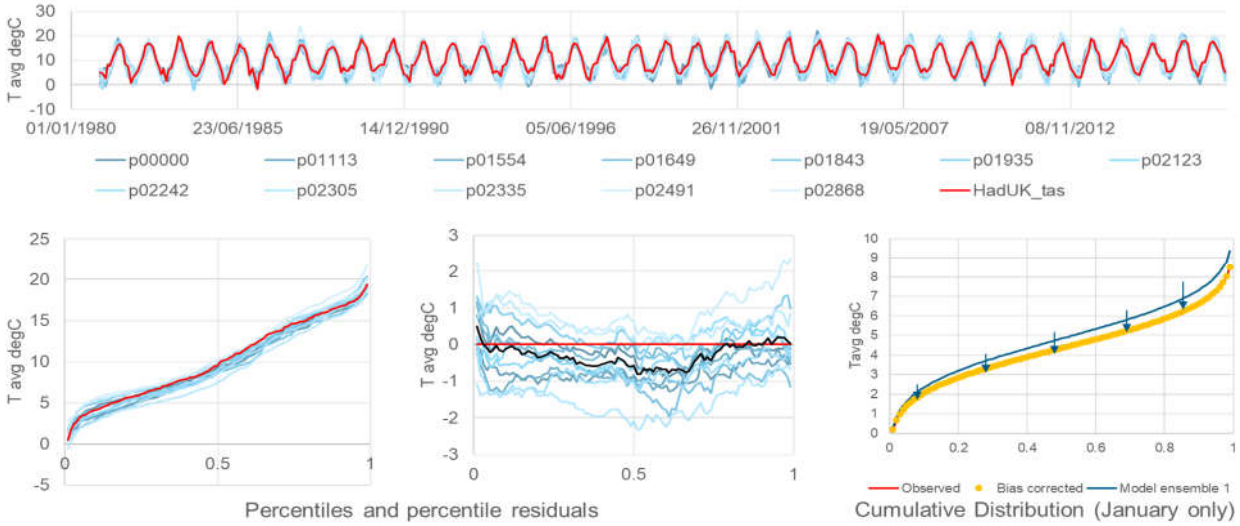
C.9. Principles of bias correction using quantile mapping

Quantile mapping approaches seek to adjust modelled data considering the distribution of modelled versus observed data rather than using a single annual, seasonal or monthly linear scaling factor (see Fung, 2018; Navarro-Racines, 2015, Appendix D).

The results of a very simple example using monthly temperatures is summarised in Figure 3-2. The UKCP RCM monthly data are compared to the HadObs 12km data as a time series and as percentiles in Fig. 3-1 (a) to (c). Overall the RCMs appear to match the lowest and highest temperatures well but are too cool around the median values by 0.5 – 1°C (black line). Bias correction in this case would consider all months or individual months and compare the modelled to the observed distributions and map, then shift the modelled distribution for each model to the observed distribution.

Fig. 3-2 (d) shows one model ensemble member that is too warm for January and therefore the shift in this case would be downwards to make it match the observed distribution. For the correction of the baseline or future periods there are different ways these can implemented mathematically, e.g. using a look up table of change factors/differences or mapping the data using standard and the inverse of statistical distributions, typically the gamma distribution for precipitation. Further details on the implemented methods are included in Appendix D.

Figure 5-18 - Average temperature biases in the Thames River basin in RCMs (a) monthly time series, (b) percentiles, (c) residuals of modelled minus observed and (d) correction of one model for January



The results of the bias correction for the baseline period 1981-2000 are shown in Appendices B.4 and B.5. An example of the impacts of bias correction on monthly precipitation and seasonal precipitation and temperatures is shown in Figures 3.2 and 3.3 for the baseline period 1981-2000.

By design, linear scaling perfectly matches the observed data set at a monthly scale, although the daily pattern of precipitation is not corrected and the variance of the data is substantially reduced, which means the results are not appropriate for the assessment of extremes, including droughts.

Implementing QM on daily precipitation using the percentiles of the whole data set corrects for the annual errors in precipitation (in this case reducing the average precipitation effectively) and errors in the daily pattern but fails to correct for monthly and seasonal biases. This method was used for the Future Flows project but is not sufficient for UKCP18 due to the large seasonal bias in Southern England in UKCP18.

QM31 based on the Equidistant CDF method, corrects the data using the percentiles of 15 days prior and 15 days after each day. This method worked well at all time scales, correcting daily rainfall distributions, monthly averages and annual average precipitation. This method considers the differences in the modelled historic and observed historic and assumes that the differences can be carried forward and applied to future time periods. It therefore avoids some of the limitations of basic QM, e.g. related to extrapolation. The risk of this approach is over-fitting a model to a relatively short baseline period. It involves are very large number of parameters.

The impacts of bias correction on seasonal precipitation and temperature are shown best using scatterplots of the means and variances versus the HadObs data (Figure 3.3). In the case of Anglian, the modelled winter precipitation for the baseline period is far too high. QM on the daily data for the year does not correct this and variance in each data set is also too great. Linear scaling corrects the means but hugely reduces variance in winter and spring. Only the QM31 method corrects adequately for means and variance of both precipitation and temperatures.

The impacts of the QM31 bias correction method are shown in Figure 3-4, including the observed data and clearly showing its impact in the historic and future periods version the raw climate model data. In the case of Anglian river basin, precipitation is reduced, seasonal errors are corrected, and temperatures are increased. It is likely that bias correction will substantially increase the impacts of climate change on river flows in Southern England due to the increased temperatures/PET and an increased likelihood of low seasonal rainfall. The project case studies will test the impacts of using raw versus bias corrected data in hydrological models.

Figure 5-19 - Impacts of linear scaling and Quantile Mapping on monthly precipitation in the Anglian river basin

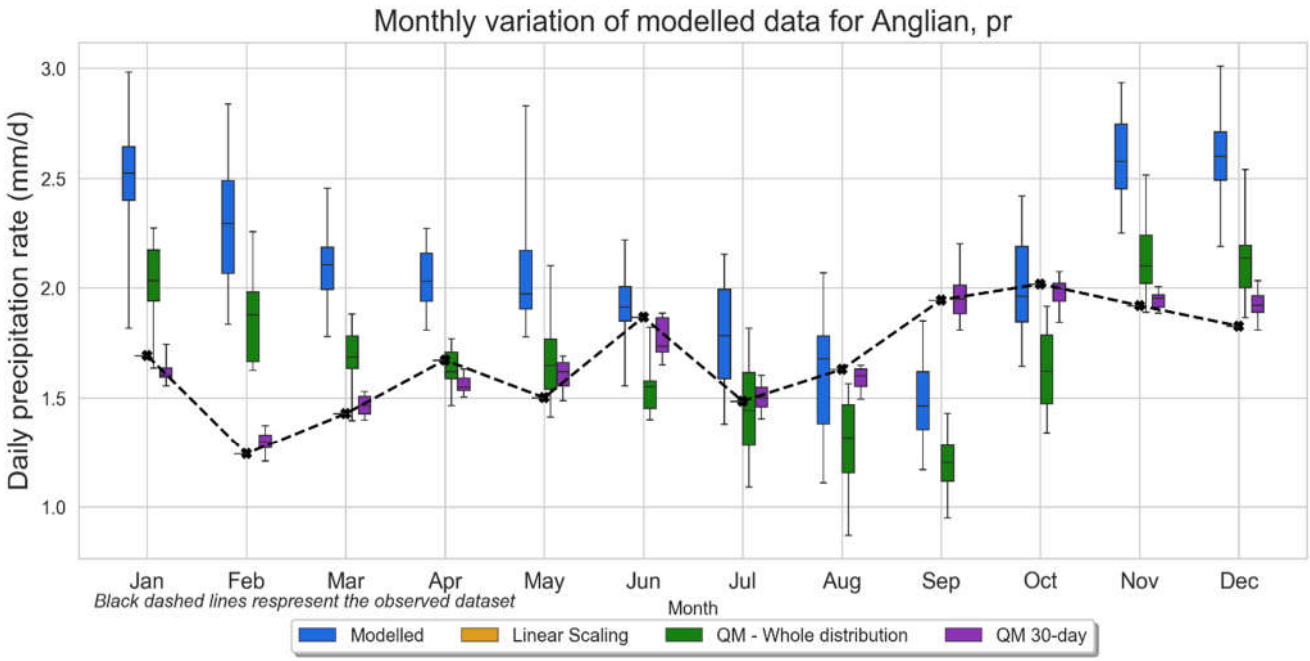


Figure 5-20 - Impacts of linear scaling and Quantile Mapping on seasonal precipitation and temperatures in the Anglian river basin

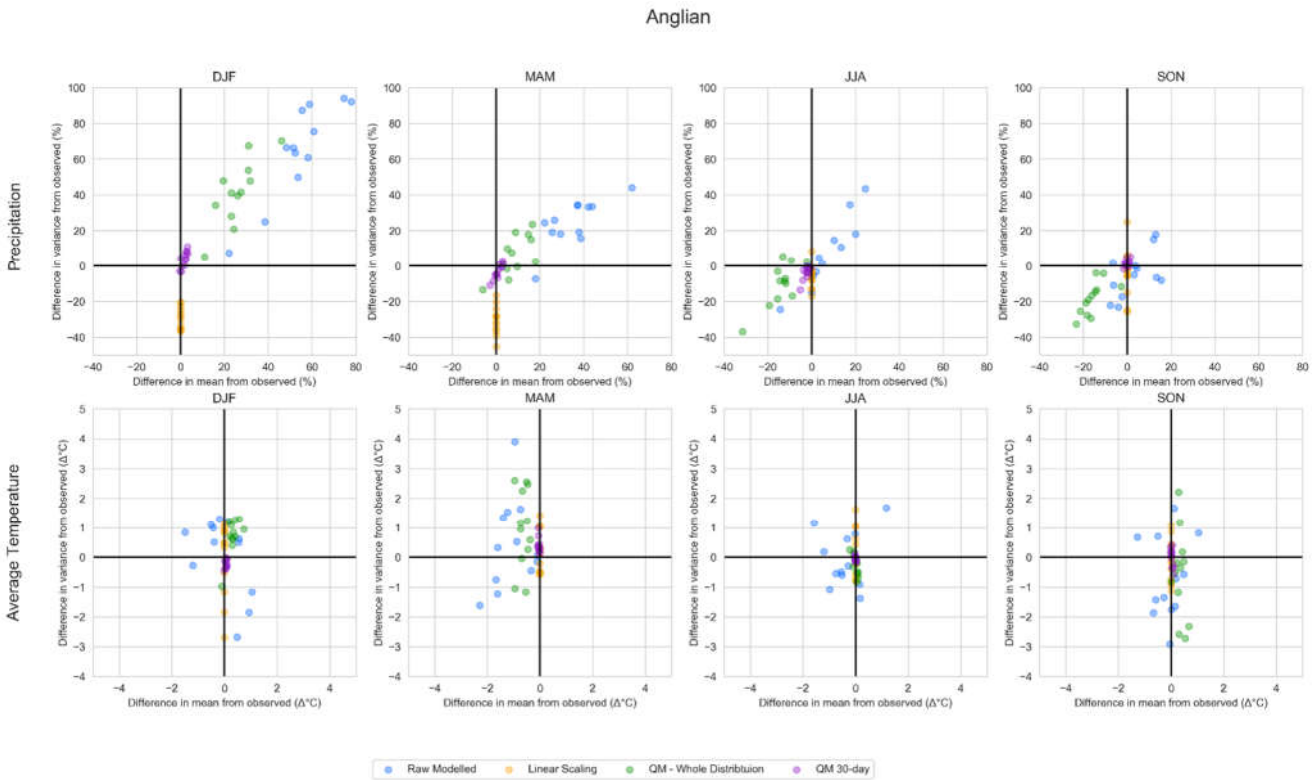
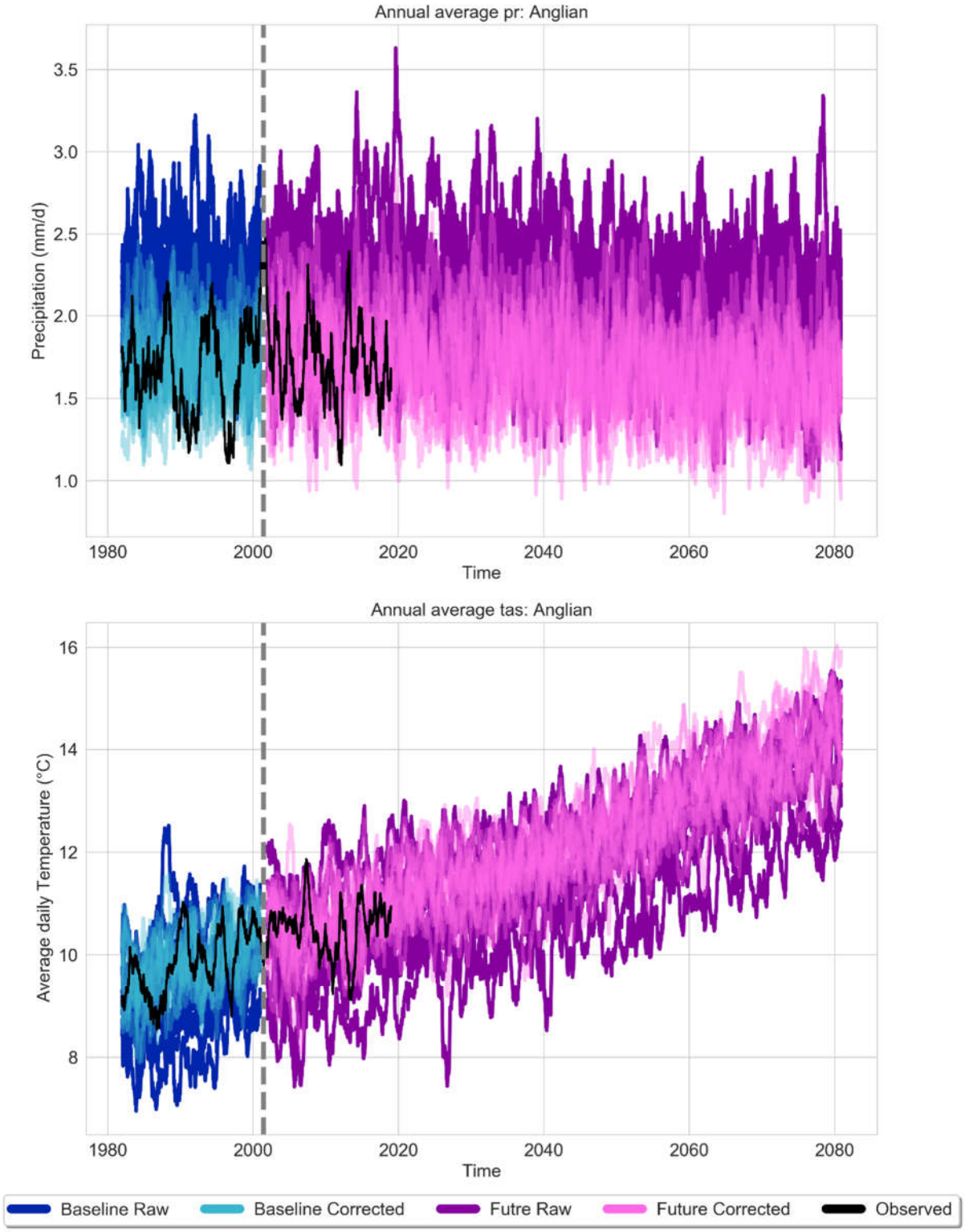


Figure 5-21 - Impacts of EDCDF on baseline and future evolution of precipitation and temperature time series [to be updated]



C.10.Conclusion

There is an increasing number of climate data sets available for water resources planning; the UKCP18 climate projections have updated the UKCP09 probabilistic projections but also provide more complex choices of products including global models at 60km resolution and regional models at 12km resolution. In addition, the Met Office have now released new *'HadObs'* 1km and 12km observed data sets and there are alternative modelling products available from recent NERC research projects, such as the MaRIUS data sets.

The UKCP18 probabilistic data are very similar to the UKCP09 data but are presented as RCP scenarios rather than Low, Medium, High Special Report on Emissions Scenarios. A Medium A1B scenario is also available that can be used for direct comparison to UKCP09. The UKCP river basin or administrative area data could be used for regional water resources planning for some regions; however, caution is needed combining UKCP probabilistic data from adjacent regions because these data are not spatially coherent.

The Met Office RCMs provide a poor fit to river basins in England and Wales and require bias correction before model timeseries are used for impact assessment. The project has reviewed several bias correction methods and shown that the EDCDF mapping method provides a pragmatic approach to correcting the data for use in regional planning. Further case study work with water company data will demonstrate the use of these data for risk assessment.

The Met Office Global and Regional Climate Models are relatively hot and dry in future periods compared to models from many other climate modelling centres. Some studies have questioned the physical plausibility of the changes in extreme temperature and precipitation modelled and suggested that these models should be excluded from impacts studies. This needs to be considered further because it influences how and what the models could be used for in regional water resources plans. One possibility is that the RCMs should only be used for stress testing proposed schemes rather than water resources planning *per se*, which may continue making use of the probabilistic data to characterise future change in climate.

Further case study work is needed but the limitations and systematic errors in regional climate models indicate that there is still a clear requirement to plan using good quality historical data, supplemented by the application of stochastic methods to explore possible drought scenarios.

The key parts of the climate and hydrological impacts assessment process are summarised in Figure 4.1. including the weather generator and its interaction with climate change models for development of future scenarios.

An outline roadmap for the longer-term development of tools is shown in Table 4.1. Available tools are shaded in green, this project's work in yellow and other future developments (under contract) in orange.

Figure 5-22 - The overall drought risk assessment process combining weather generator outputs with climate change models

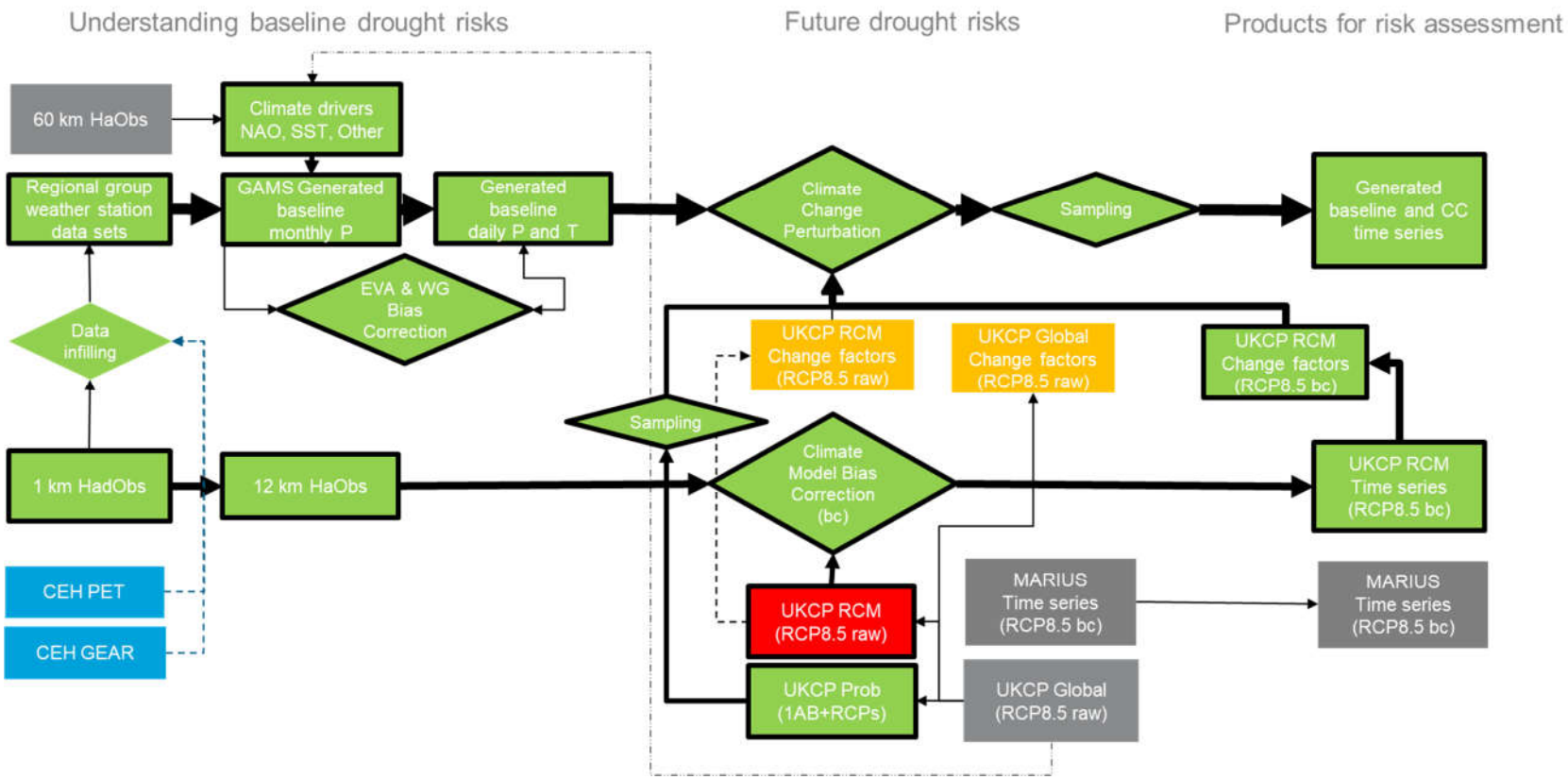


Table 5-7 - Outline road map for the development of climate data tools

Tools for PR19	Regional Plans 2020	WRMP 24	WRMP29	Comments
Regional point rainfall data sets	Extended HadObs 1km 1873-2018; new regions	Longer hindcasts Better EVA	UKCPNext	Better hindcasts and higher resolution data; new areas modelled
CEH GEAR & PET	EA PET 1km (due March 2020)	Recalibration of hydro and GW models		Model recalibration will be needed if inputs are updated
Drought/rainfall generation GAMS model with NAO/SST indicators	'Drought Studio' better post processing; EA/SCA indicators; better guidance and implementation	'Drought Studio 2' Weather Types (UKCP due to release in April 20) Met Office Drought Explorer	'Drought Studio 3' National drought libraries Met Office DePreSys & 'UNSEEN' methods	Evolution towards non-stationary multi-variate daily Weather Generators or use of Numerical-Weather-Prediction reanalysis
UKCP09 Probabilistic data; smart sampling	UKCP18 Probabilistic (sampled at national scales)	UKCP18 spatial new "smart sampling" tools	UKCPNext	Sample over large areas. Lack of spatial coherence means that new sampling methods may be needed
n/a	UKCP18 Global Models (60km)		UKCPNext	Possible use of GCM CMIP5 models as simple scenarios
UKCP09 SCPs	n/a	n/a	UKCPNext	Discontinued but were used in WRE in 2019.
Future Flows RCM data (bias-corrected)	'Climate Studio' UKCP18 RCMs (bias corrected P/T with QM30)	Met Office SPF Project UKCP18 RCMs (Oct 2020), river flows & recharge (March 2021)	UKCPNext HiRes RCMs (bias correction)	Bias corrected precipitation only
n/a	MaRIUS (100 x bias corrected precipitation and PET)	n/a	Future research	Difficult to apply – to be tested further (x 100 time series @ 25km)
Flow generator (SAMS)	n/a	Will companies still use flow generation methods?		Some zones may still lack hydrological models

Extreme Value Analysis (Frequentist)	Extreme Value Analysis (Frequentist/Bayesian)		EVA (Non-stationary and multivariate)	Move towards more sophisticated methods

Notes: Drought Studio and Climate Studio are Atkins python and R codes for water resources risk assessment. The Met Office Drought Explorer and DePreSys work are under contract with Anglian Water services. The Met Office SPF project is being implemented by CEH.

C.11. Sampling climate change projections

C.11.1. Introduction

The UK Climate Projections 2018 (UKCP18) provide Global Climate Models (60km), Regional Climate Models (12km), a high-resolution RCM (2.2/5km) and probabilistic data (25km) for scenario RCP8.5. Probabilistic data are also provided for scenarios RCP2.6, RCP4.5, RCP6.0 and A1B Medium Emissions.

The strengths and weaknesses of each data set for regional water resources planning was presented in our first report.

C.11.2. Choice of RCPs and the sampling problem

Most products are focused on RCP8.5 because this is a “business as usual” type scenario that demonstrates the impact of climate most clearly, over and above natural variability and model uncertainties. The UKCP probabilistic data for RCP8.5 present a wide range of outcomes and in the mid-century is not much warmer than RCP4.5, RCP6.0 and A1B. In fact, the probabilistic results for RCP8.5 encompass the range of possible outcomes from other scenarios.

The Met Office RCMs are driven by the Met Office RCM HadGEM3 and these models are at the *“warm and dry”* end of possible outcomes by the end of he century. In fact, they average 1 ^{o}C warmer than the average of the probabilistic data in the 2070s compared to a 1981-2000 baseline. This makes RCMs very useful for risk assessment of low probability-high impact outcomes and for stress testing plans but less useful for considering adaptive planning that requires consideration of a wider range of outcomes. The Met Office GCMs include HadGEM3 models but also 13 CMIP5 models that have average warming of 2.5 ^{o}C above 1981-2000 for the same future period, which is much closer to the average of the probabilistic data.

The UKCP probabilistic data has 3000 possible outcomes and most companies will find it impractical to model this number of scenarios. The main issue with this approach for regional planning is the that factors for England and Wales would need to be used to ensure spatial coherence in future climate change signals. In the last round of plans a sampling method was used to present subsets of 100 and 20 (10 + 10 dry) scenarios for risk assessments. The same could be done again but a more even and unweighted sampling strategy is now more appropriate.

C.11.2.1. Proposed approach

It is proposed that Regional Plans make use of RCP8.5 RCMs for the regions/basins plus RCP8.5 CMIP5 change factors for England and Wales (or the regions) for climate change impacts assessment. They may wish to use all 25 scenarios (12 RCMs plus 13 GCM) or select a sub-set but these should indicate average warming of 2-3 ^{o}C by the 2070s rather than 3 to 4.5 ^{o}C in the HadGEM3 subset.

We are waiting for guidance on WRMPs but for these plans the RCMs could effectively replace the 10 “dry” scenarios used in the previous assessments and the CMIP GCMs would replace the 10 additional scenarios that companies used in PR19. This has the advantage that all companies would use the same scenarios rather than sample the probabilistic data in different ways.

C.11.3. Methods

To test the impact of different methods, we used the RCMs (raw and bias corrected P and T factors), CMIP5 GCMs and full probabilistic data for case studies 1, 4 and 5.

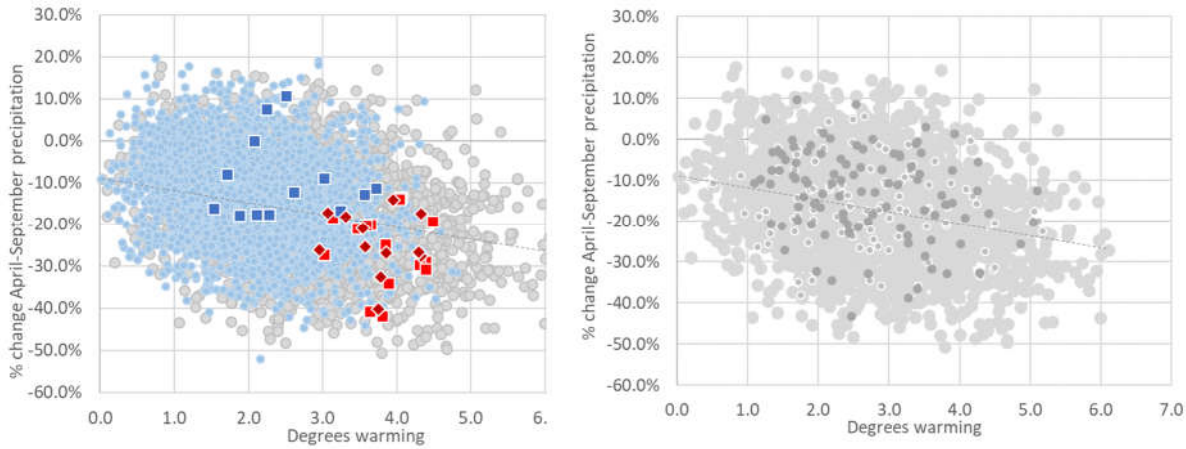
To illustrate key differences the England and Wales data from all UKCP source were downloaded for monthly average temperatures and precipitation. A key indicator for systems in the Midlands is April to September precipitation so this was plotted against average warming to compare data sets.

To explore the impacts of sub-sampling UKCP probabilistic data, e.g. selecting a representative sub-set of 100 outcomes of changes in monthly precipitation and temperature, a simulator was developed in @Risk. This fitted distributions to the 3000 UKCP samples for 24 change variables and modelled the correlations between these variables. The simulator can then be used to resample these distributions and produce coherent sub-samples of the full data set.

C.11.4. Results

C.11.4.1. England and Wales climate change scenarios for the 2070s

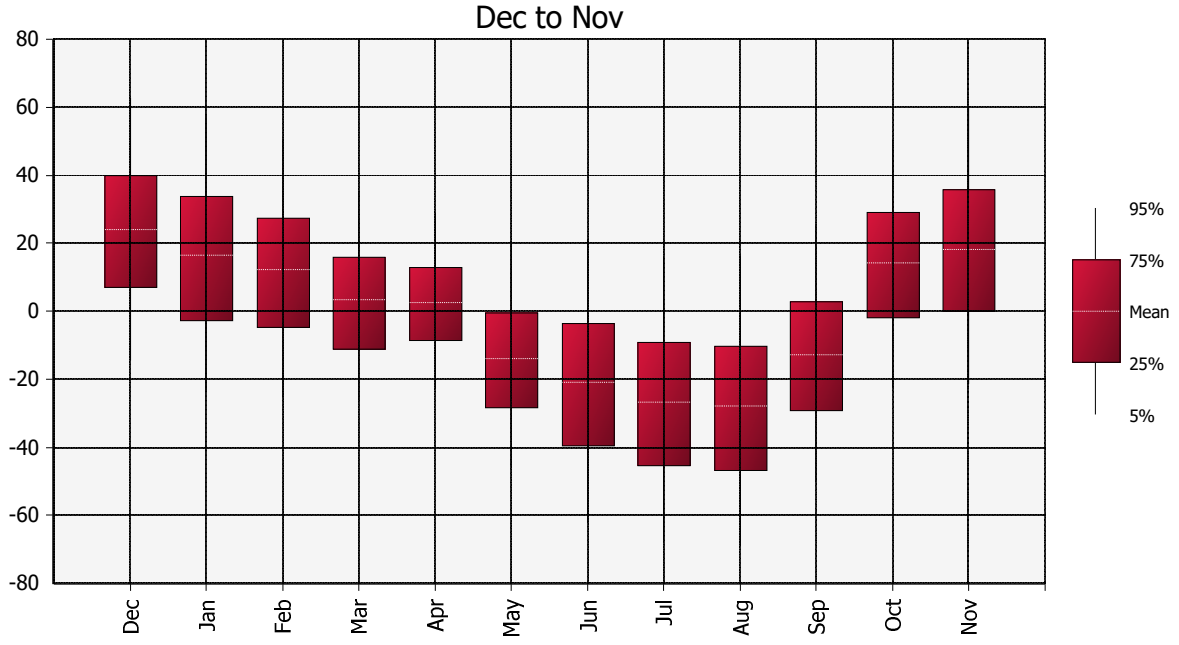
Changes in future seasonal rainfall and average annual temperature are shown in the figure below. The Met Office global models are shown as red squares and the RCMs as red diamonds; the CMIP5 models are shown as blue squares; the probabilistic data are light grey dots along with two simulated sub-samples of 100 scenarios. The blue dotted lines ate the 10th and 90th percentiles of the probabilistic data are show that three of the RCMs are very hot or dry and three CMIP scenarios show no change or increased seasonal precipitation.

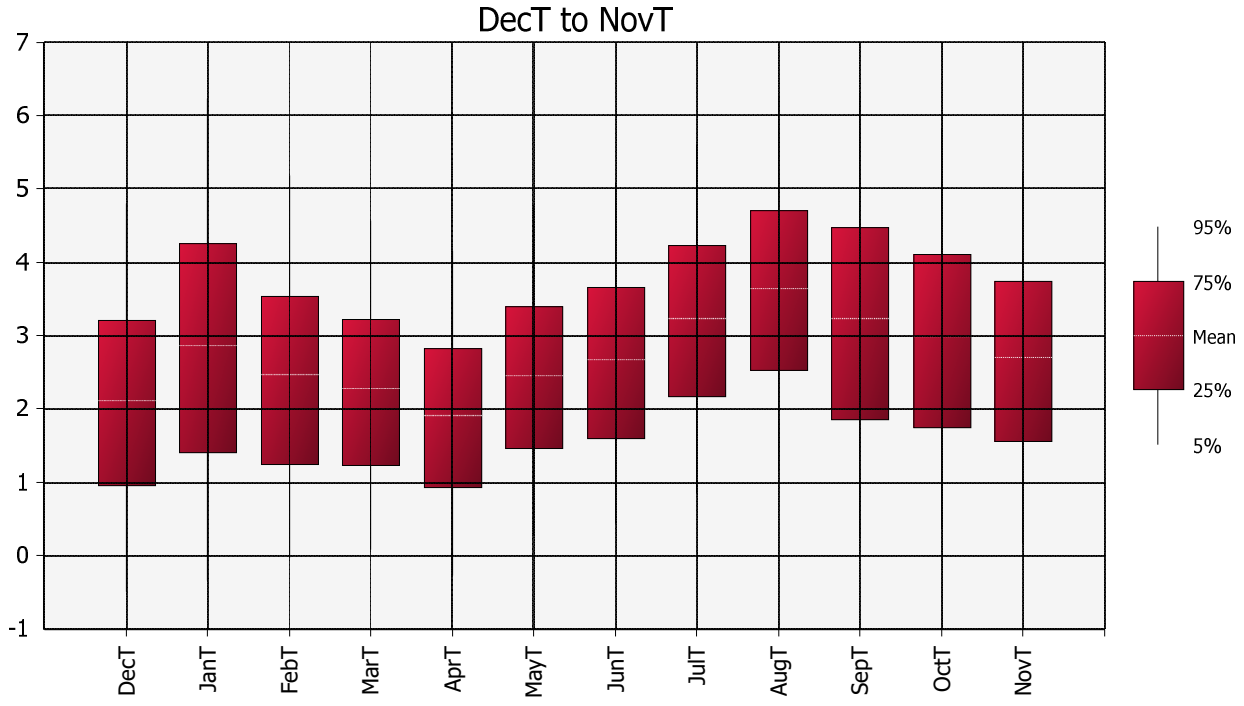


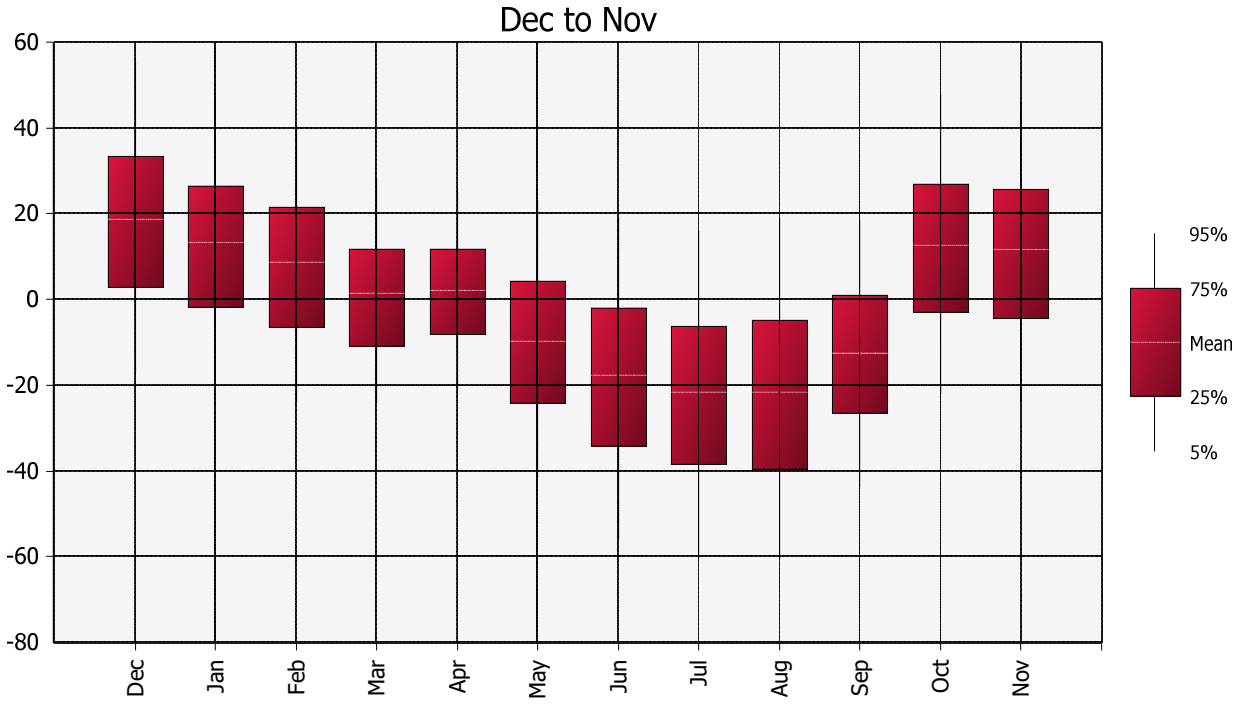
2060-2079

Summary statistics	RCP 8.5					A1B		
Annual average temperature rise °C	Probabilistic 3000	Random 100	LHS 100	RCM HadGEM3 n=12	GCM CMIP5 n=13	Probabilistic 3000	Random 100	LHS 100
Median warming	2.7	2.5	2.7	3.8	2.3	2.0	2.0	2.0
10th percentile	1.4	1.5	1.4	3.1	1.7	1.0	1.0	1.0
90th percentile	4.1	3.9	4.2	4.3	3.5	3.1	3.1	3.1
April-Sept rainfall change								
Median change	-17%	-12%	-17%	-26%	-12%	-13%	-13%	-13%
10th percentile	-32%	-27%	-28%	-32%	-18%	-27%	-26%	-27%
90th percentile	-2%	-1%	-2%	-17%	6%	0%	-1%	0%

Simulated UKCP change factors (n=100) precipitation % and degrees warming for 2060-2079


Dec to Nov
80
60
40
20
0
-20
-40
-60
-80
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
95%
75%
Mean
25%
5%


DecT to NovT
7
6
5
4
3
2
1
0
-1
DecT
JanT
FebT
MarT
AprT
MayT
JunT
JulT
AugT
SepT
OctT
NovT
95%
75%
Mean
25%
5%


Dec to Nov
60
40
20
0
-20
-40
-60
-80
Dec
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Feb
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Apr
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Jun
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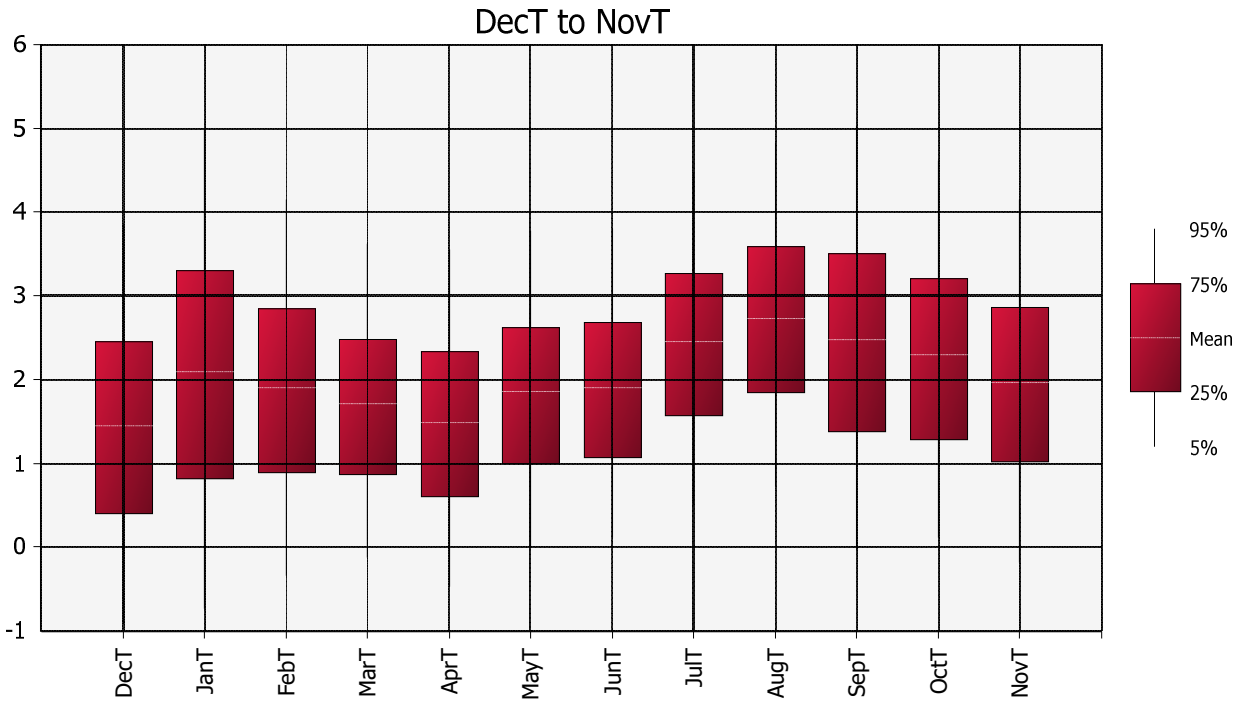
Oct
Nov
95%
75%
Mean
25%
5%


DecT to NovT
6
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4
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DecT
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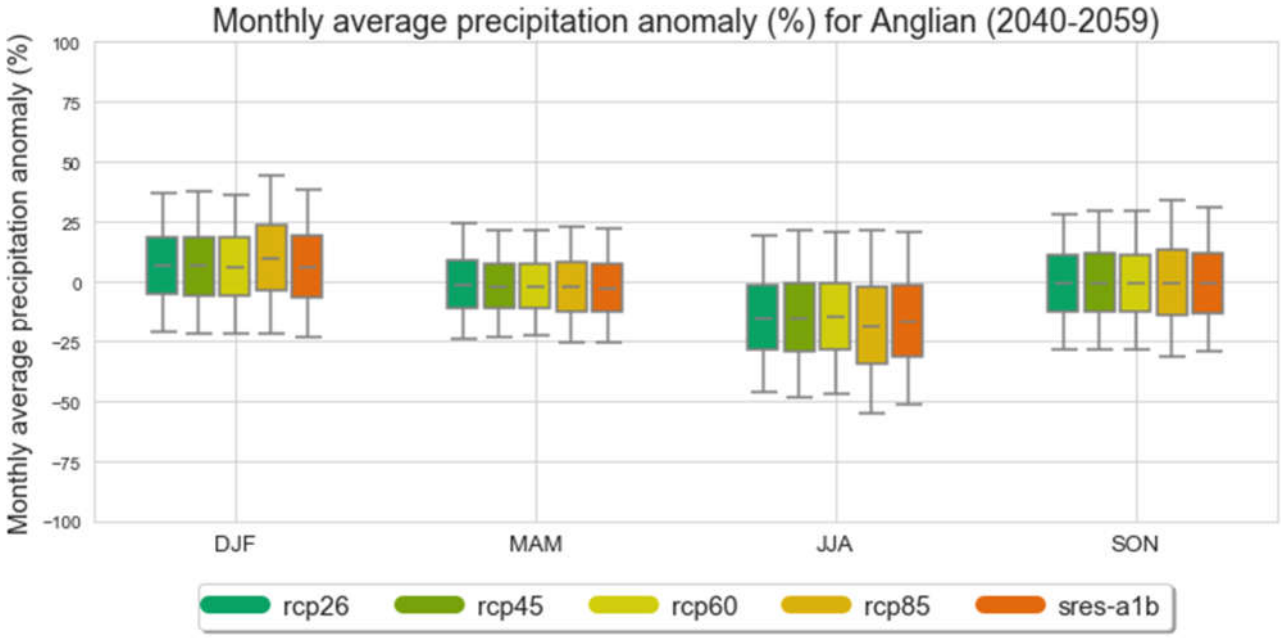
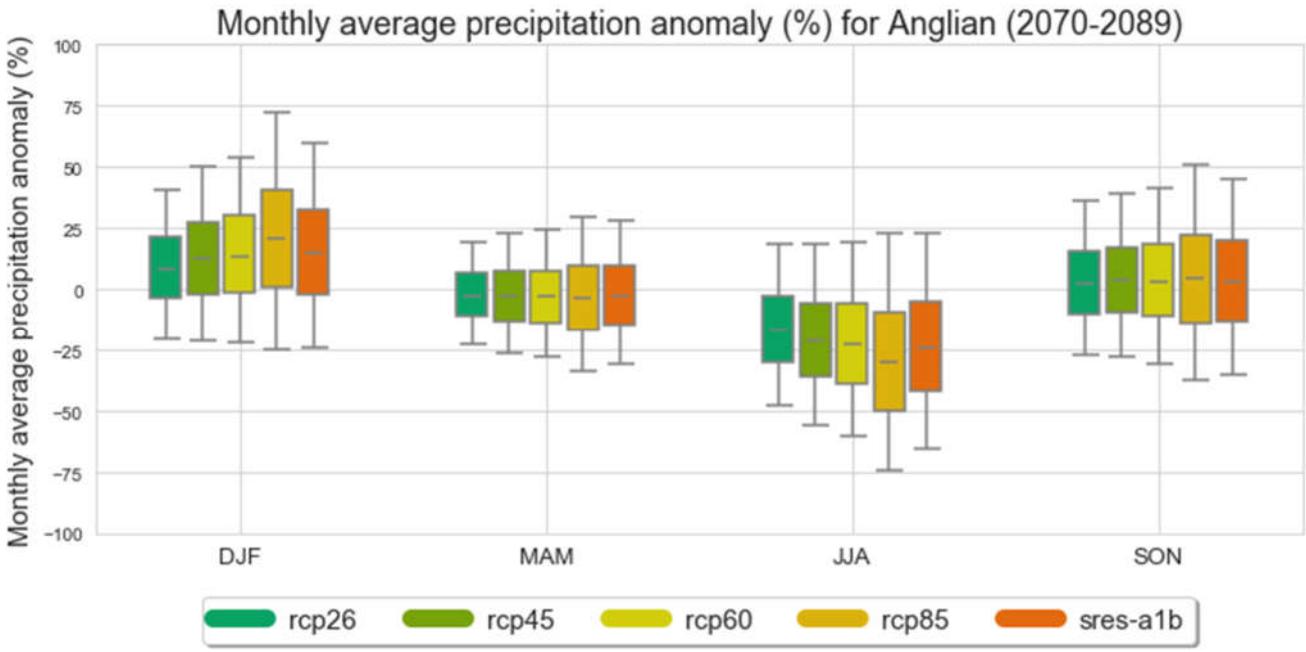
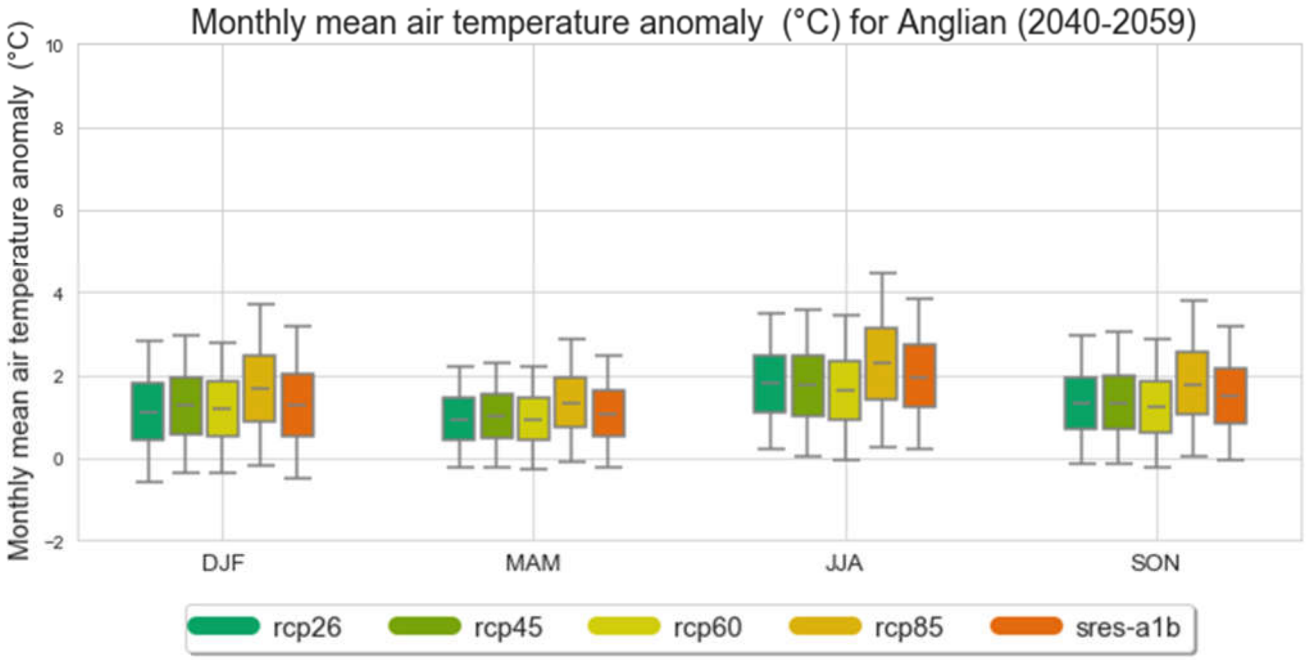
JunT
JulT
AugT
SepT
OctT
NovT
95%
75%
Mean
25%
5%

C.12. UKCP Probabilistic data for river basins

C.12.1. Precipitation and temperature anomalies for all RCPs and river basins






Monthly mean air temperature anomaly (°C) for Anglian (2040-2059)
Monthly mean air temperature anomaly (°C)
10
8
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−2
DJF
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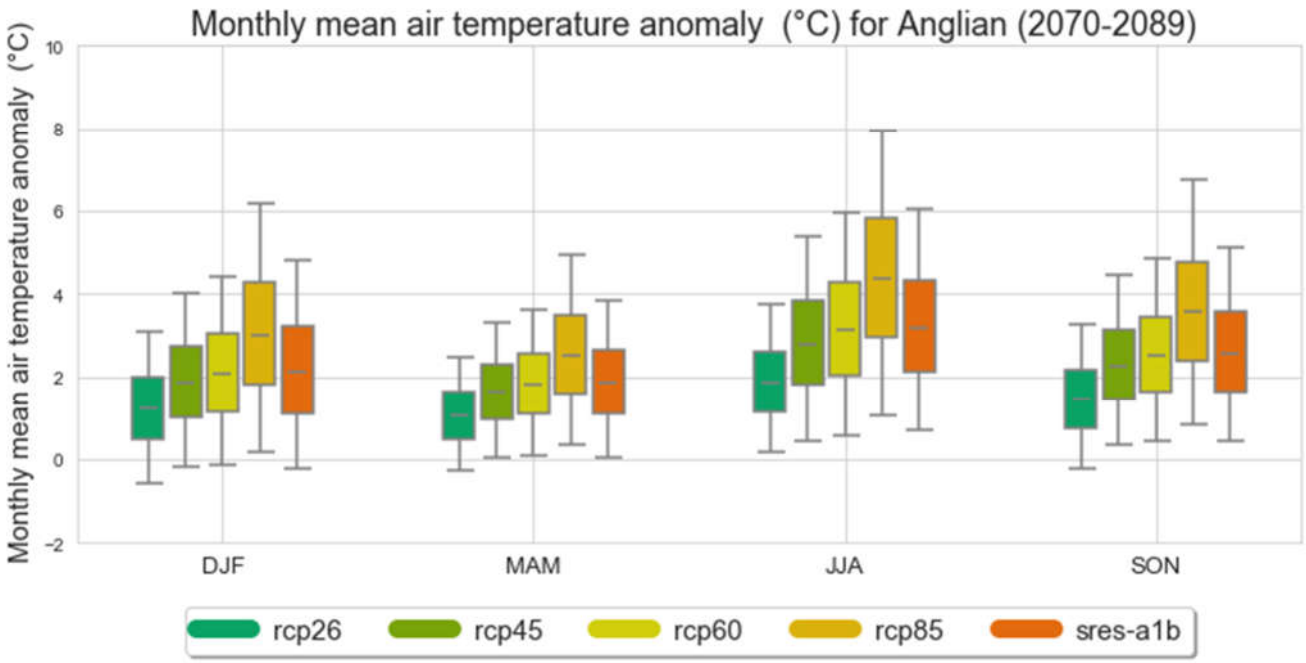
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b


Monthly mean air temperature anomaly (°C) for Anglian (2070-2089)
Monthly mean air temperature anomaly (°C)
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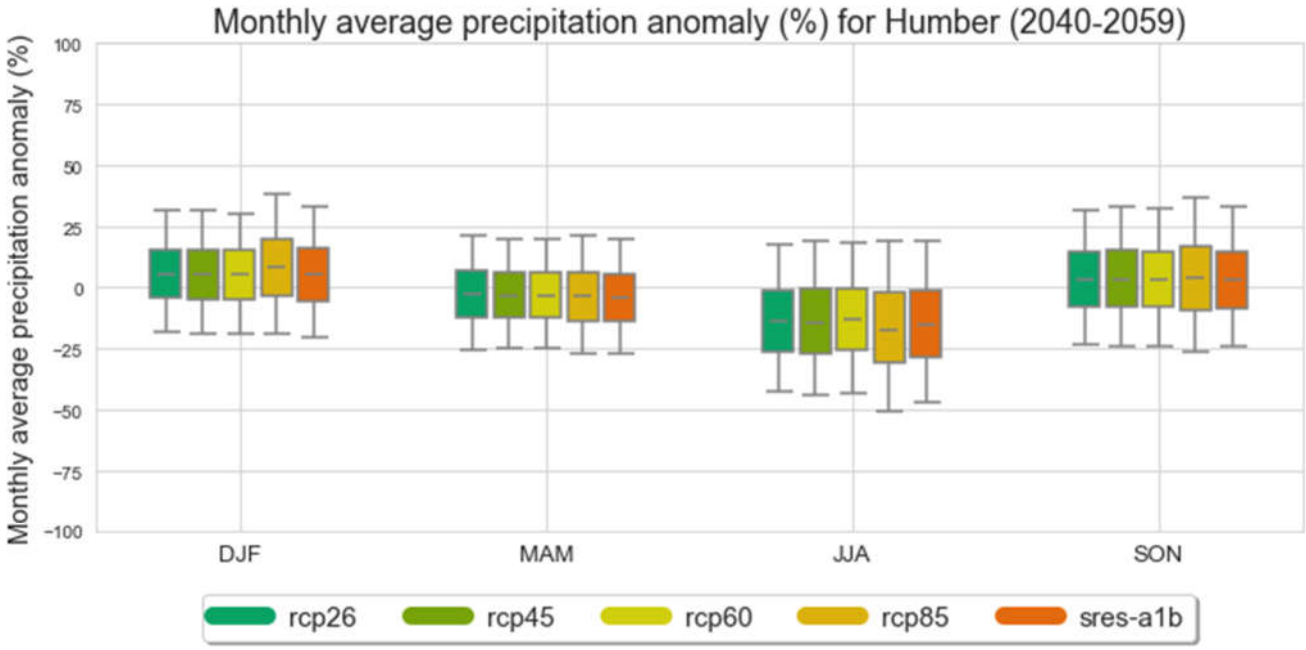
Monthly average precipitation anomaly (%) for Humber (2040-2059)
Monthly average precipitation anomaly (%)
100
75
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0
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−100
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JJA
SON
rcp26
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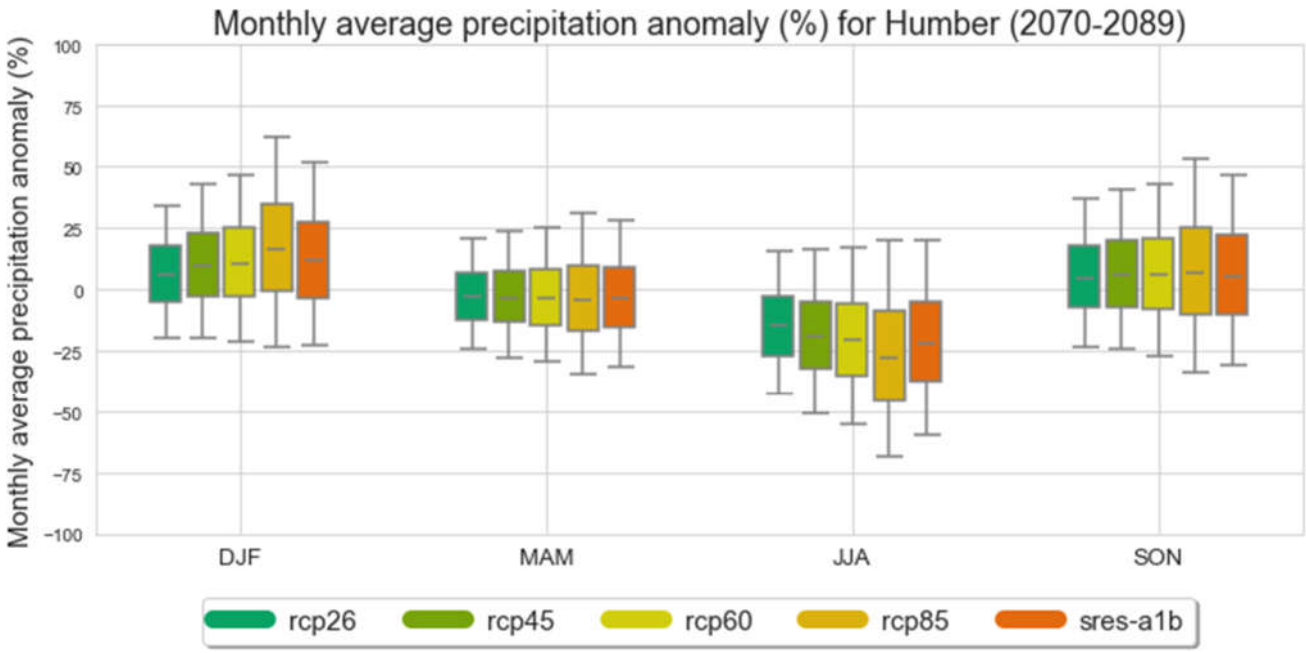
rcp85
sres-a1b


Monthly average precipitation anomaly (%) for Humber (2070-2089)
Monthly average precipitation anomaly (%)
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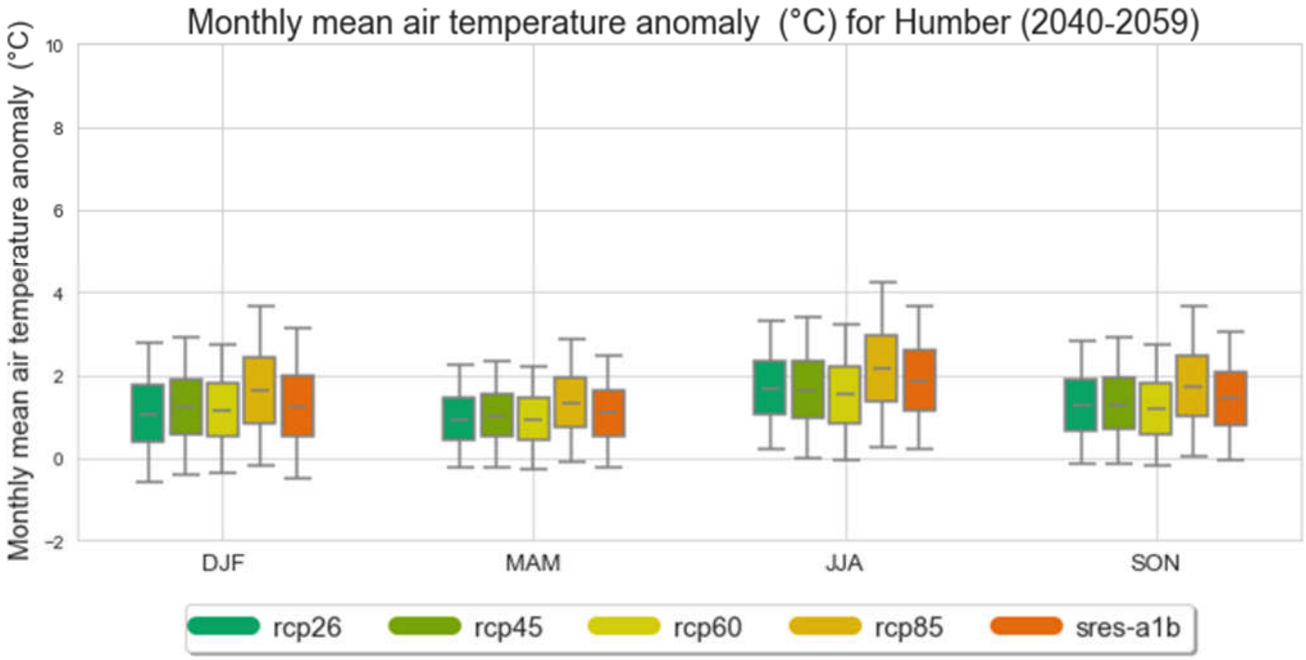
Monthly mean air temperature anomaly (°C) for Humber (2040-2059)
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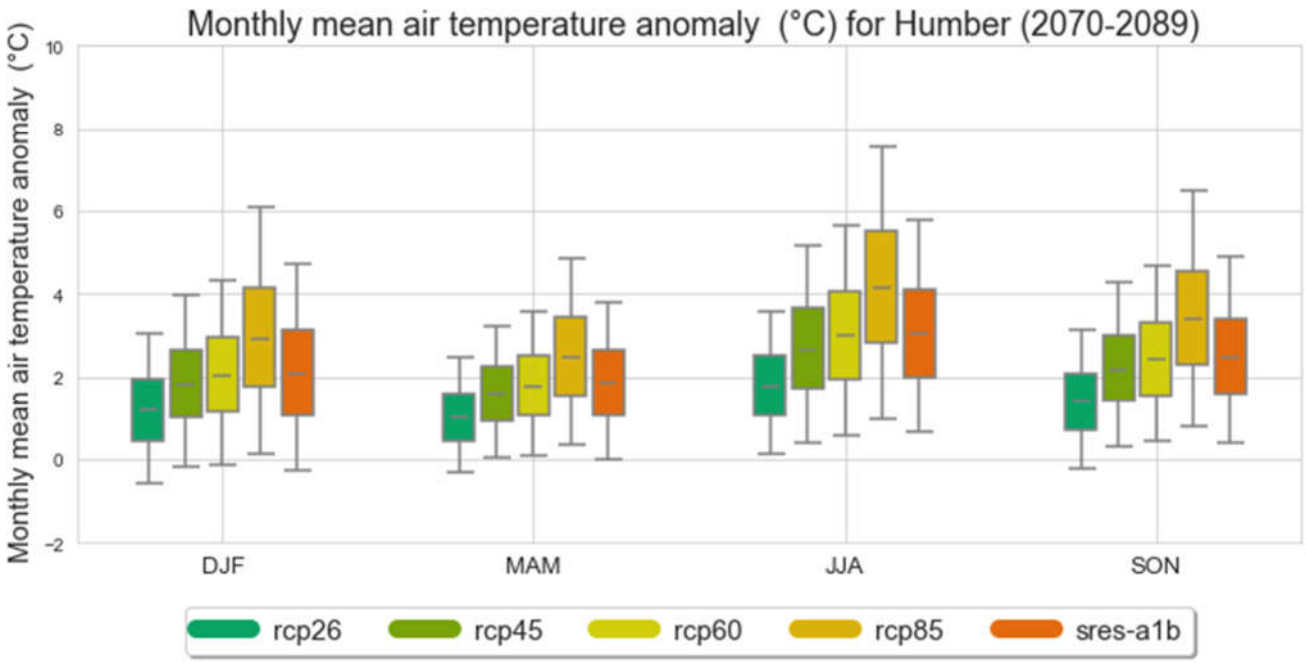
Monthly mean air temperature anomaly (°C) for Humber (2070-2089)
Monthly mean air temperature anomaly (°C)
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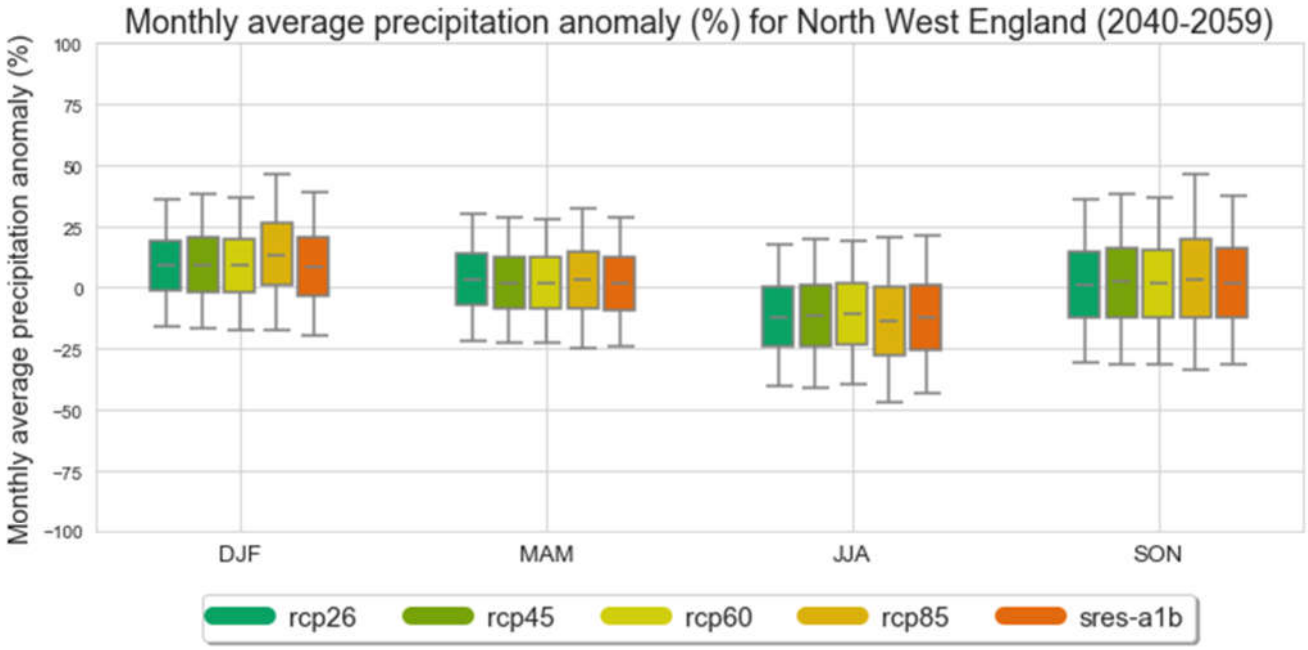
Monthly average precipitation anomaly (%) for North West England (2040-2059)
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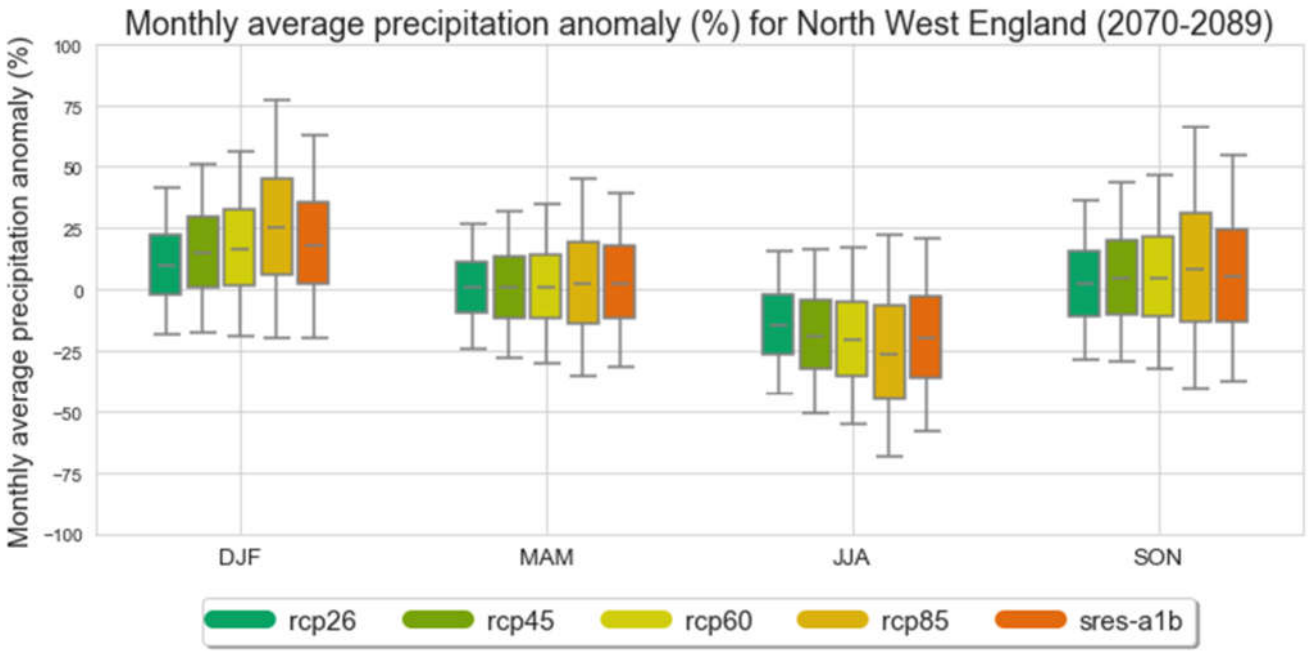
Monthly average precipitation anomaly (%) for North West England (2070-2089)
Monthly average precipitation anomaly (%)
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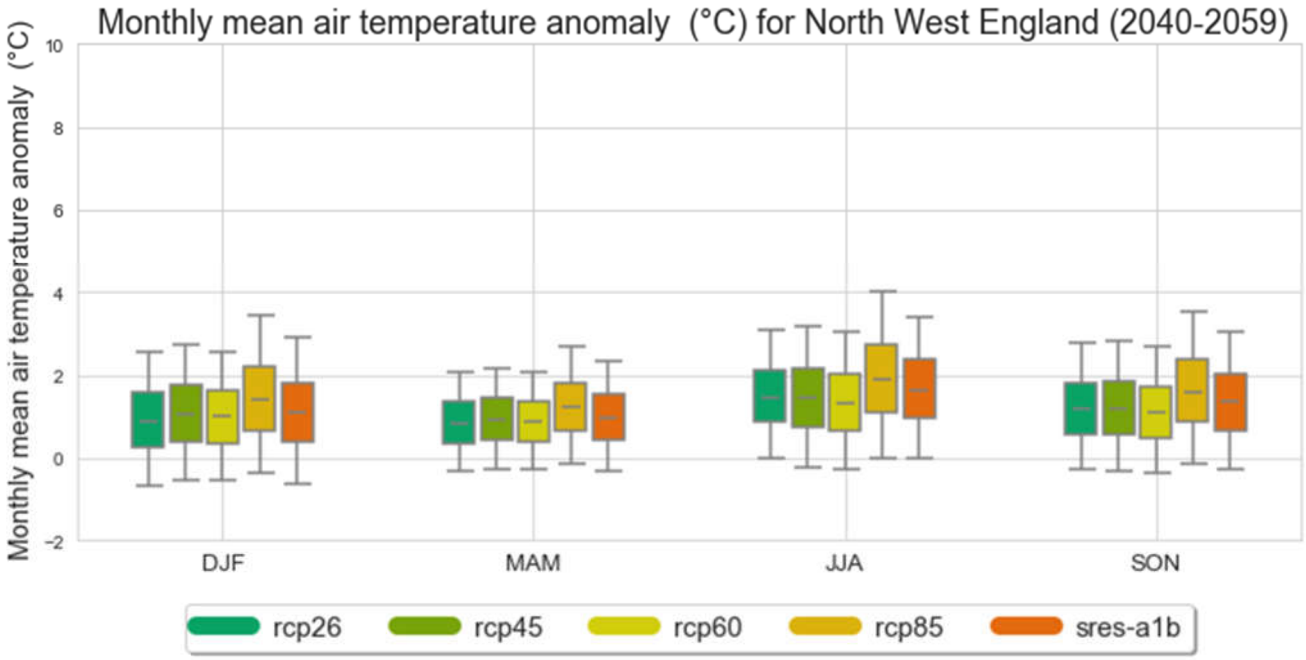
Monthly mean air temperature anomaly (°C) for North West England (2040-2059)
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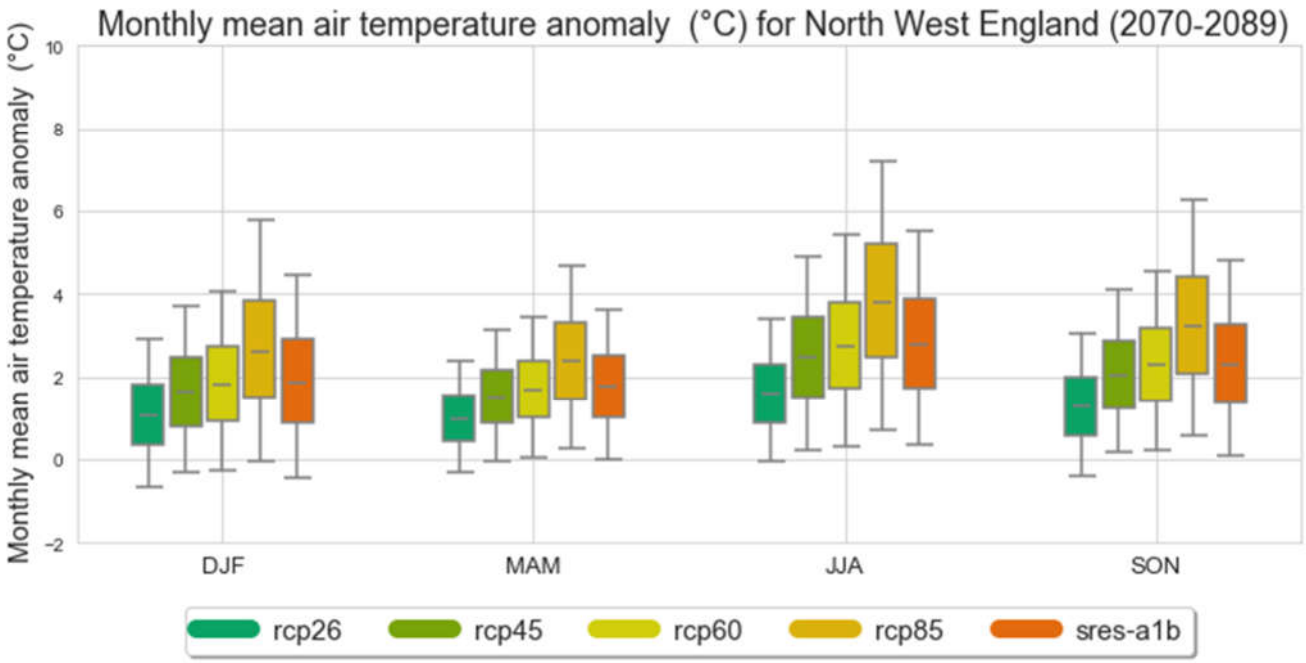
Monthly mean air temperature anomaly (°C) for North West England (2070-2089)
Monthly mean air temperature anomaly (°C)
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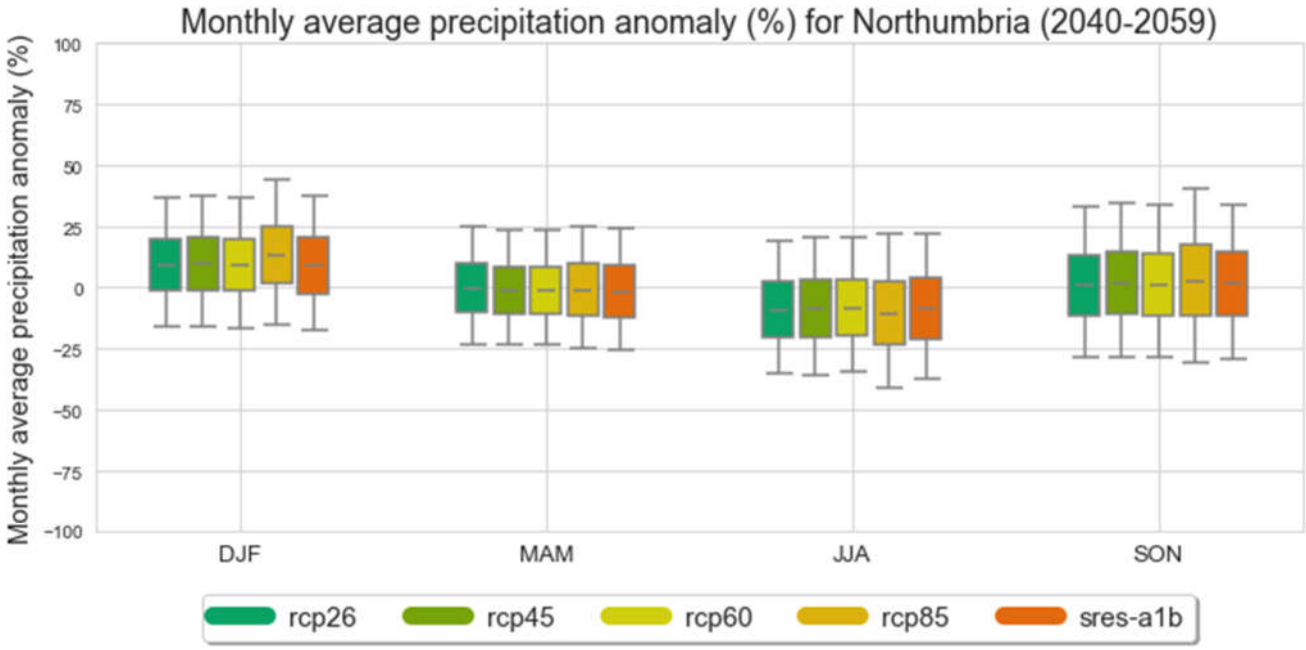
Monthly average precipitation anomaly (%) for Northumbria (2040-2059)
Monthly average precipitation anomaly (%)
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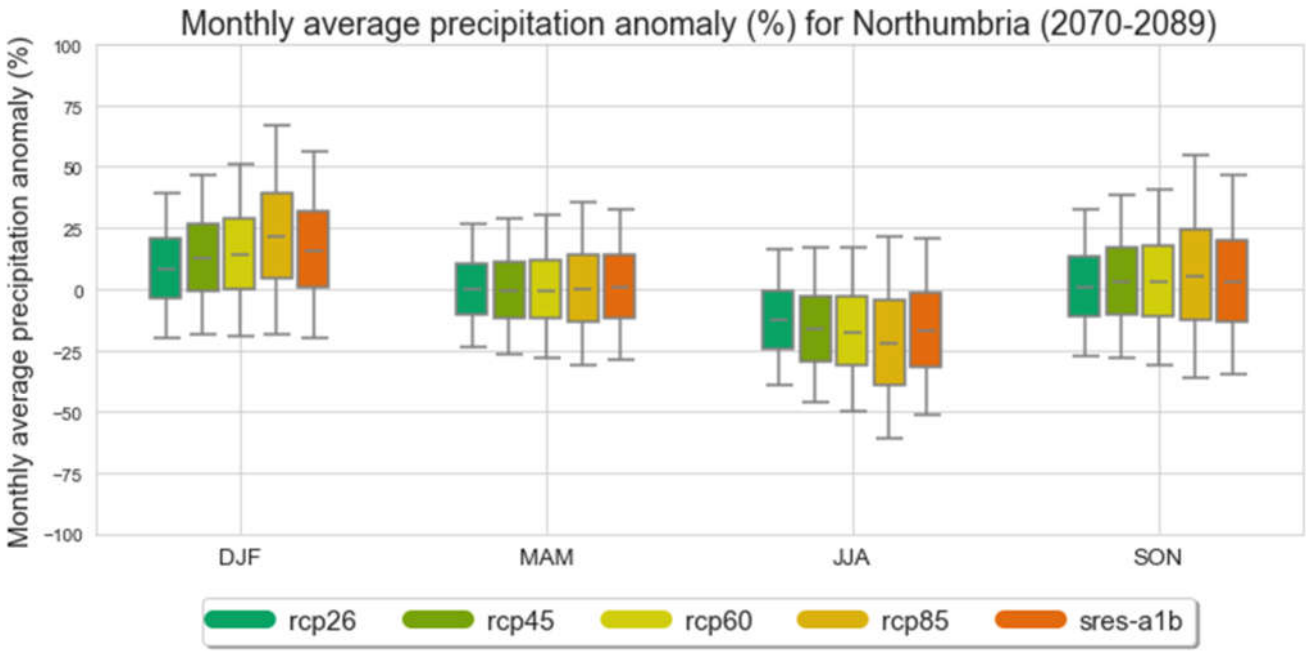
Monthly average precipitation anomaly (%) for Northumbria (2070-2089)
Monthly average precipitation anomaly (%)
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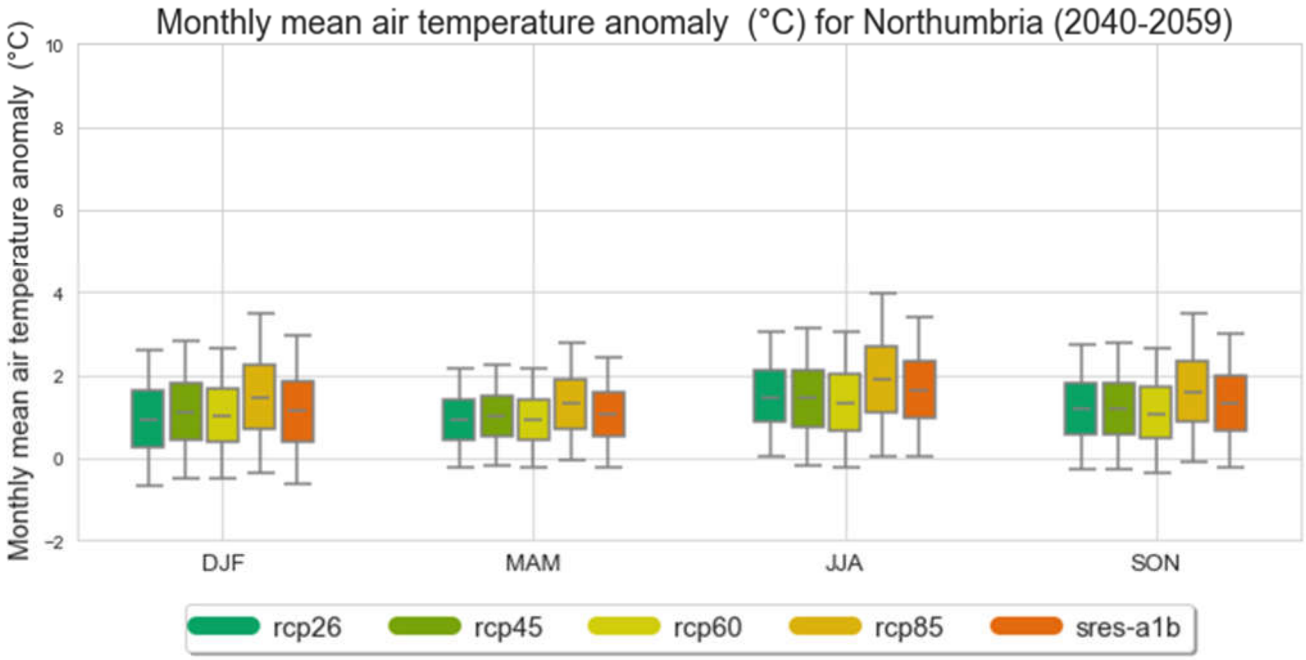
Monthly mean air temperature anomaly (°C) for Northumbria (2040-2059)
Monthly mean air temperature anomaly (°C)
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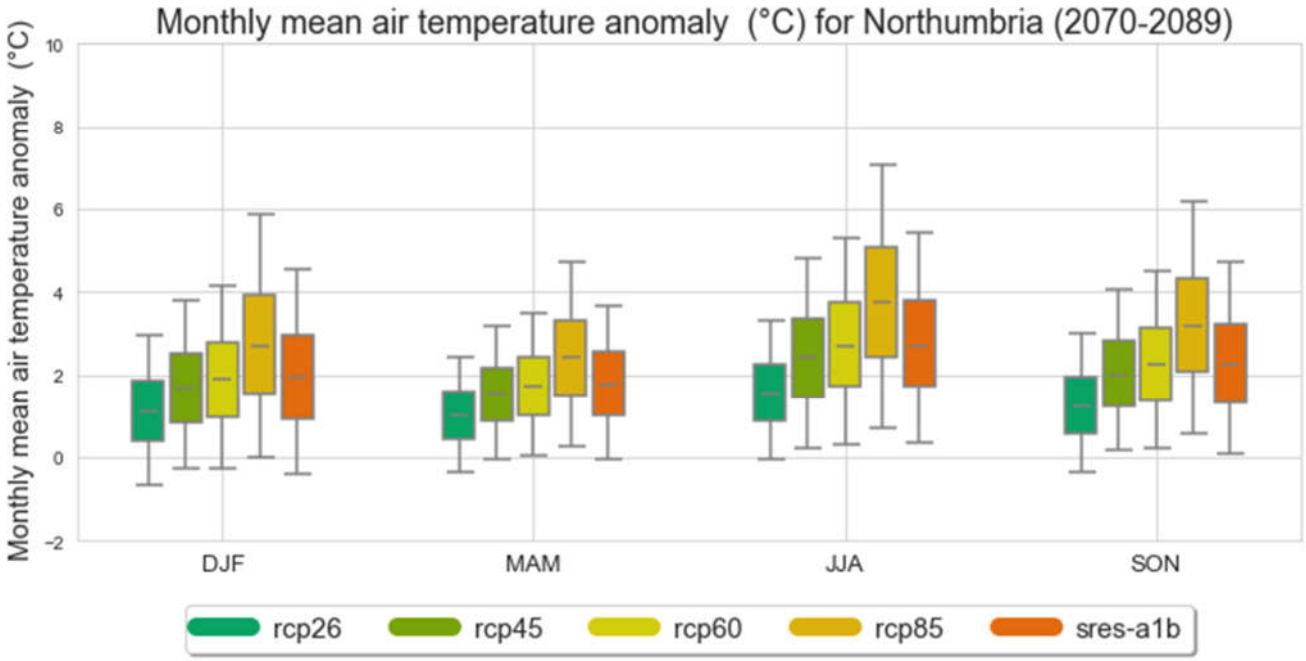
Monthly mean air temperature anomaly (°C) for Northumbria (2070-2089)
Monthly mean air temperature anomaly (°C)
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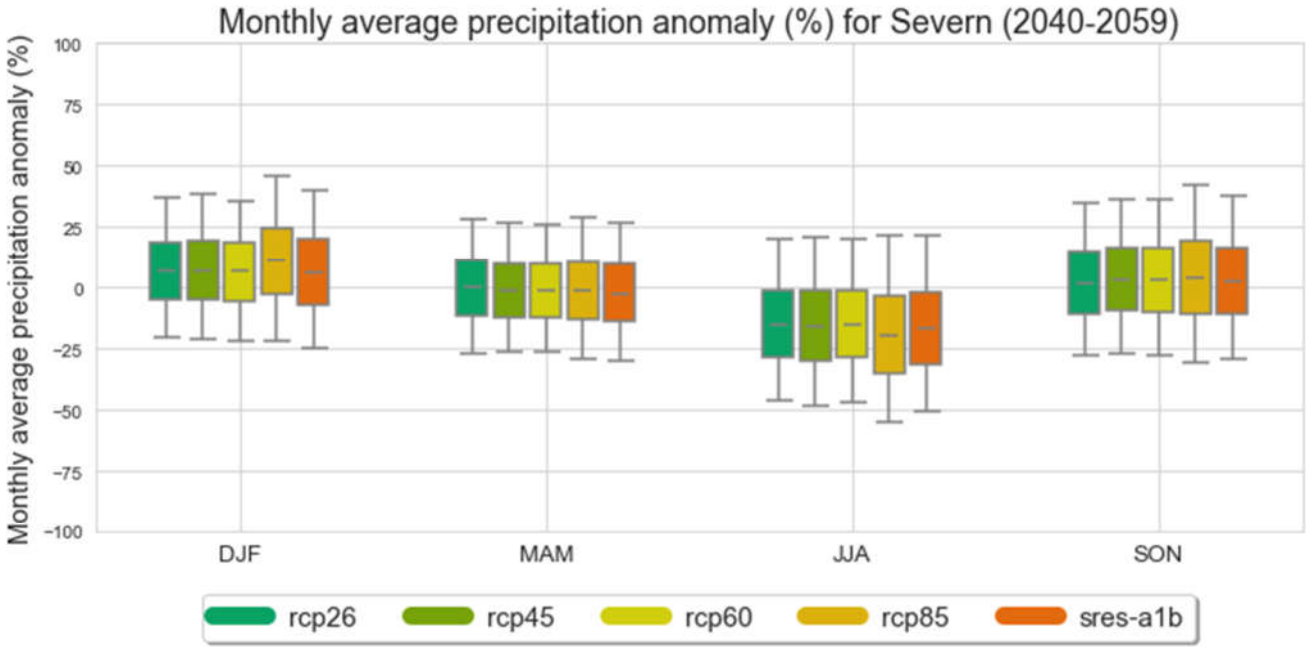
Monthly average precipitation anomaly (%) for Severn (2040-2059)
Monthly average precipitation anomaly (%)
100
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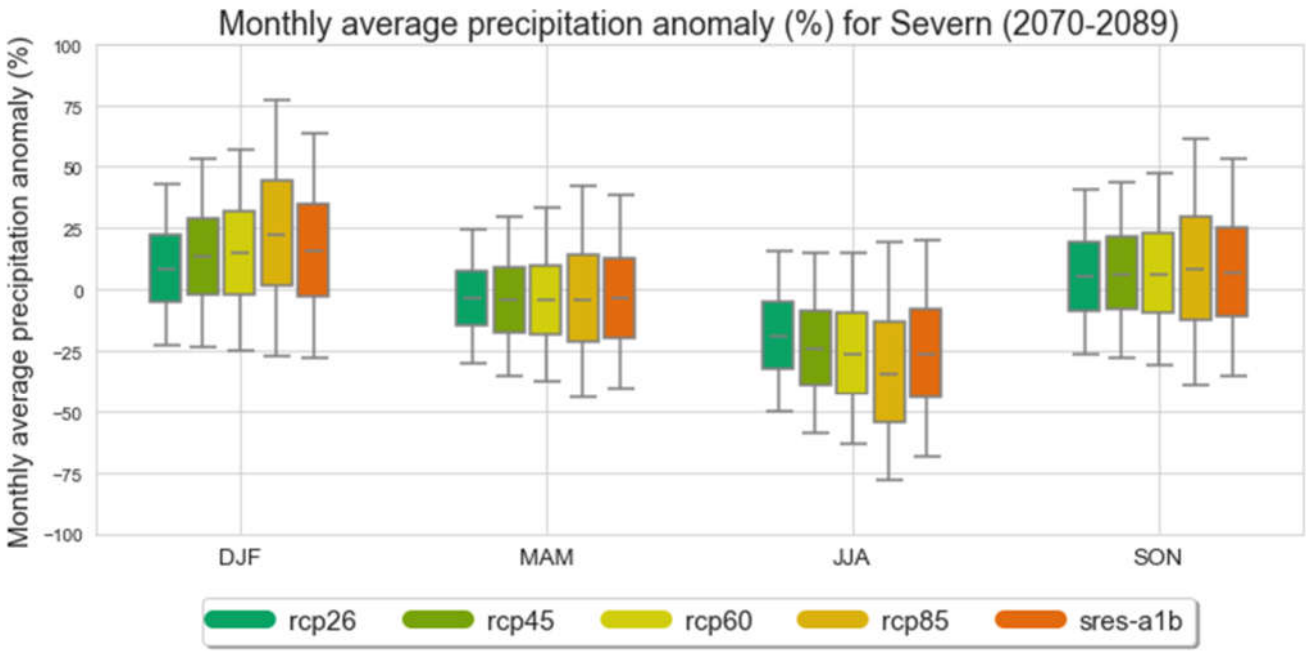
Monthly average precipitation anomaly (%) for Severn (2070-2089)
Monthly average precipitation anomaly (%)
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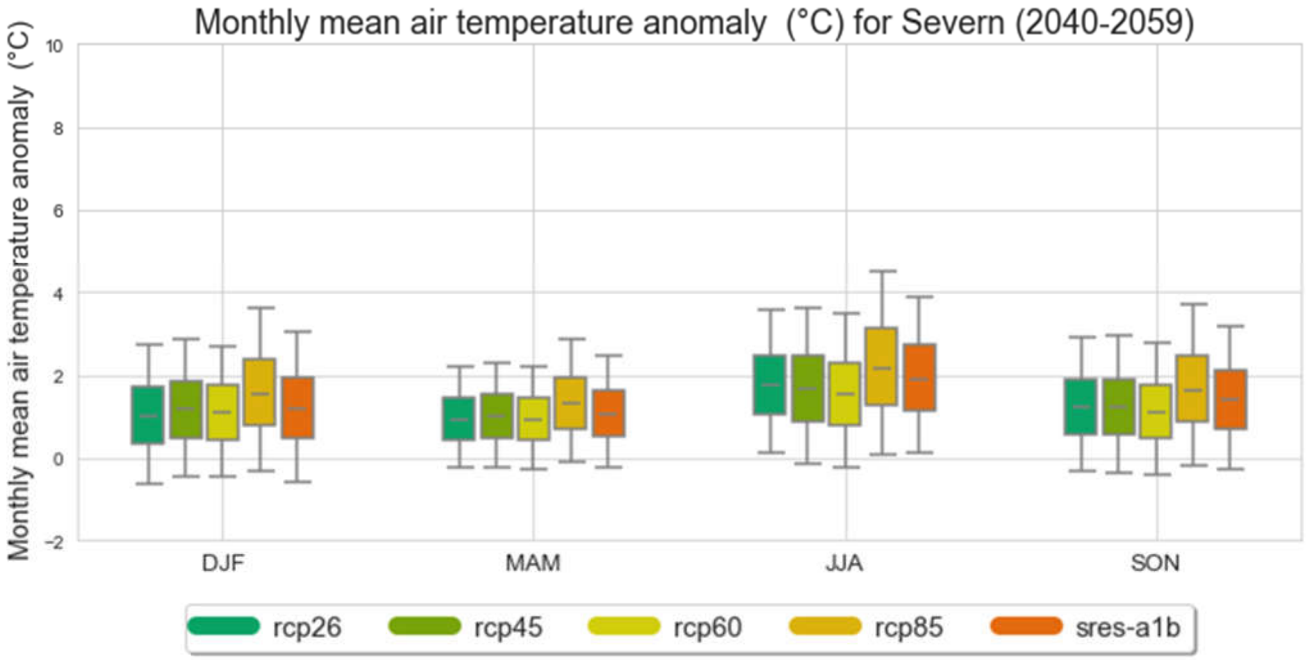
Monthly mean air temperature anomaly (°C) for Severn (2040-2059)
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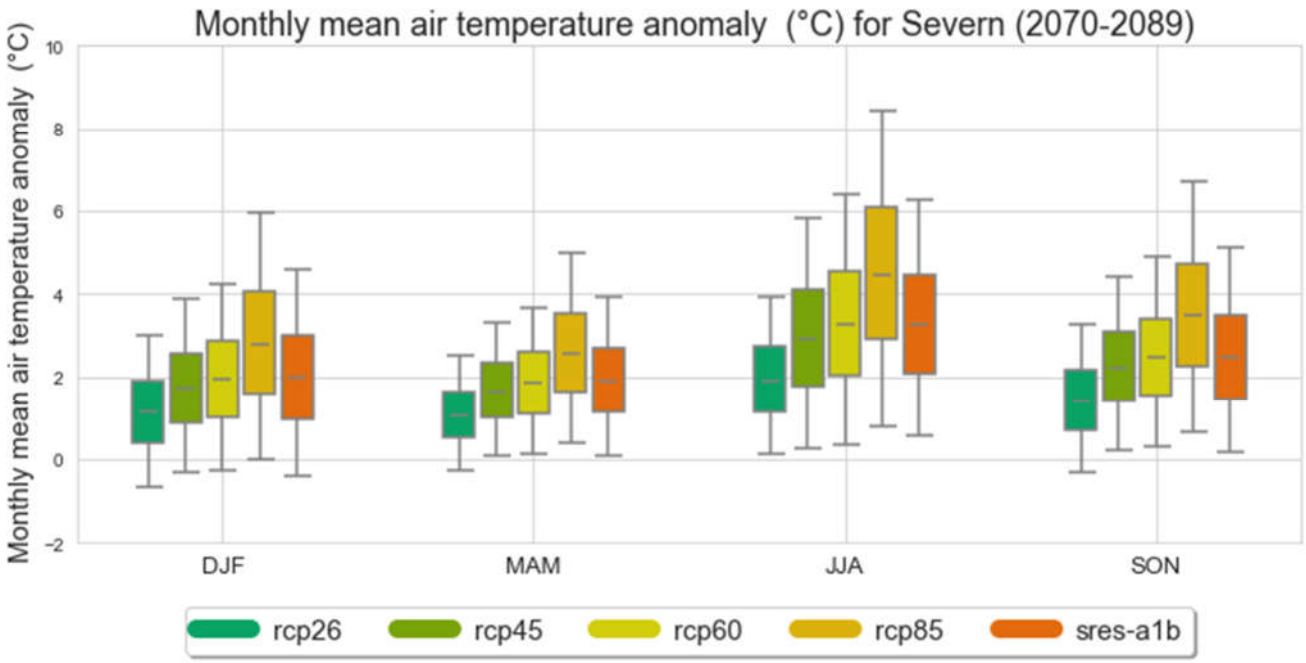
Monthly mean air temperature anomaly (°C) for Severn (2070-2089)
Monthly mean air temperature anomaly (°C)
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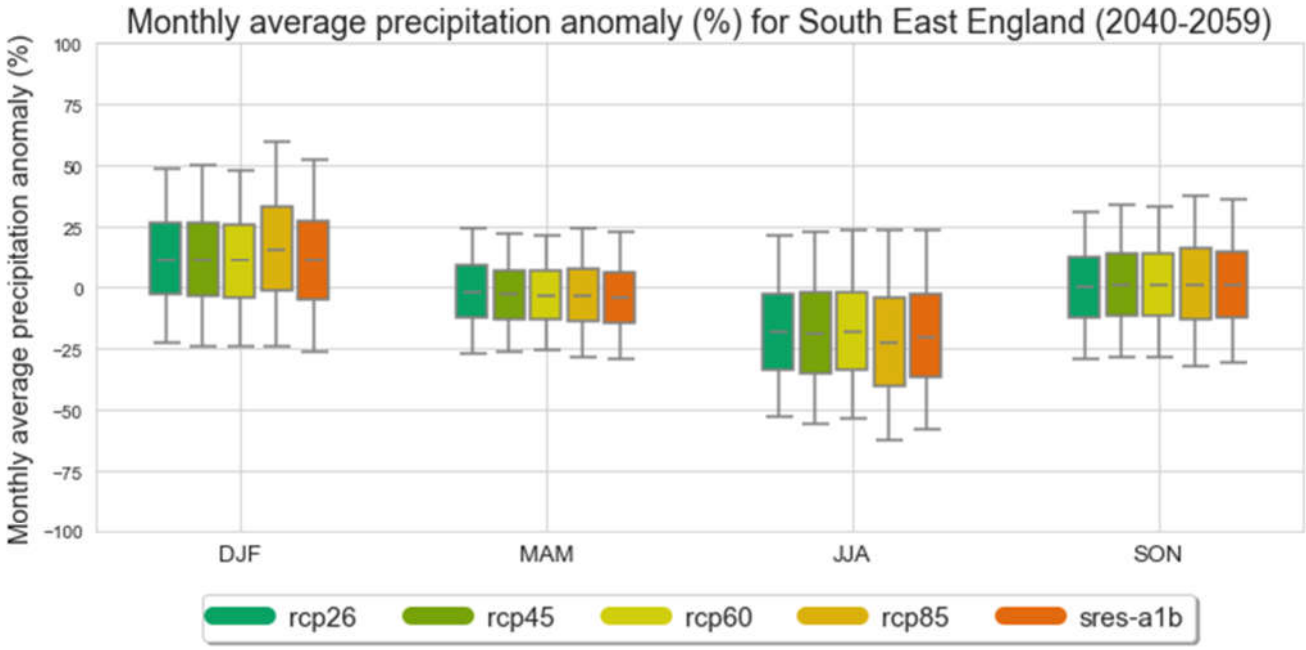
Monthly average precipitation anomaly (%) for South East England (2040-2059)
Monthly average precipitation anomaly (%)
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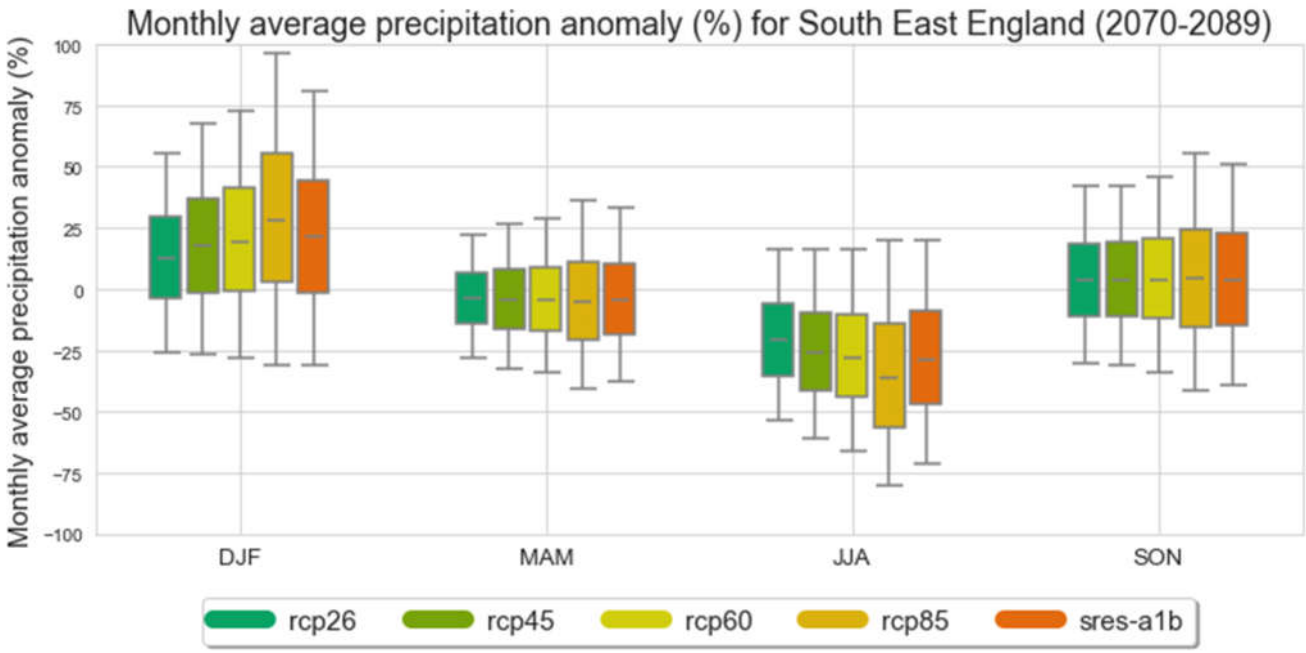
Monthly average precipitation anomaly (%) for South East England (2070-2089)
Monthly average precipitation anomaly (%)
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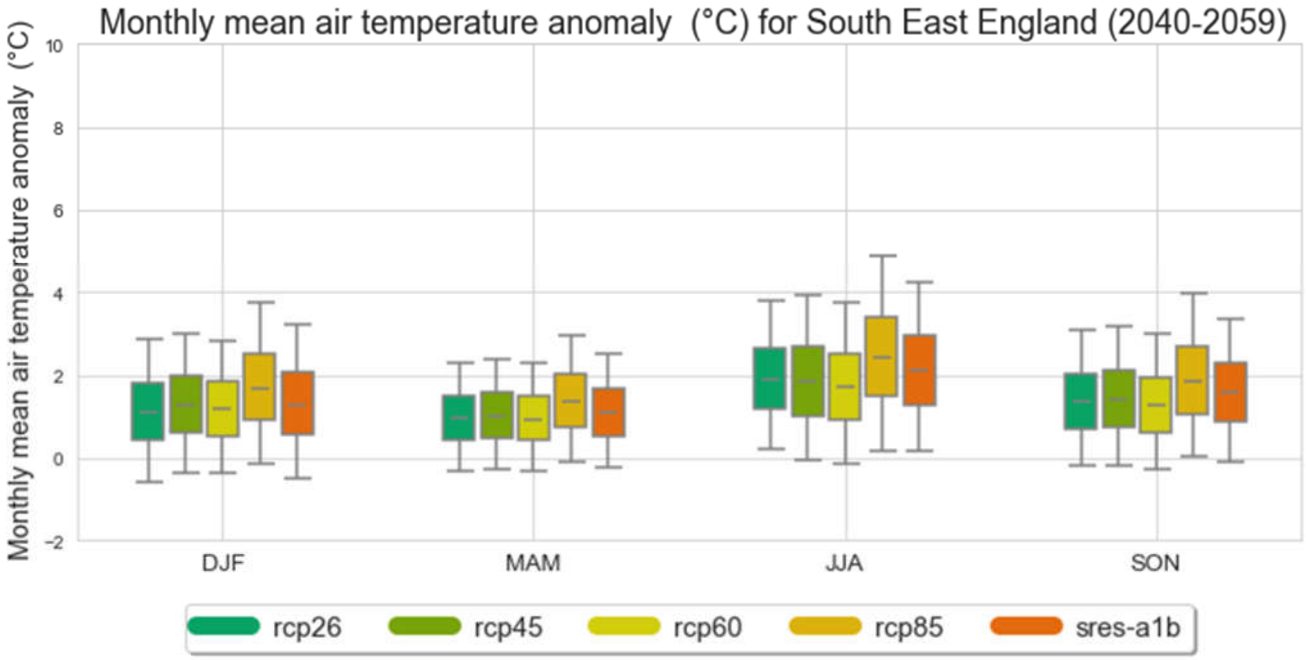
Monthly mean air temperature anomaly (°C) for South East England (2040-2059)
Monthly mean air temperature anomaly (°C)
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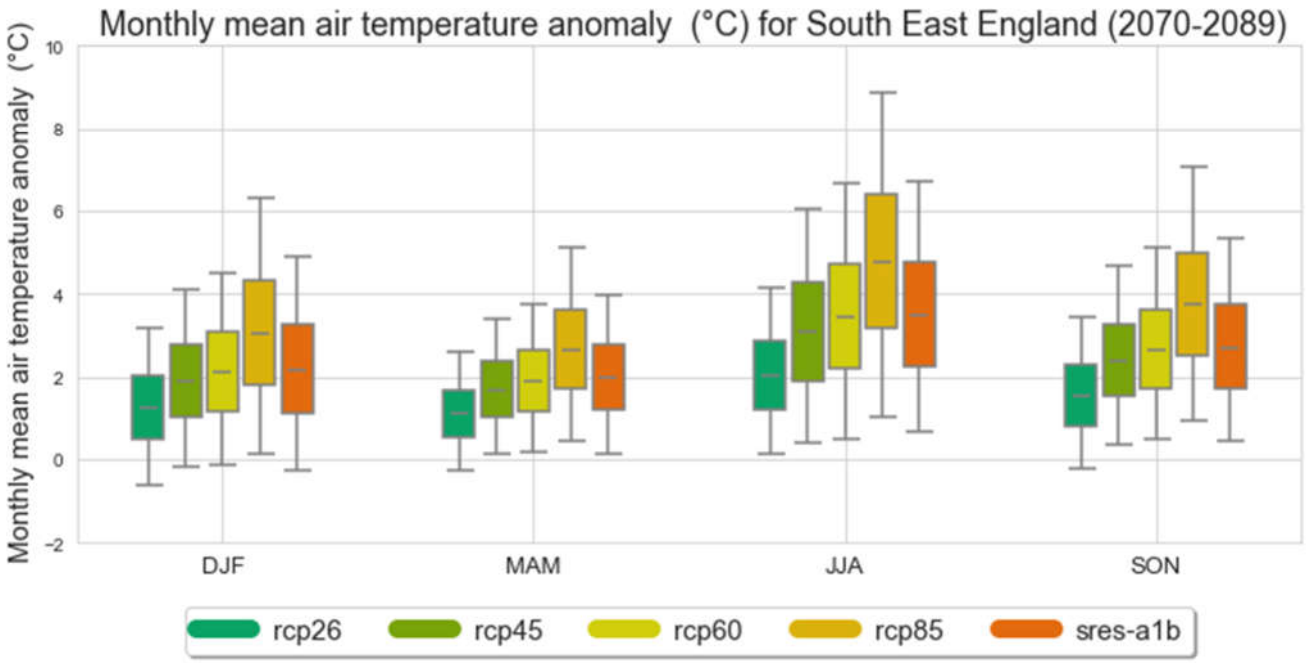
Monthly mean air temperature anomaly (°C) for South East England (2070-2089)
Monthly mean air temperature anomaly (°C)
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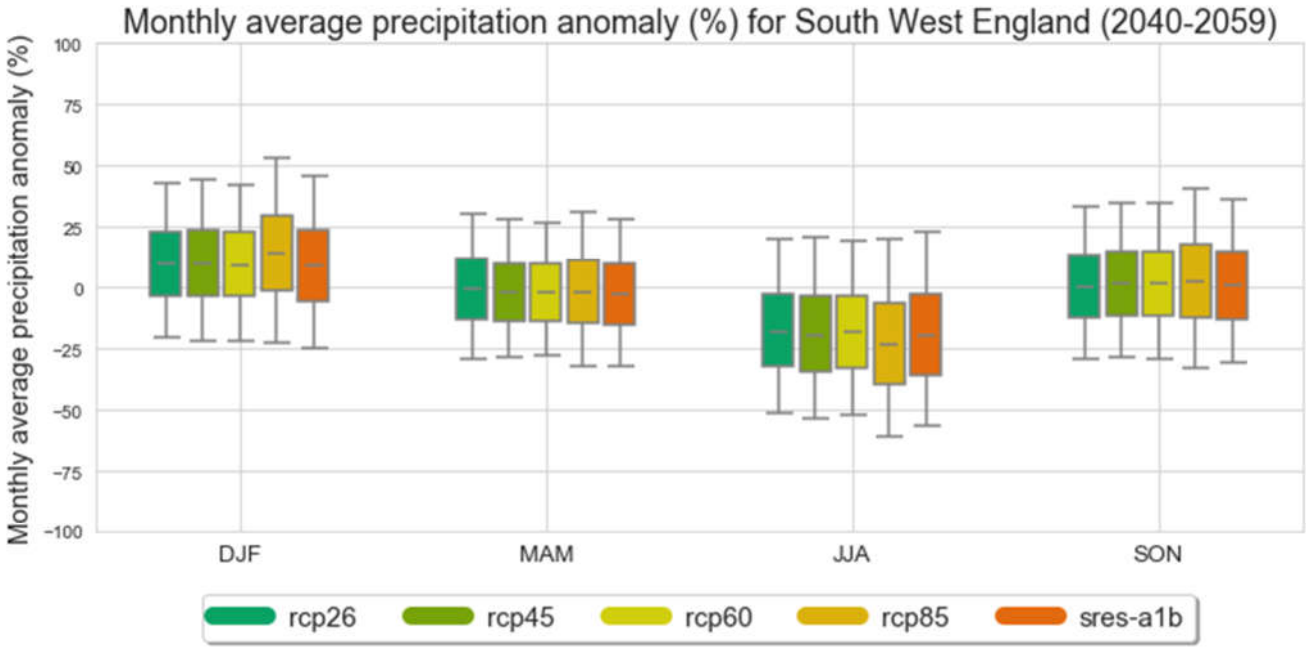
Monthly average precipitation anomaly (%) for South West England (2040-2059)
Monthly average precipitation anomaly (%)
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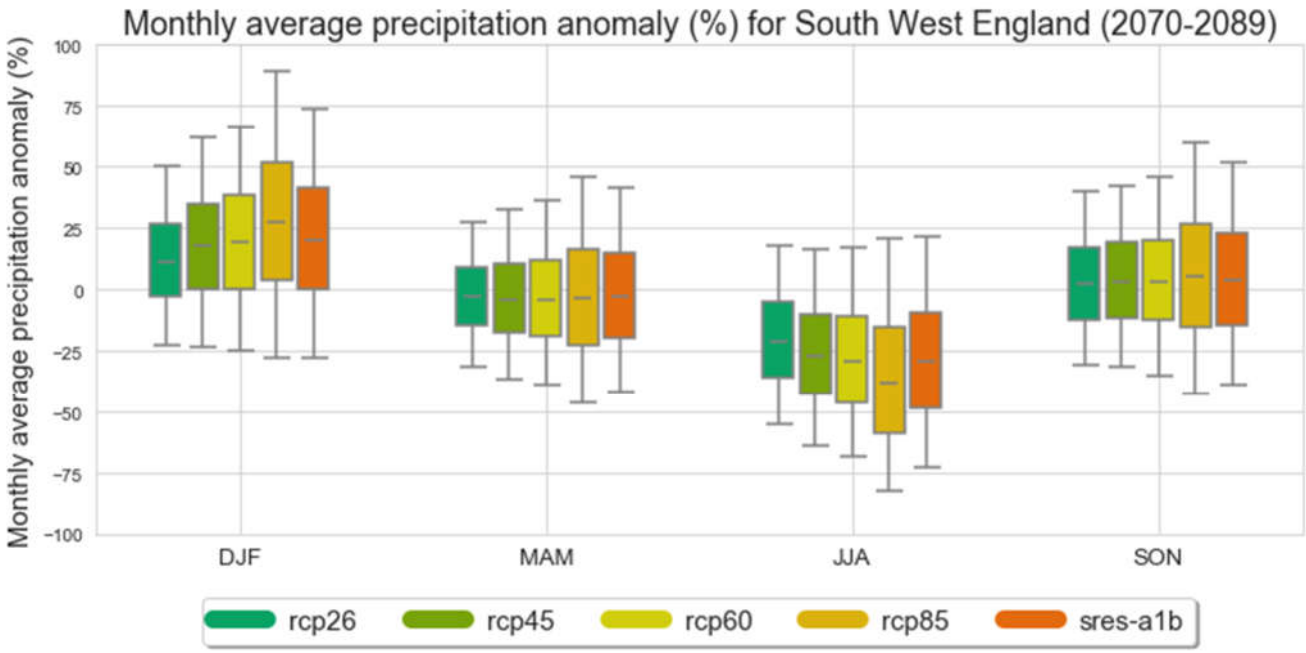
Monthly average precipitation anomaly (%) for South West England (2070-2089)
Monthly average precipitation anomaly (%)
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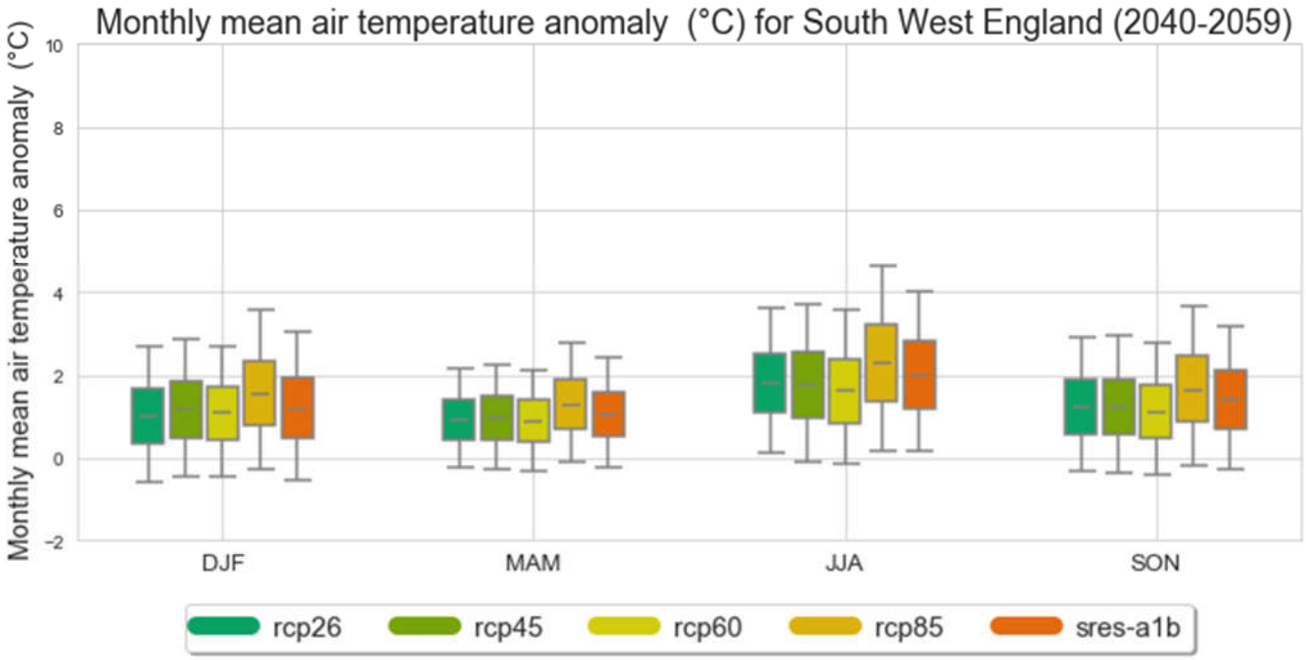
Monthly mean air temperature anomaly (°C) for South West England (2040-2059)
Monthly mean air temperature anomaly (°C)
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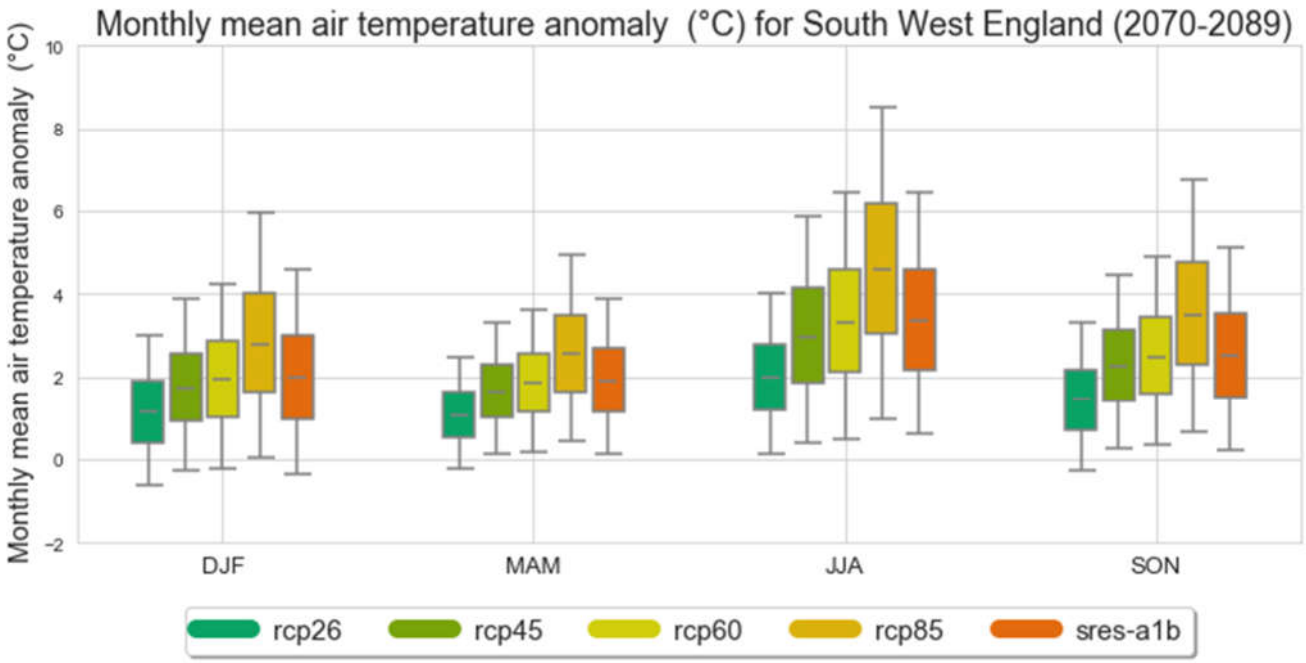
Monthly mean air temperature anomaly (°C) for South West England (2070-2089)
Monthly mean air temperature anomaly (°C)
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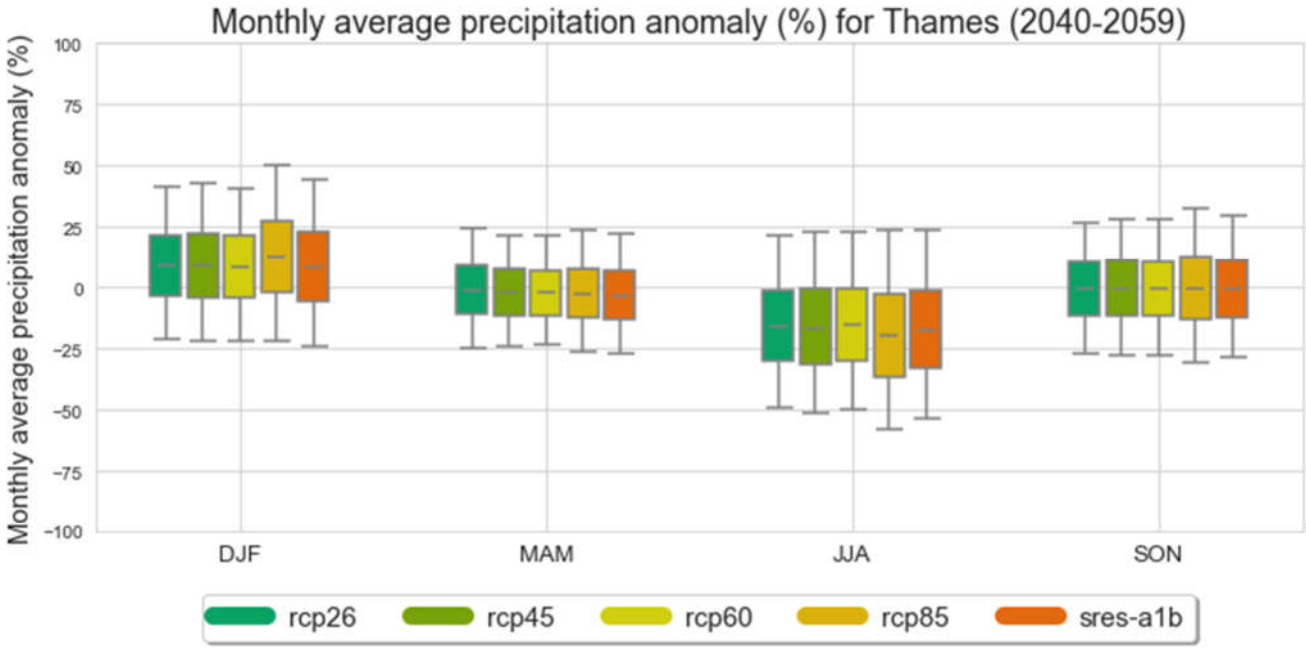
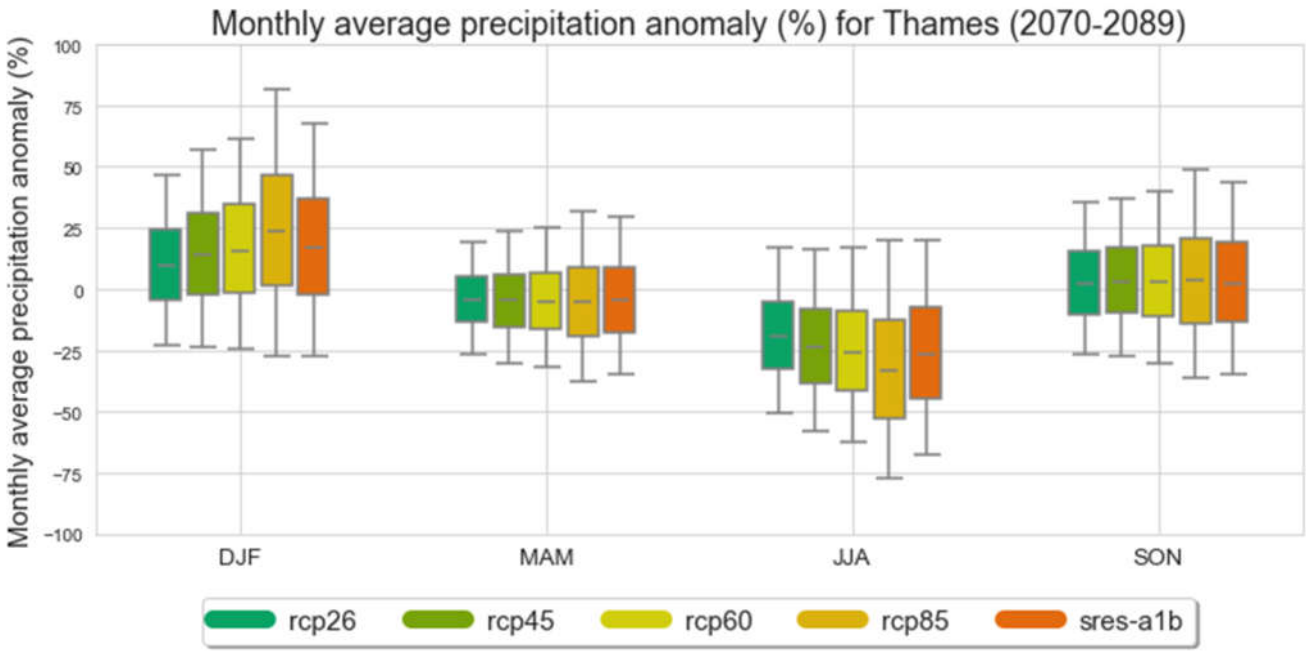
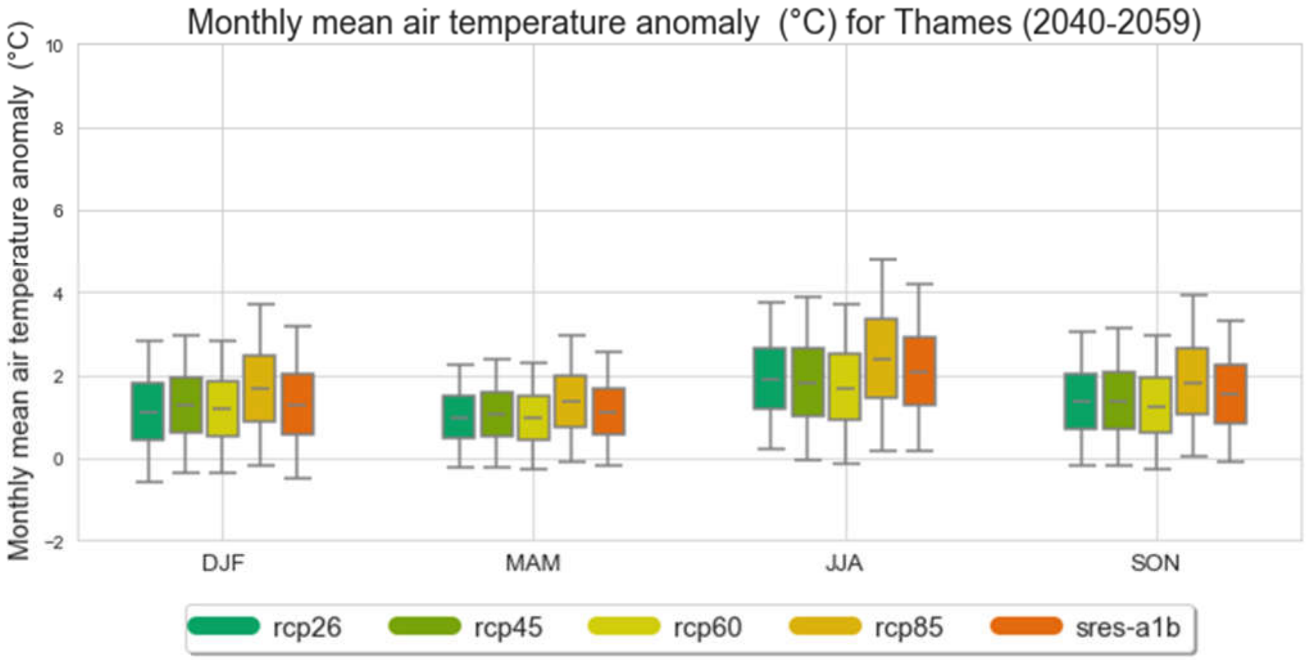
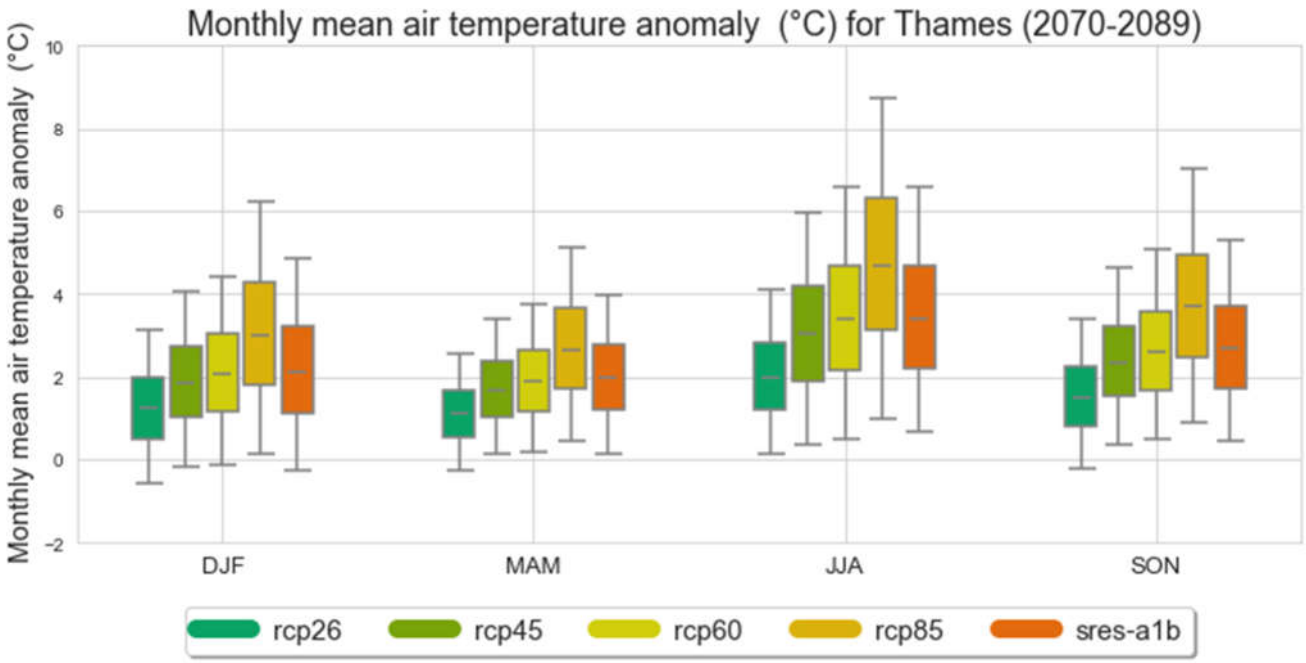
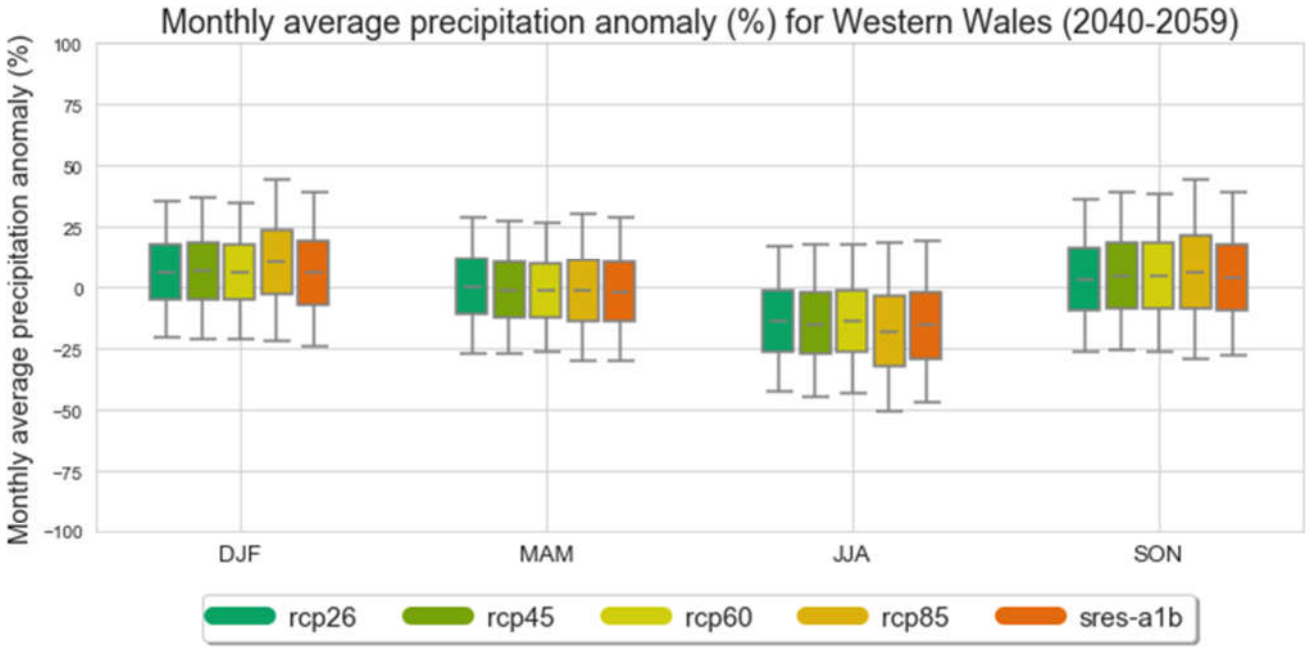
rcp26
rcp45
rcp60
rcp85
sres-a1b

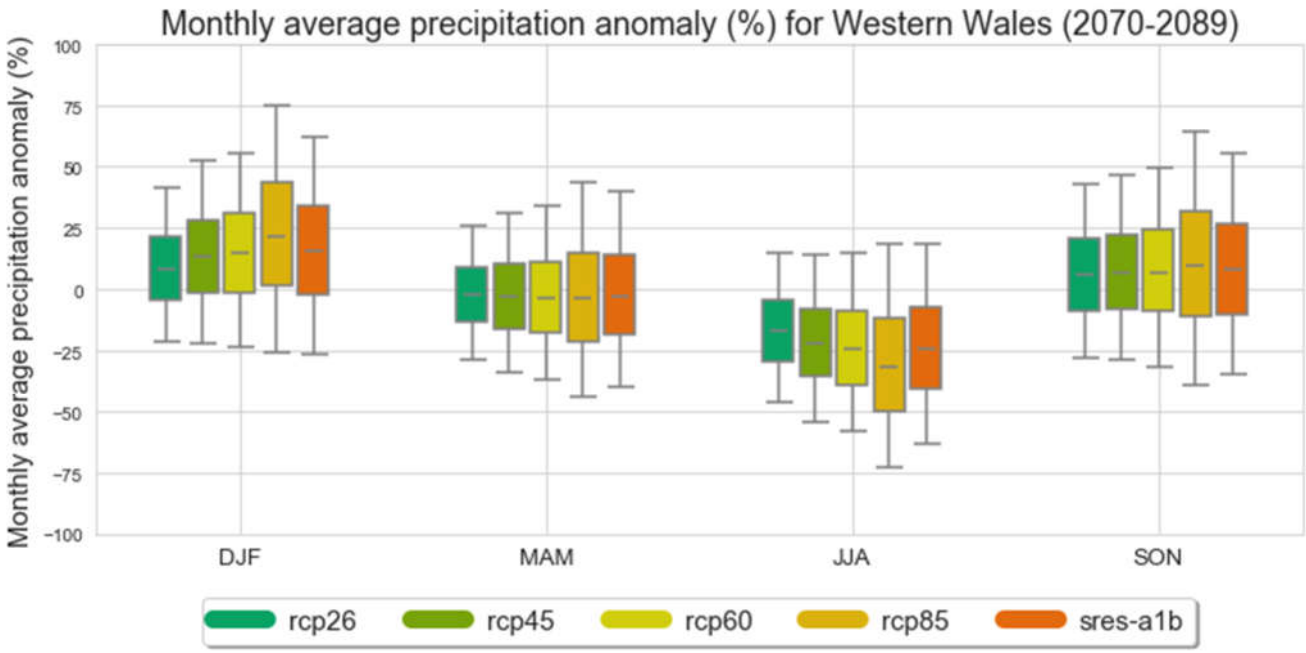

Monthly average precipitation anomaly (%) for Thames (2040-2059)
Monthly average precipitation anomaly (%)
100
75
50
25
0
−25
−50
−75
−100
DJF
MAM
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b

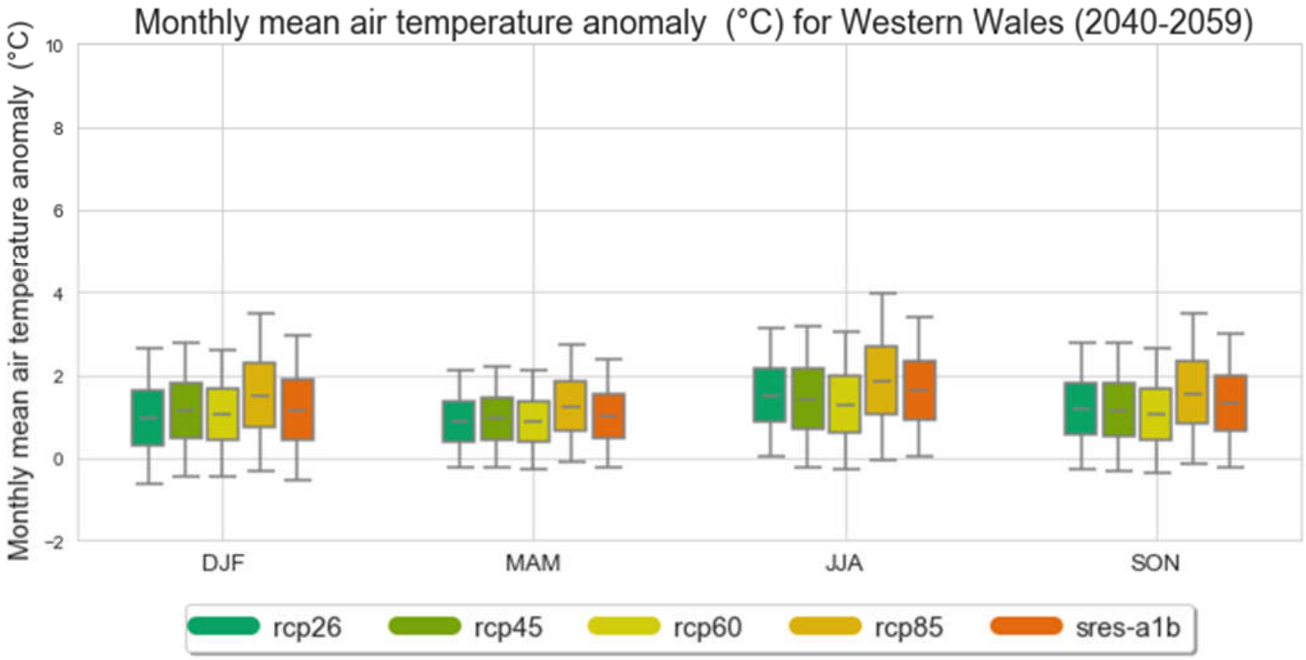

Monthly average precipitation anomaly (%) for Thames (2070-2089)
Monthly average precipitation anomaly (%)
100
75
50
25
0
−25
−50
−75
−100
DJF
MAM
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b

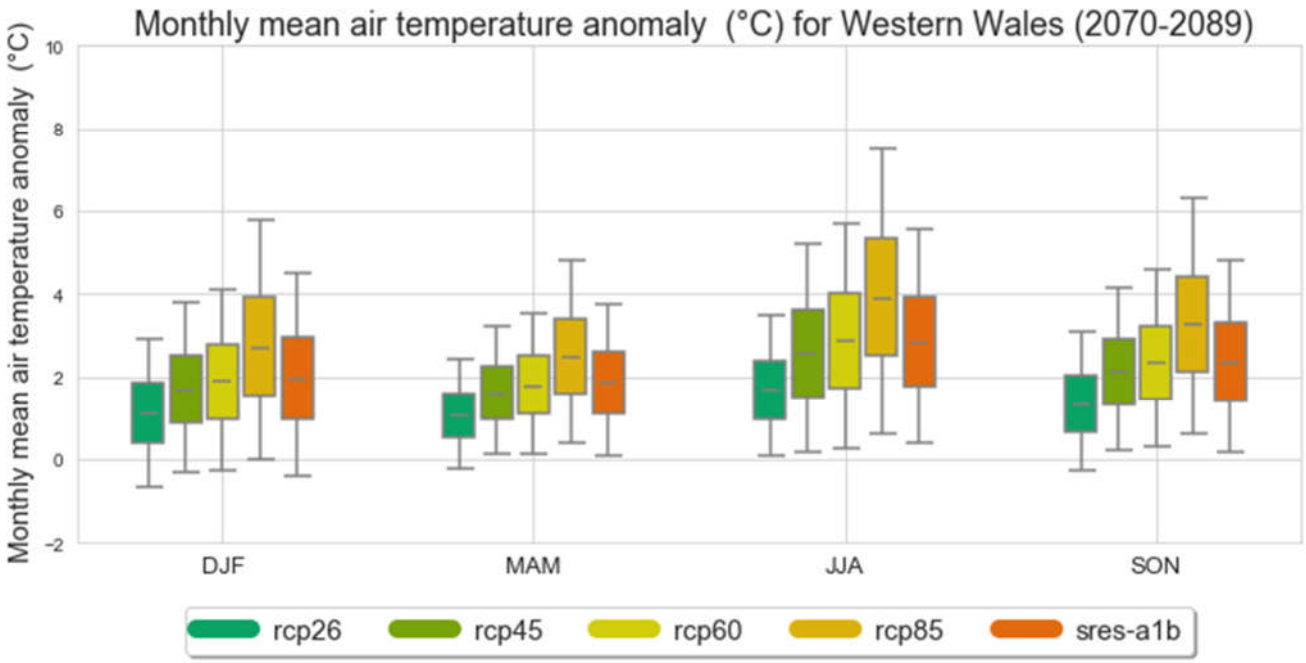

Monthly mean air temperature anomaly (°C) for Thames (2040-2059)
Monthly mean air temperature anomaly (°C)
10
8
6
4
2
0
−2
DJF
MAM
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b


Monthly mean air temperature anomaly (°C) for Thames (2070-2089)
Monthly mean air temperature anomaly (°C)
10
8
6
4
2
0
−2
DJF
MAM
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b


Monthly average precipitation anomaly (%) for Western Wales (2040-2059)
Monthly average precipitation anomaly (%)
100
75
50
25
0
−25
−50
−75
−100
DJF
MAM
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b

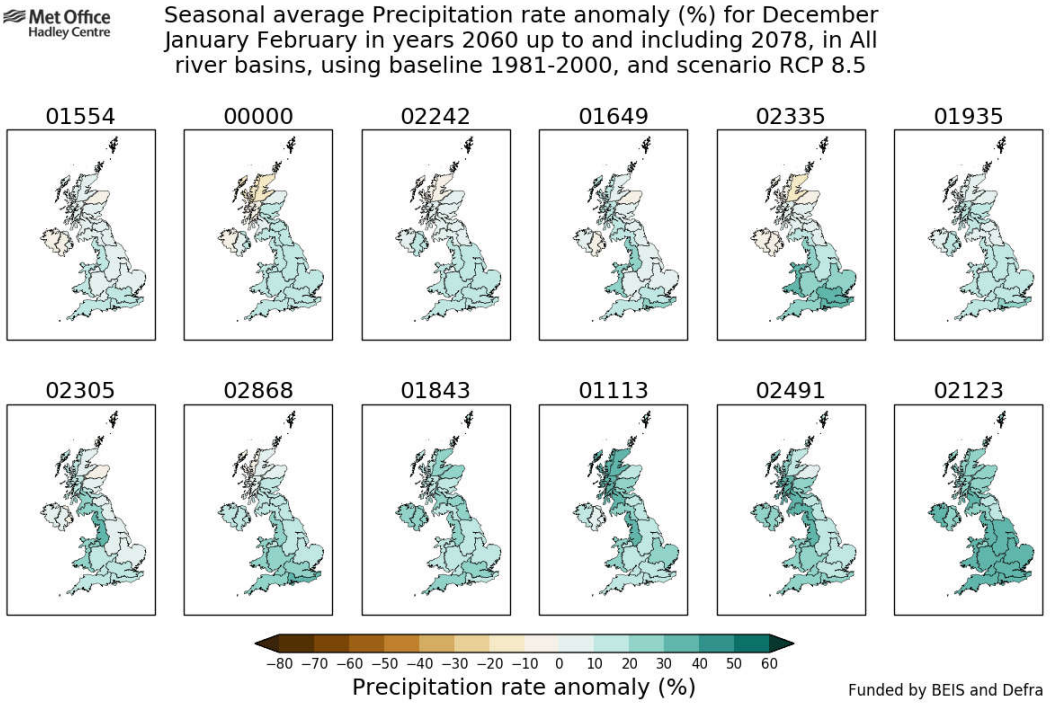

Monthly average precipitation anomaly (%) for Western Wales (2070-2089)
Monthly average precipitation anomaly (%)
100
75
50
25
0
−25
−50
−75
−100
DJF
MAM
JJA
SON
rcp26
rcp45
rcp60
rcp85
sres-a1b

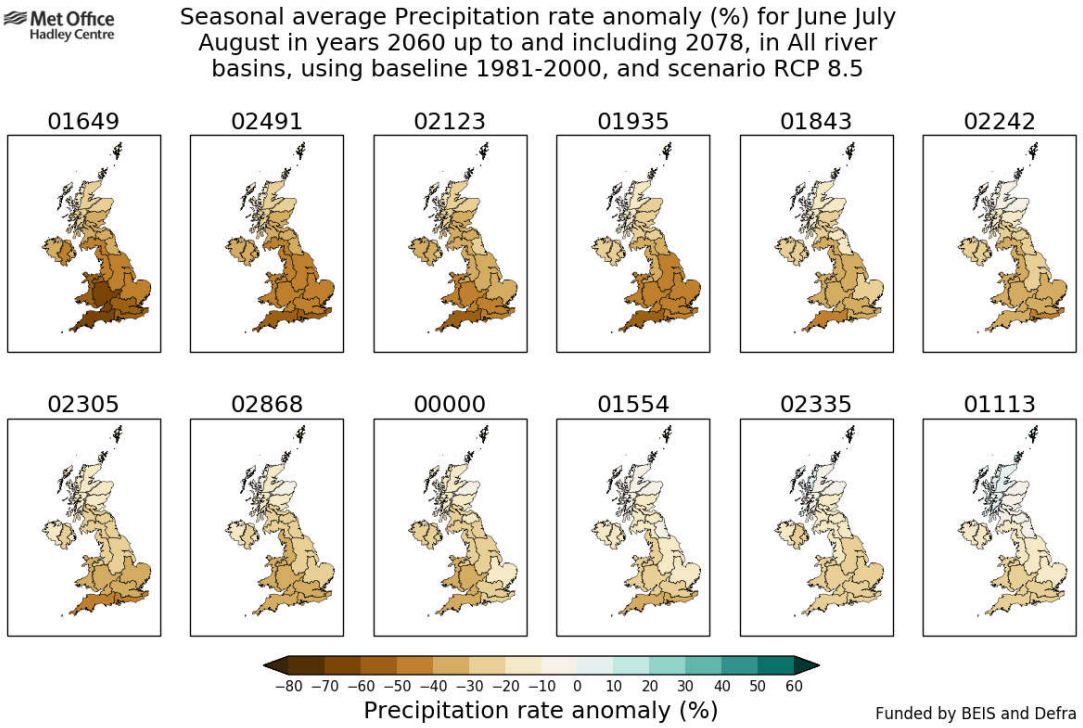




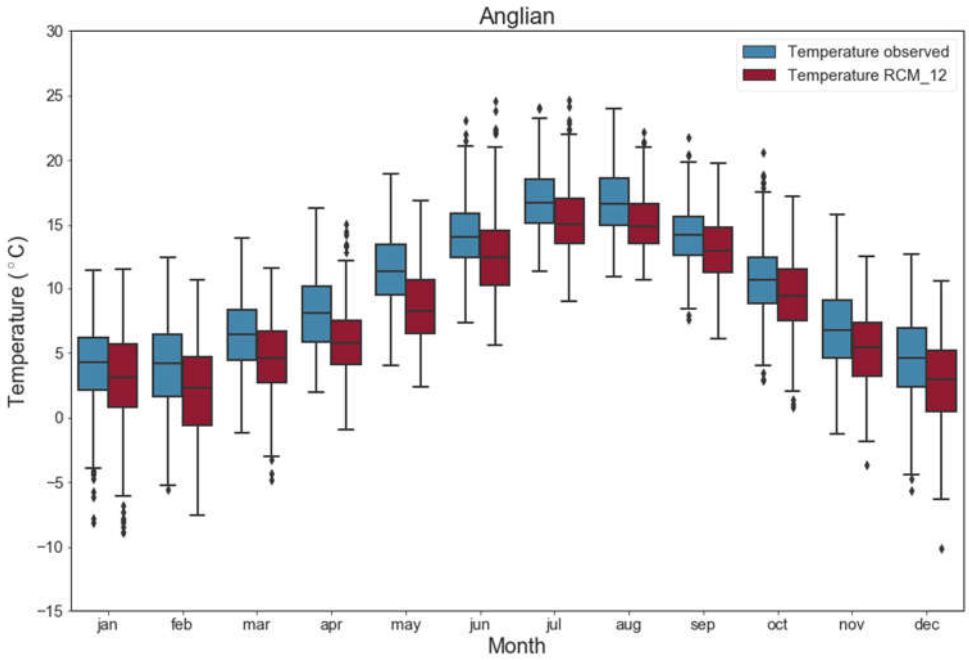
C.12.2. UKCP Regional Climate Models

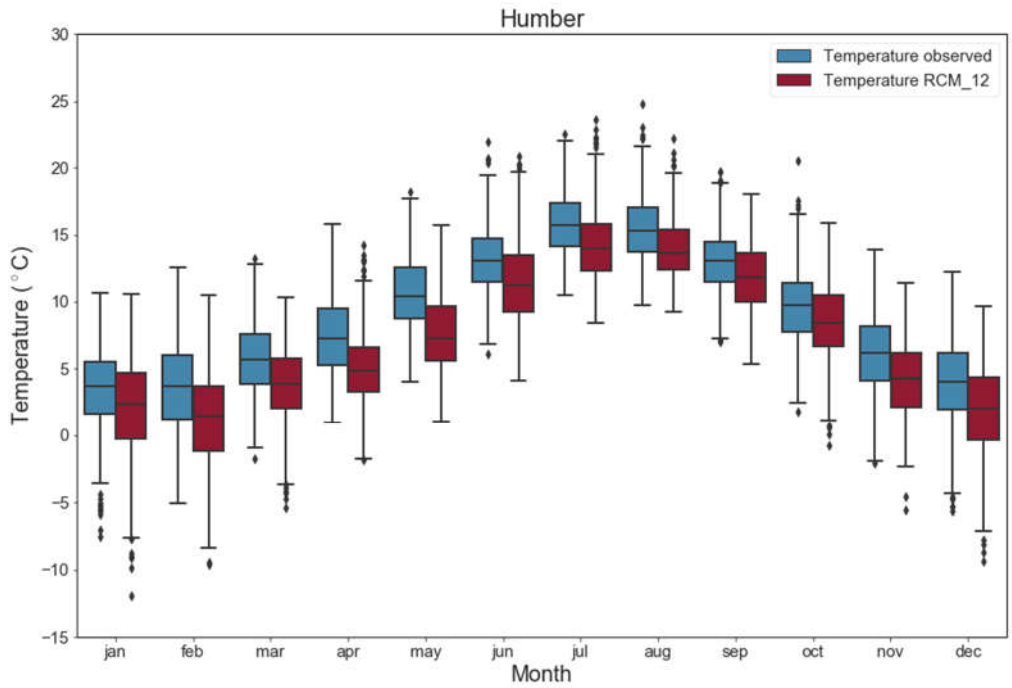
C.12.2.1. Raw RCM data maps from the UKCP User Interface

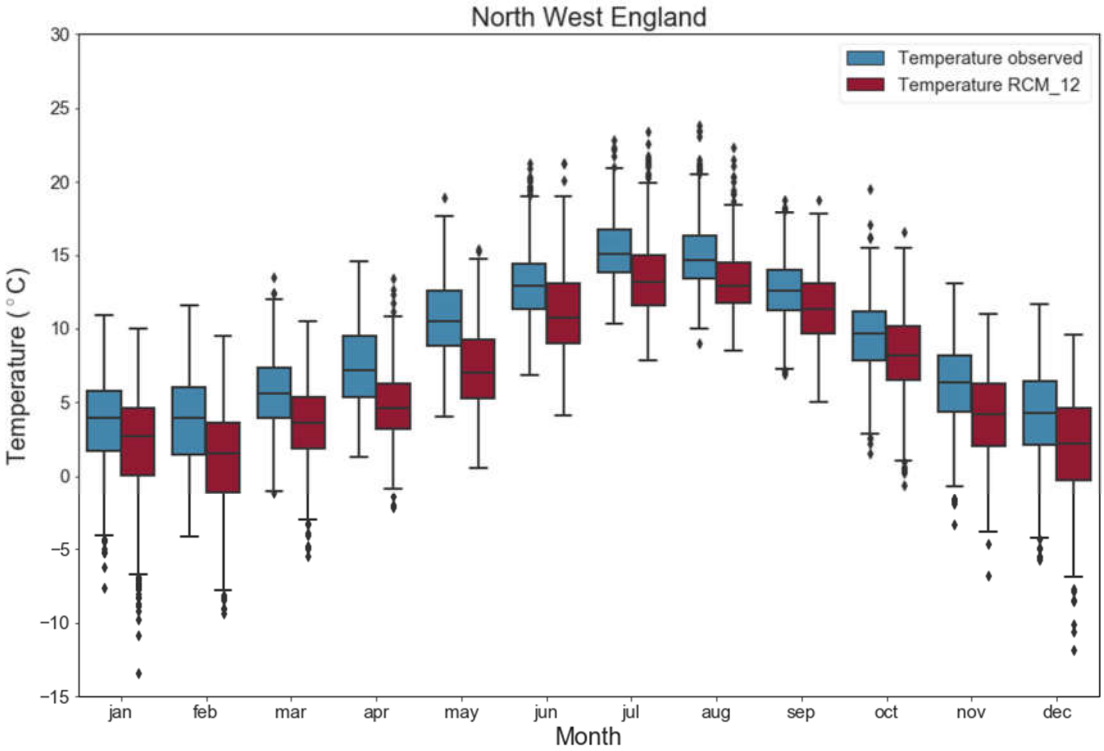

Met Office
Hadley Centre
Seasonal average Precipitation rate anomaly (%) for December January February in years 2060 up to and including 2078, in All river basins, using baseline 1981-2000, and scenario RCP 8.5
01554
00000
02242
01649
02335
01935
02305
02868
01843
01113
02491
02123
−80 −70 −60 −50 −40 −30 −20 −10 0 10 20 30 40 50 60
Precipitation rate anomaly (%)
Funded by BEIS and Defra

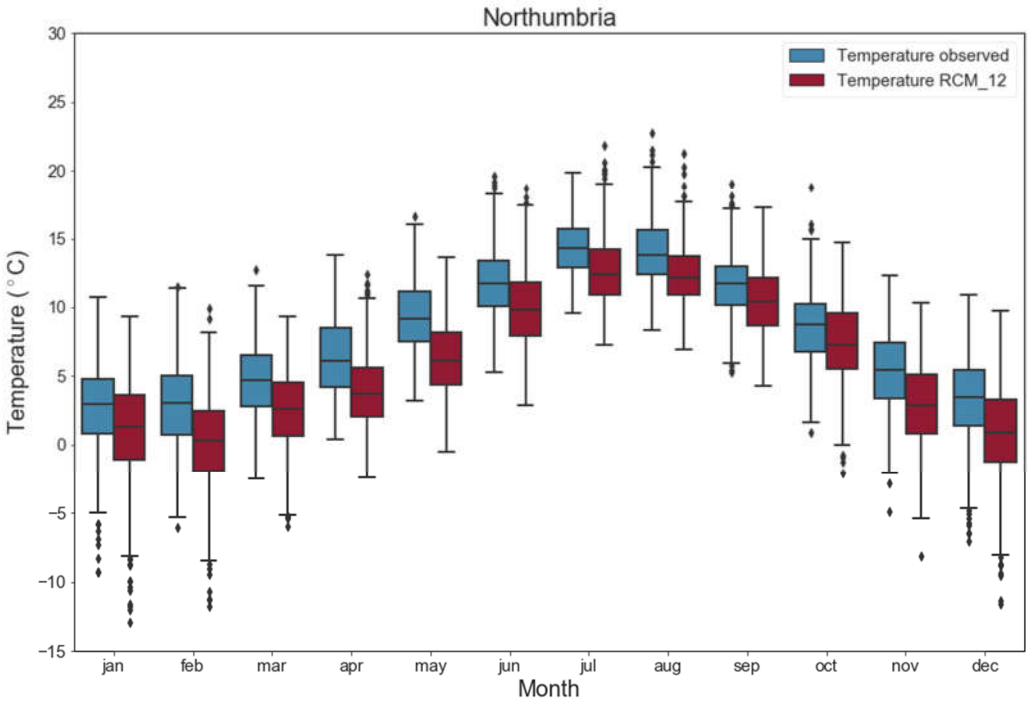

Met Office
Hadley Centre
Seasonal average Precipitation rate anomaly (%) for June July August in years 2060 up to and including 2078, in All river basins, using baseline 1981-2000, and scenario RCP 8.5
01649
02491
02123
01935
01843
02242
02305
02868
00000
01554
02335
01113
−80 −70 −60 −50 −40 −30 −20 −10 0 10 20 30 40 50 60
Precipitation rate anomaly (%)
Funded by BEIS and Defra

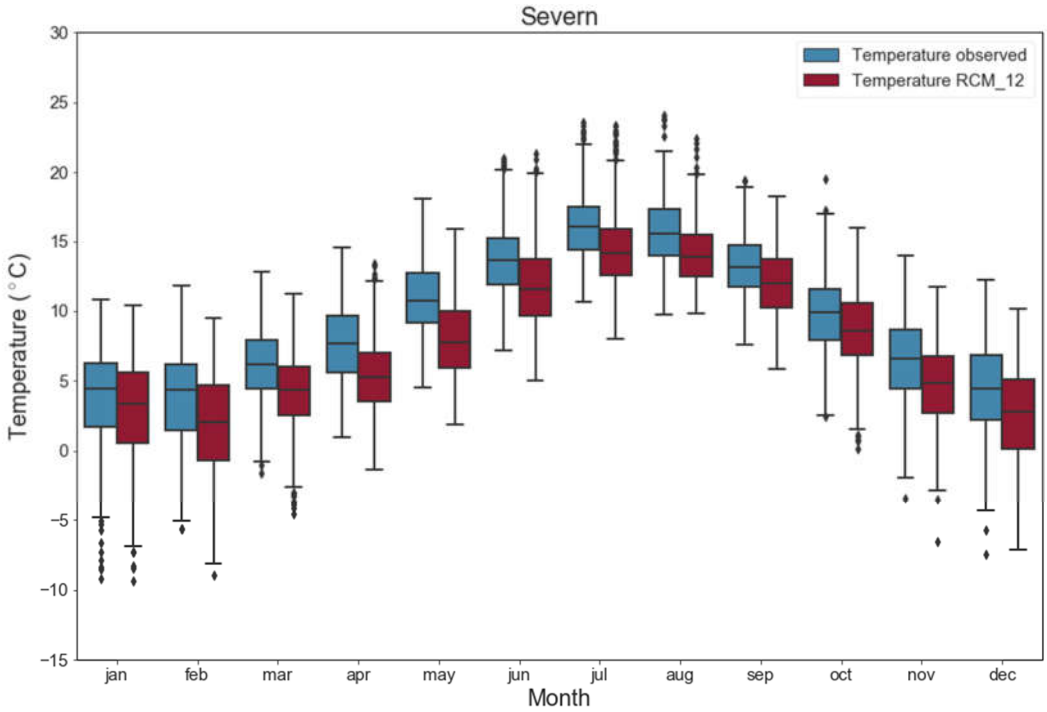
C.12.3. Comparisons between modelled and observed data: Monthly boxplots of daily average temperature

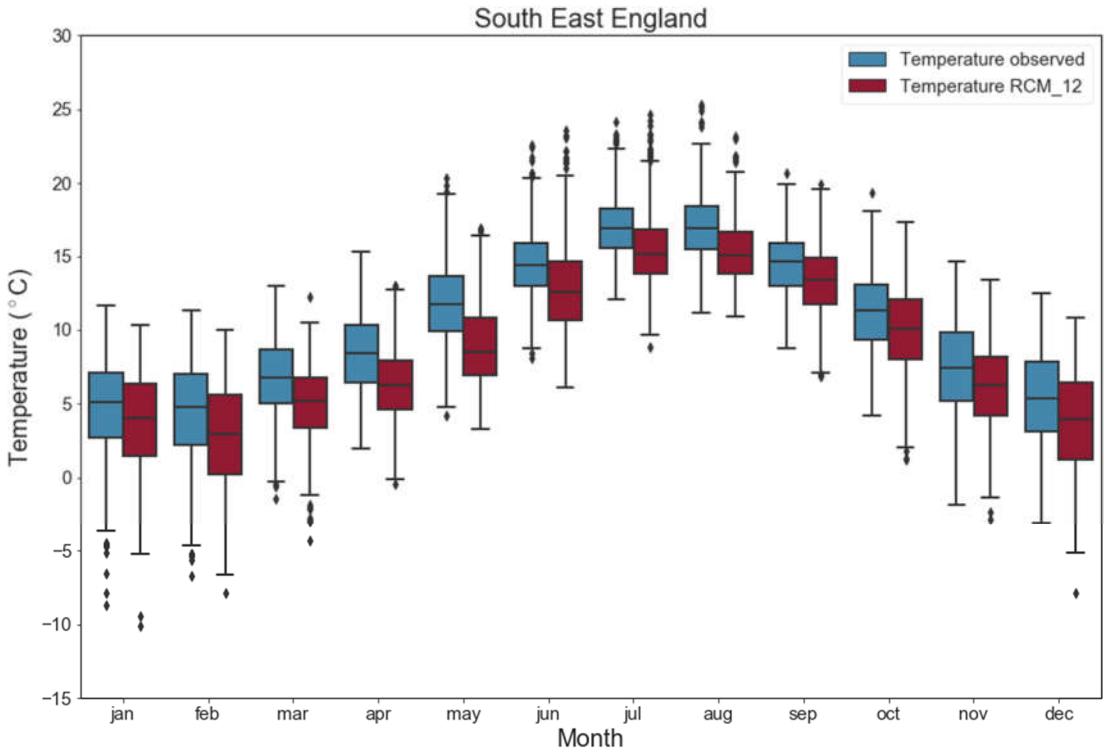


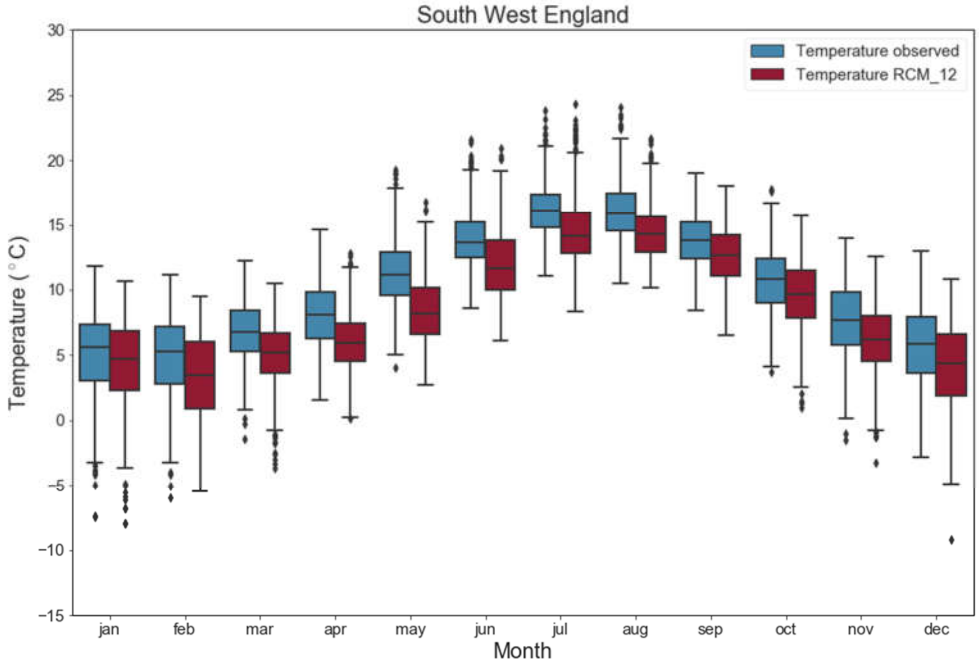


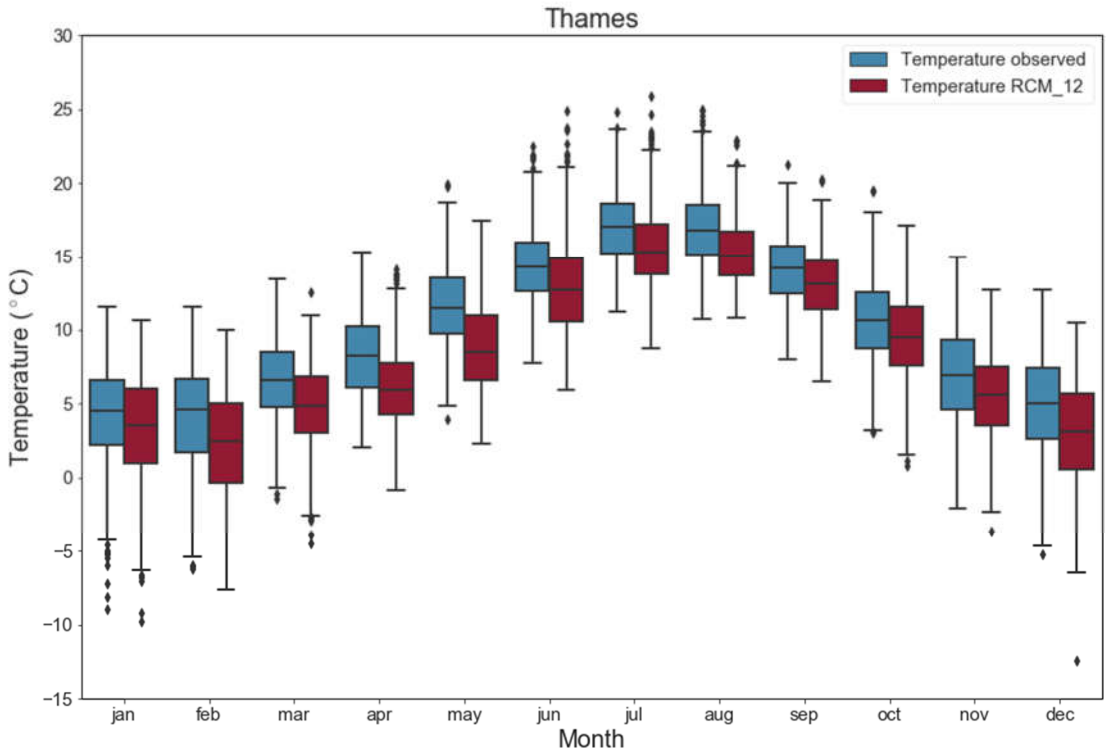

North West England
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

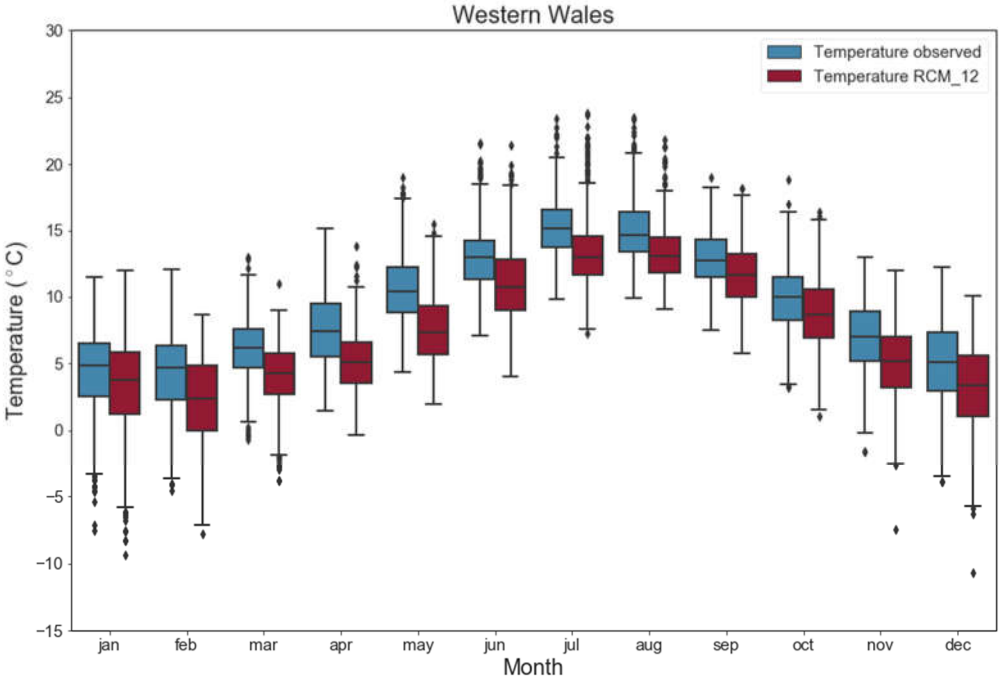

Northumbria
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month


Severn
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

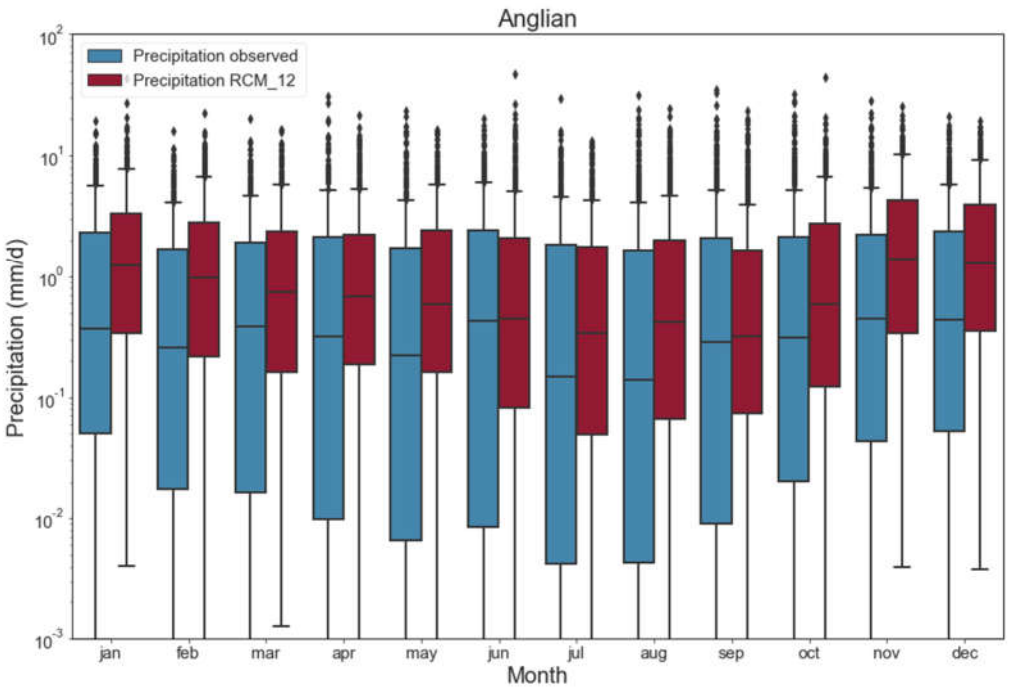

South East England
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

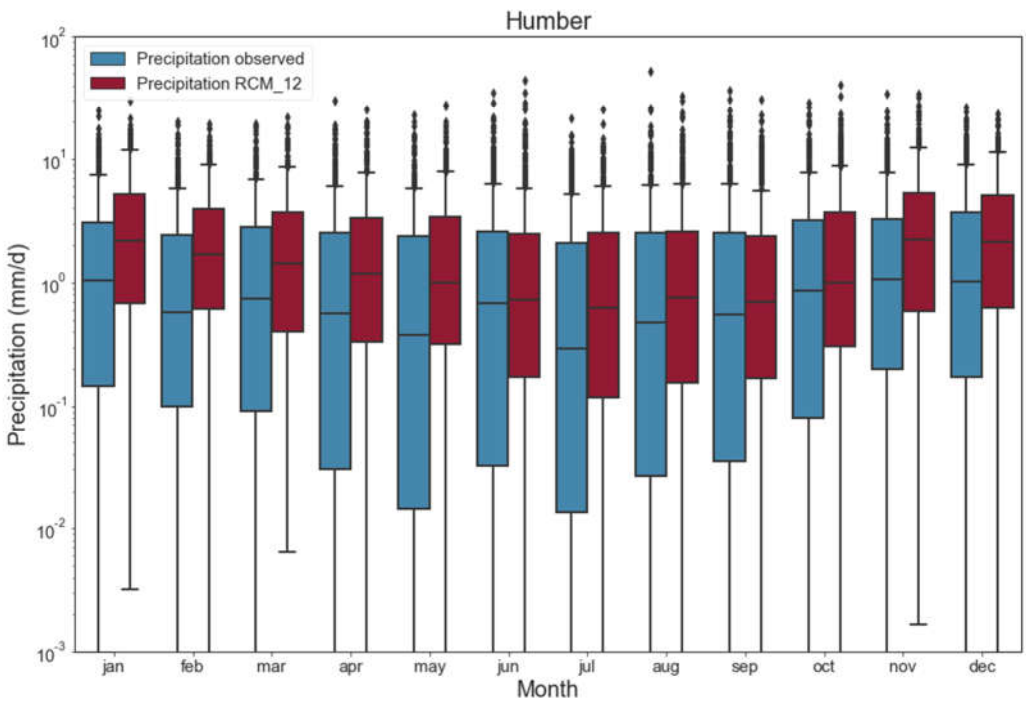

South West England
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

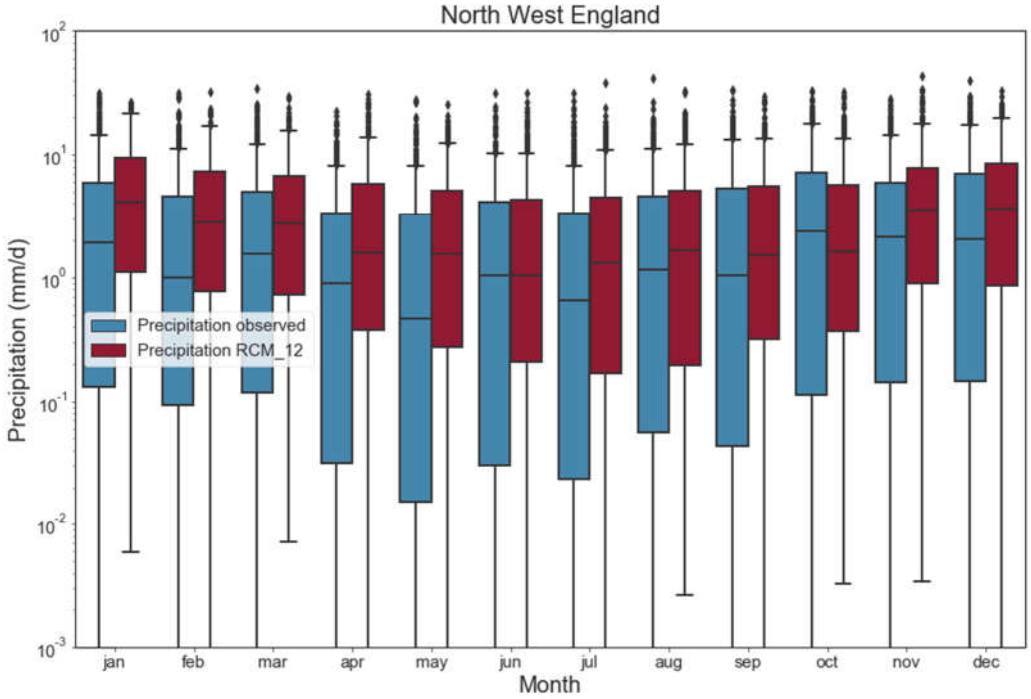

Thames
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

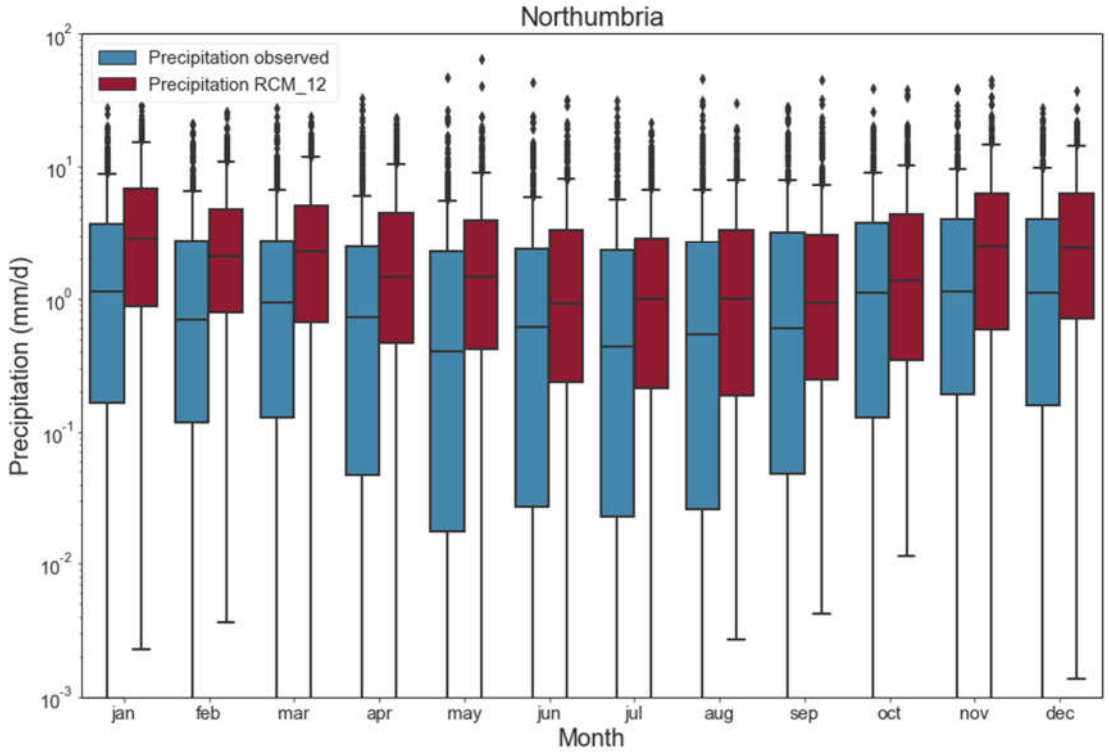

Western Wales
Temperature observed
Temperature RCM_12
Temperature (°C)
30
25
20
15
10
5
0
−5
−10
−15
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

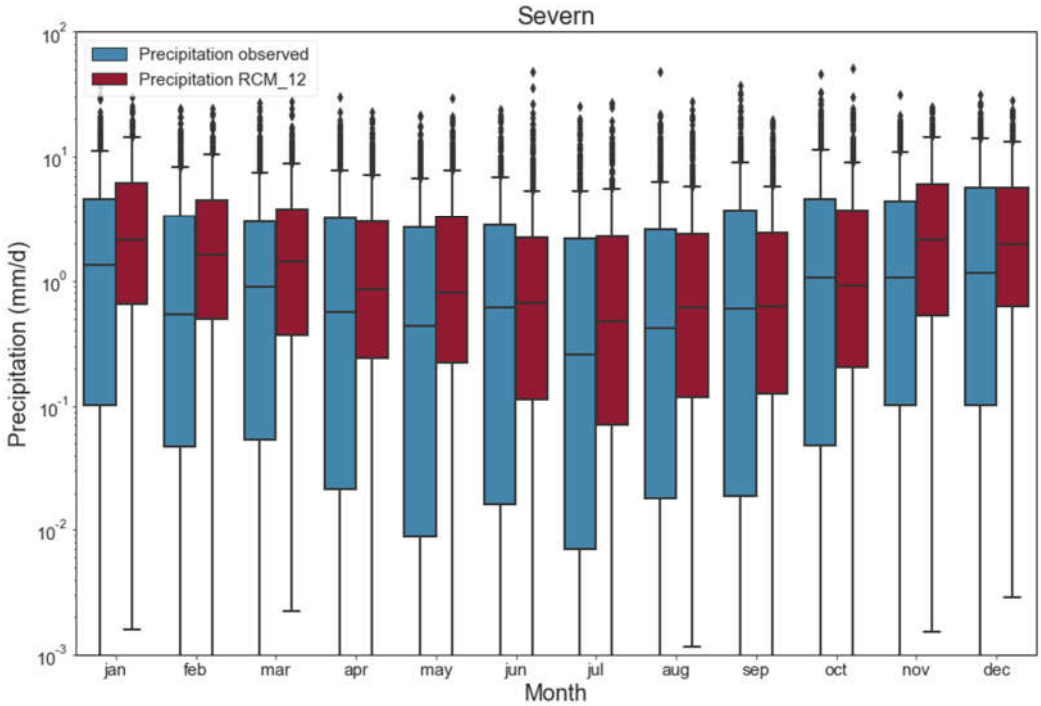
C.13. Comparisons between modelled and observed data: Monthly boxplots of daily precipitation

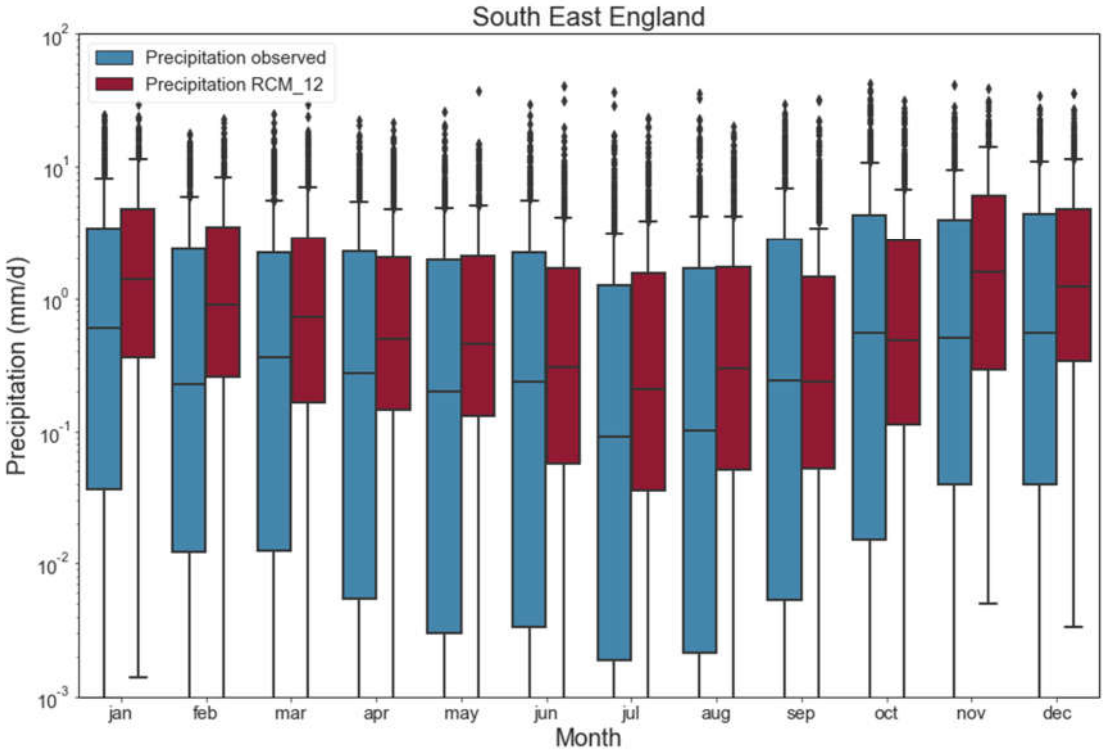


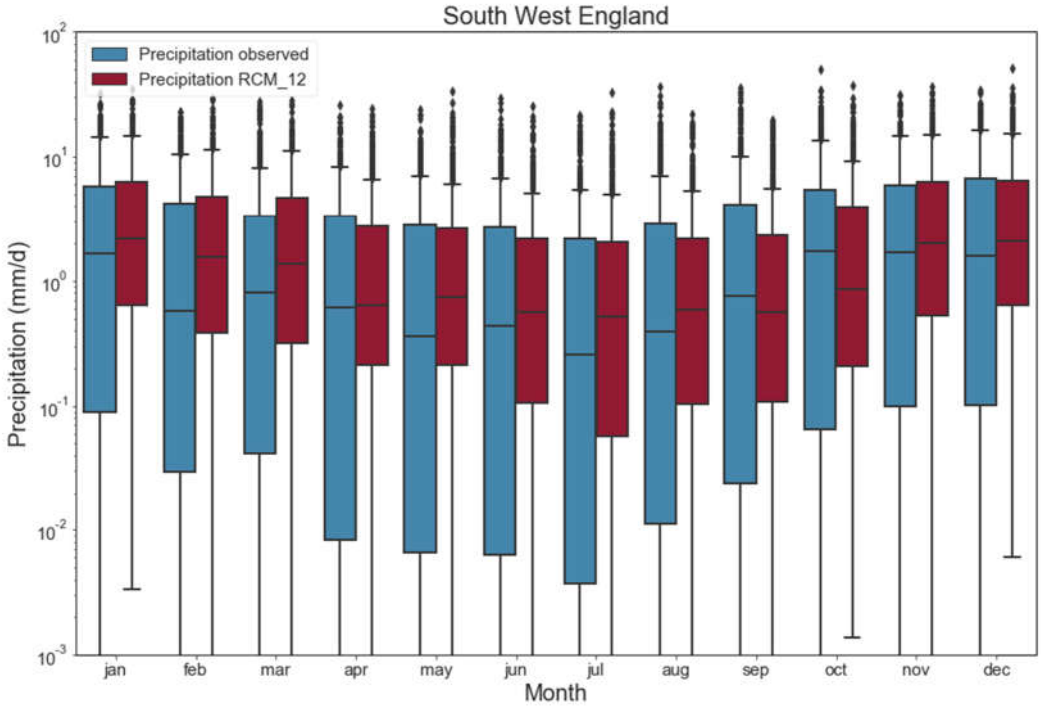


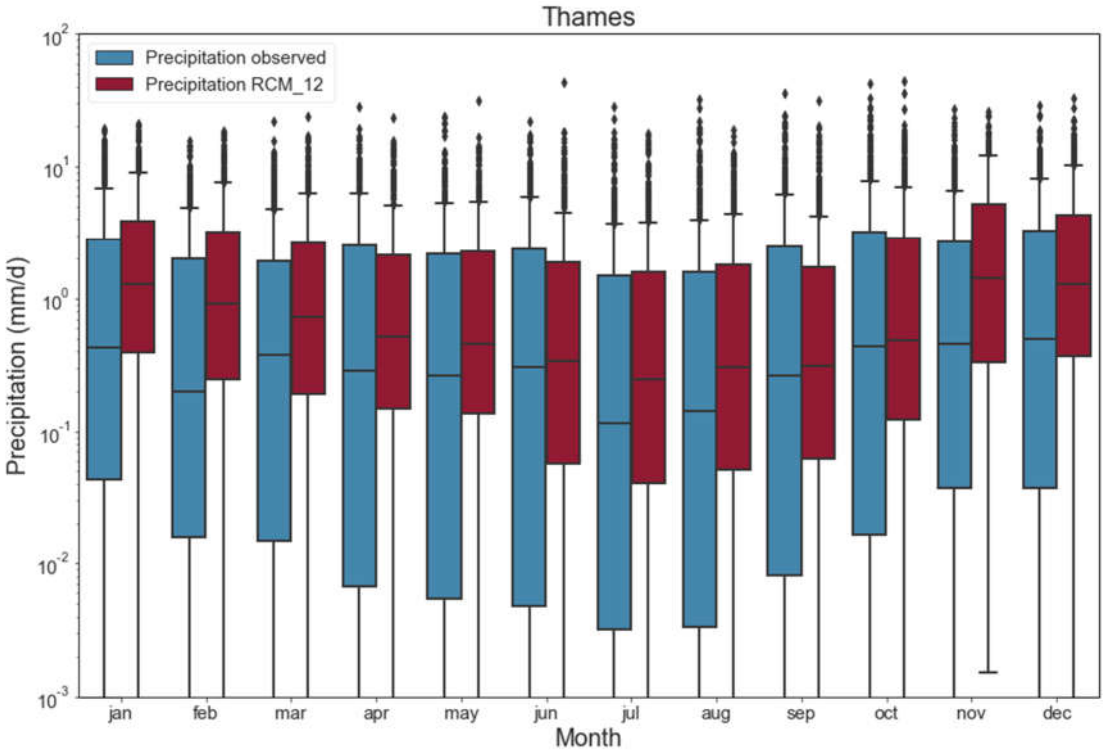

North West England
Precipitation (mm/d)
Precipitation observed
Precipitation RCM_12
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

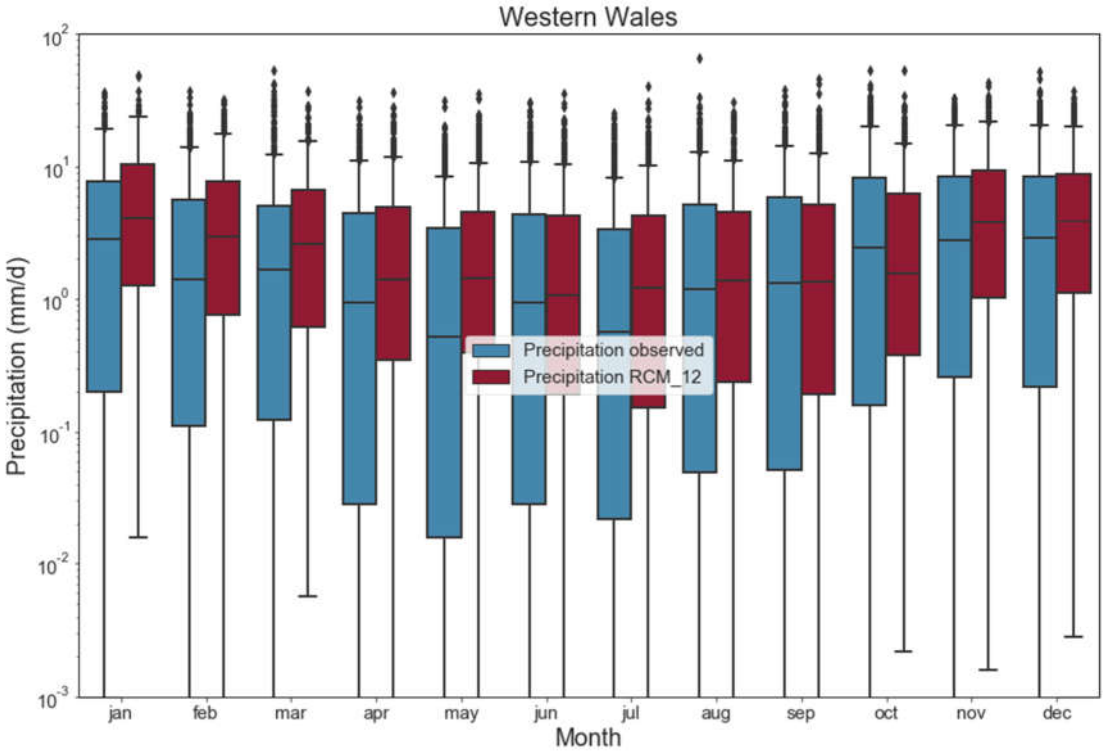

Northumbria
Precipitation (mm/d)
Precipitation observed
Precipitation RCM_12
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month


Severn
Precipitation observed
Precipitation RCM_12
Precipitation (mm/d)
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

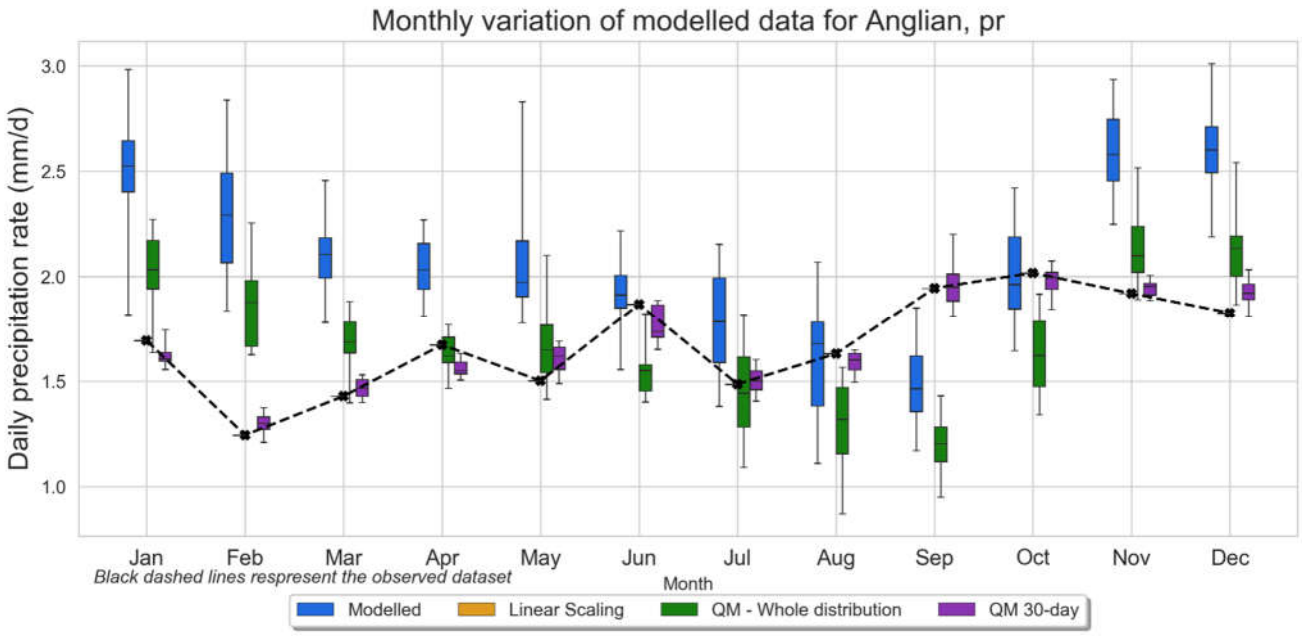

South East England
Precipitation observed
Precipitation RCM_12
Precipitation (mm/d)
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

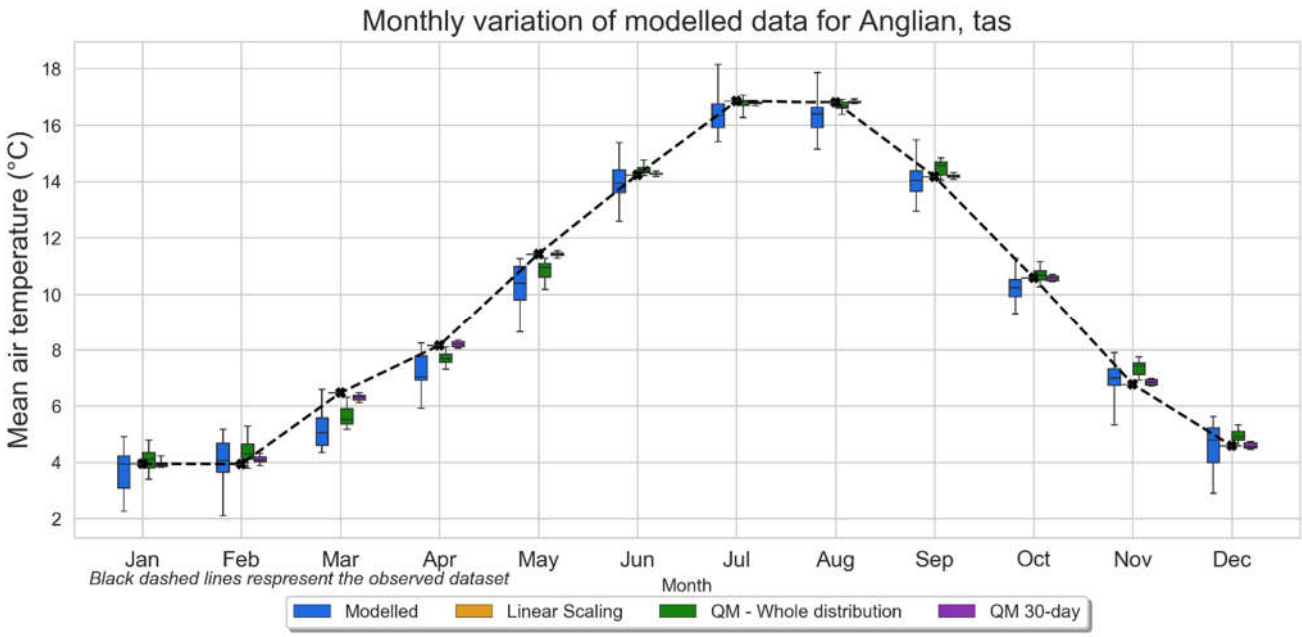

South West England
Precipitation observed
Precipitation RCM_12
Precipitation (mm/d)
Month
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec

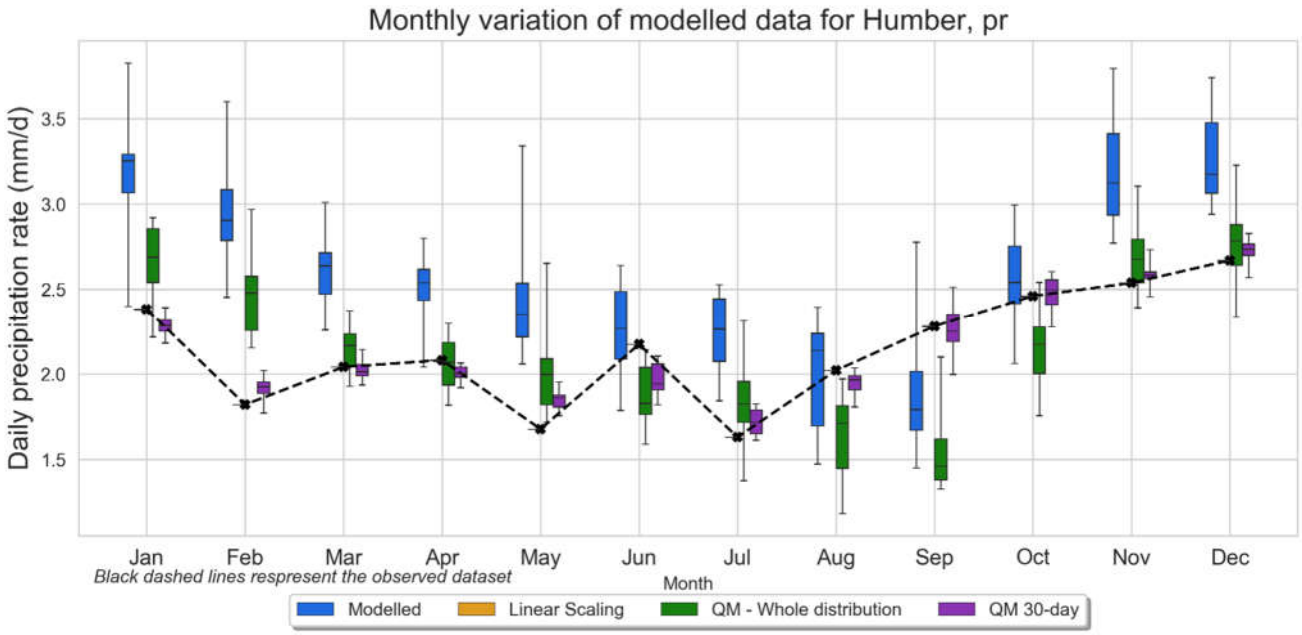

Thames
Precipitation observed
Precipitation RCM_12
Precipitation (mm/d)
Month
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec

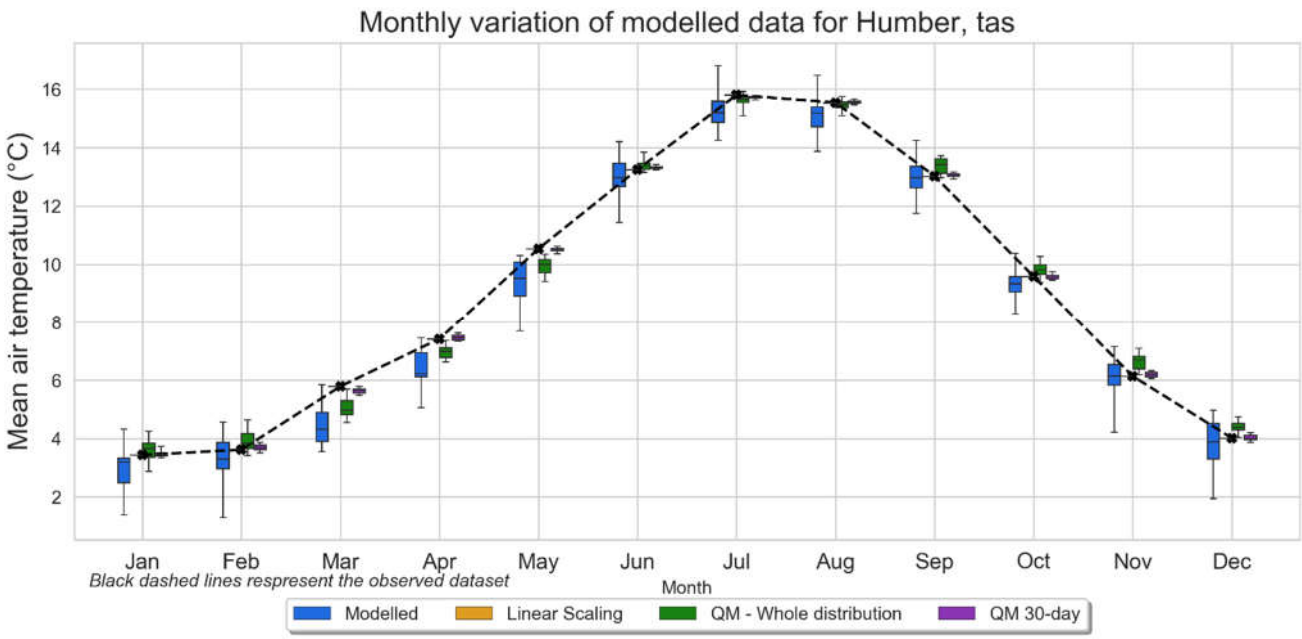

Western Wales
Precipitation (mm/d)
10^2
10^1
10^0
10^{-1}
10^{-2}
10^{-3}
Precipitation observed
Precipitation RCM_12
jan
feb
mar
apr
may
jun
jul
aug
sep
oct
nov
dec
Month

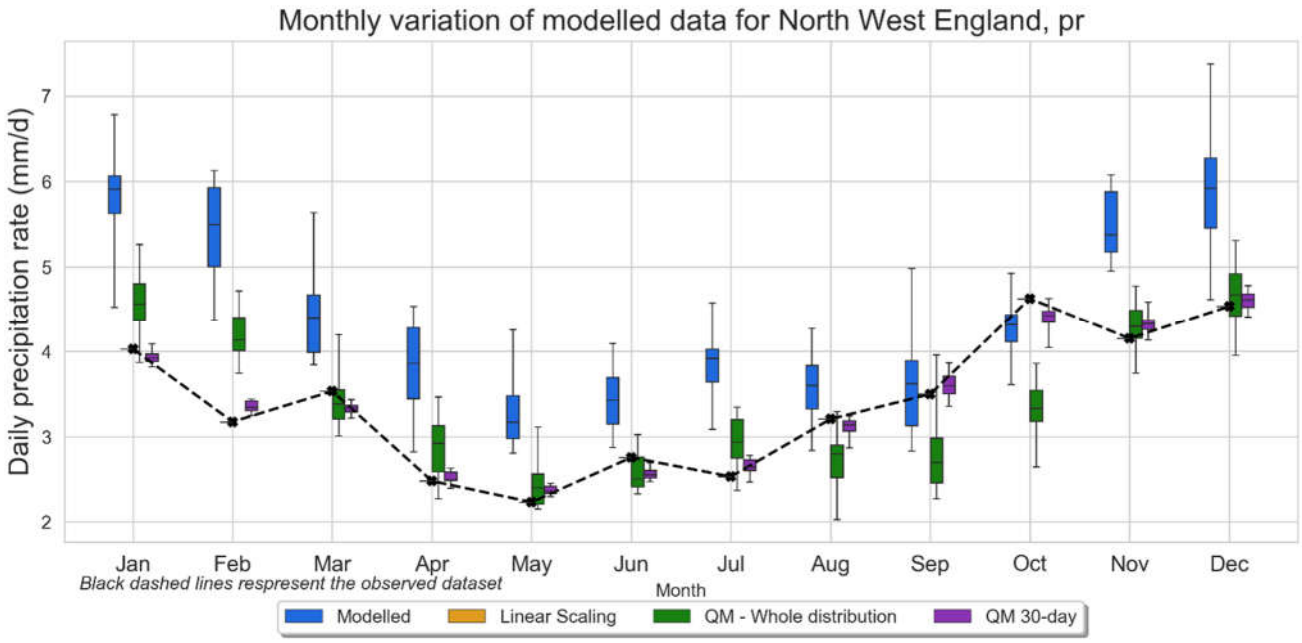
C.13.1. Bias correction: Boxplots of monthly temperature and precipitation before and after bias correction

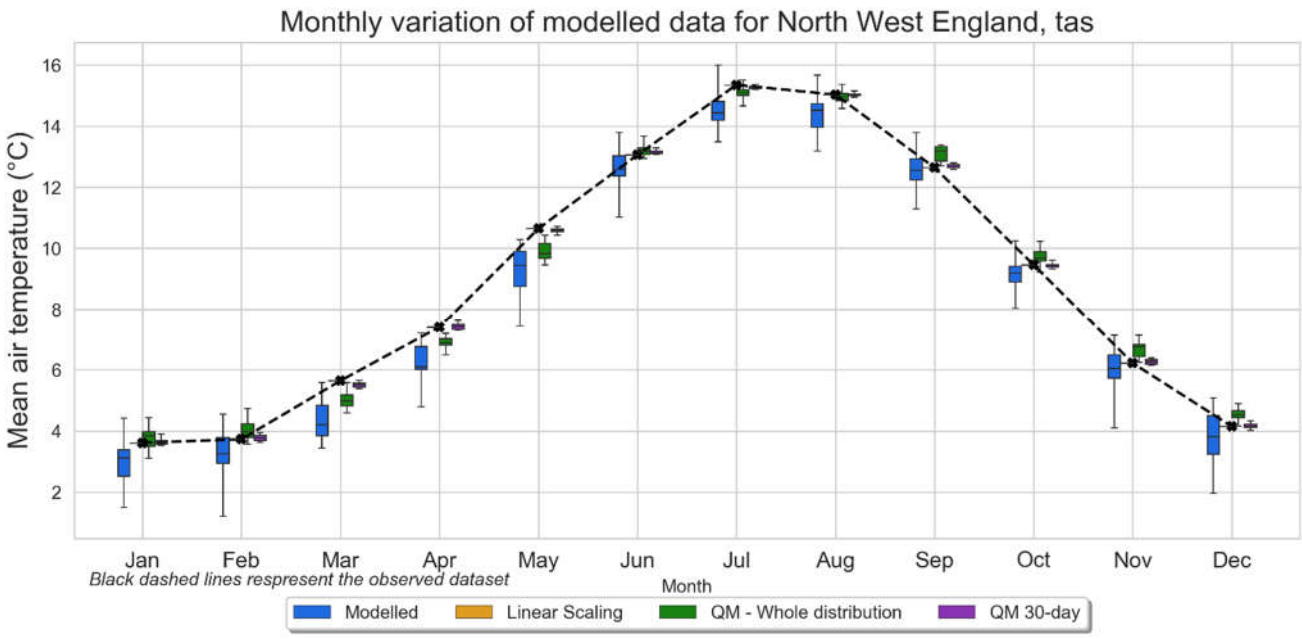


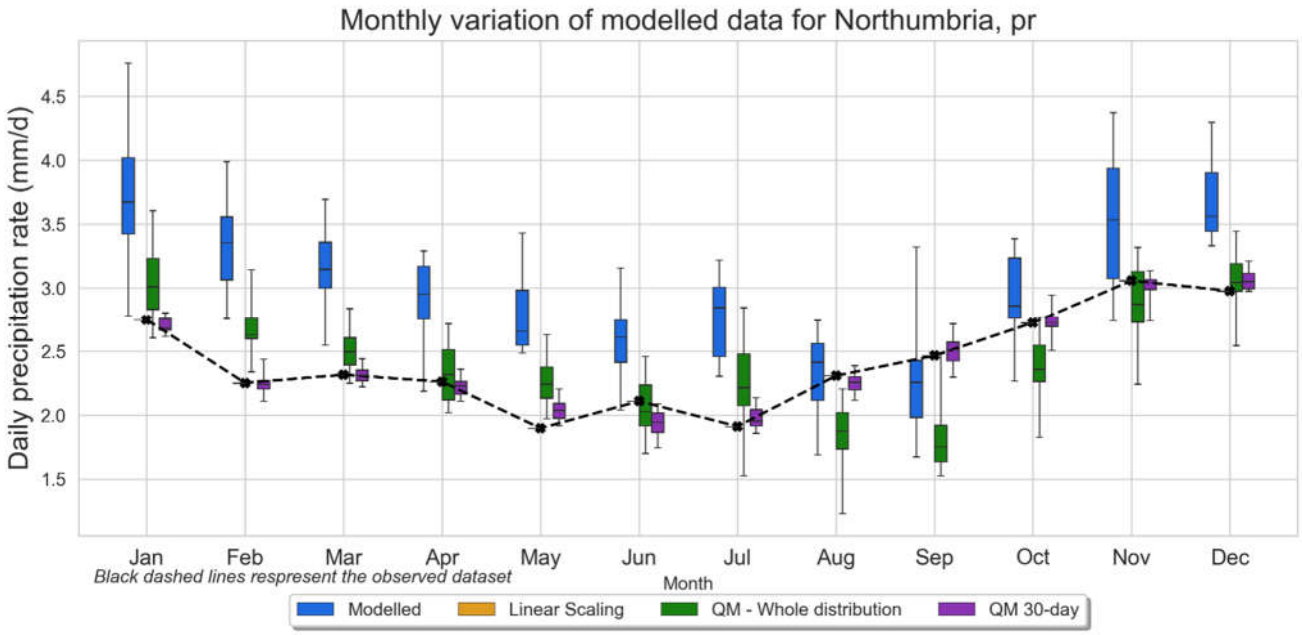


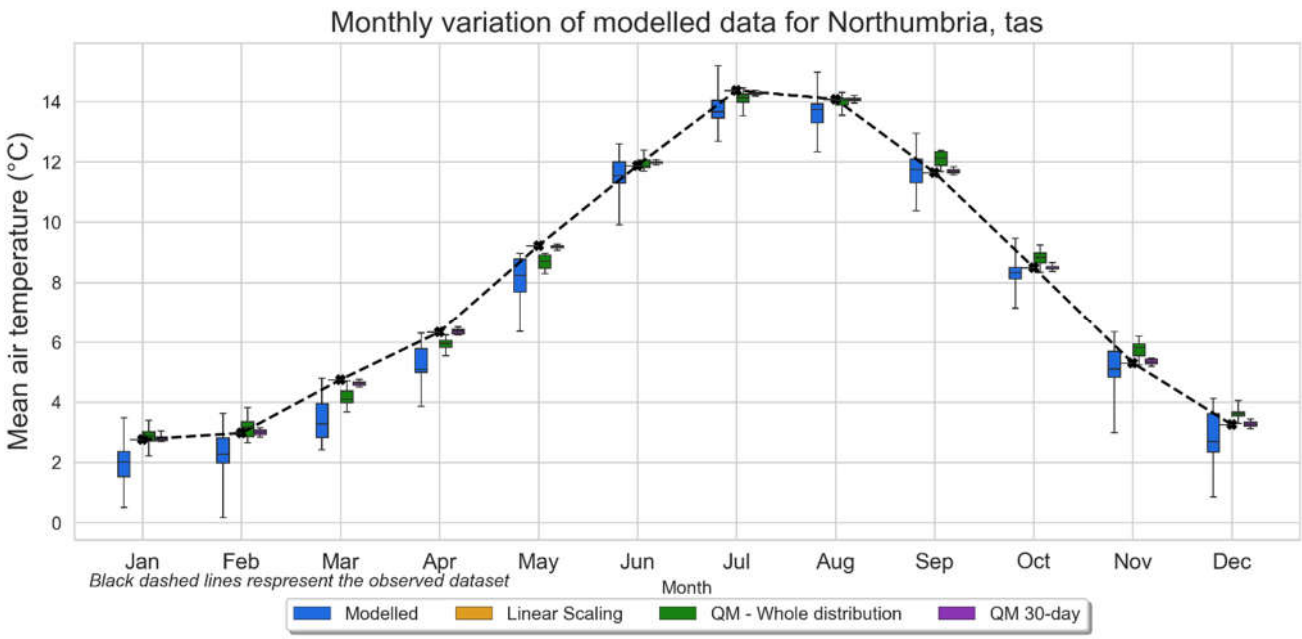

Monthly variation of modelled data for Humber, pr
Daily precipitation rate (mm/d)
3.5
3.0
2.5
2.0
1.5
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

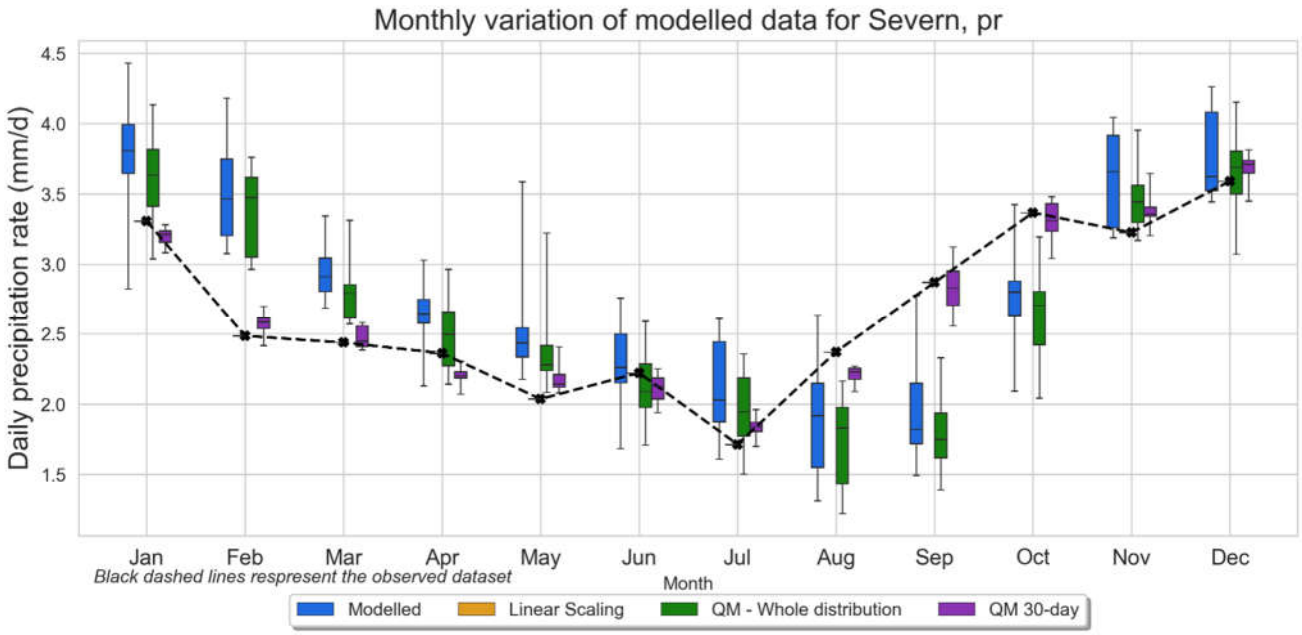

Monthly variation of modelled data for Humber, tas
Mean air temperature (°C)
16
14
12
10
8
6
4
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

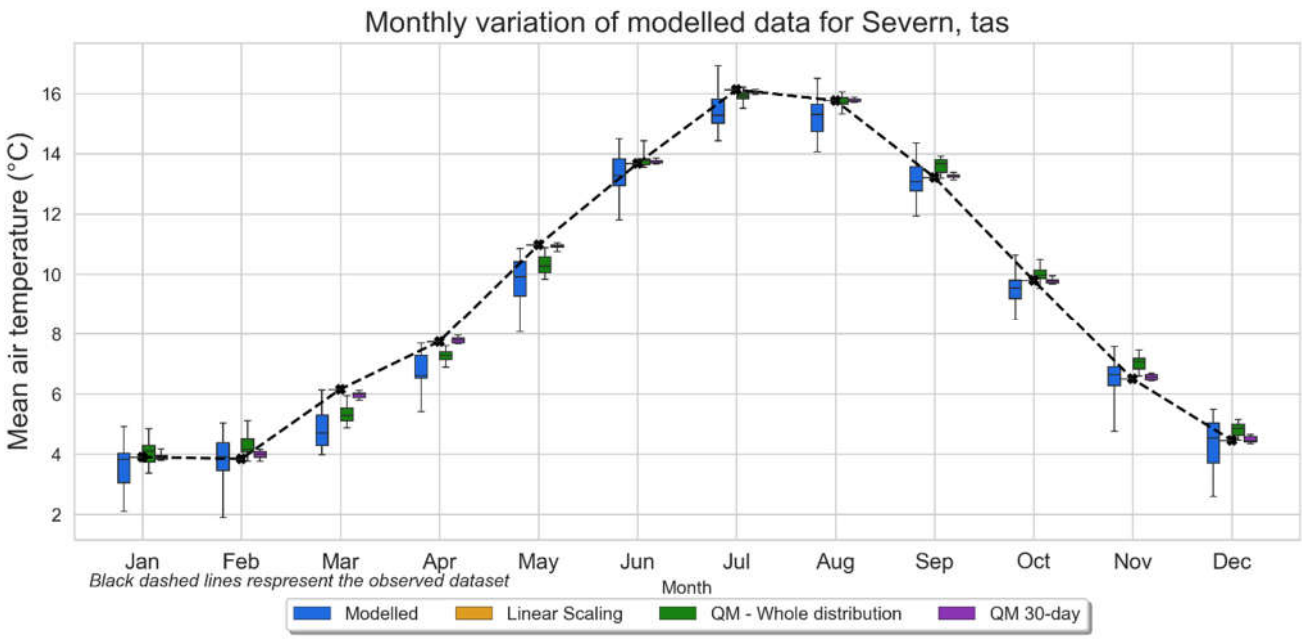

Monthly variation of modelled data for North West England, pr
Daily precipitation rate (mm/d)
7
6
5
4
3
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

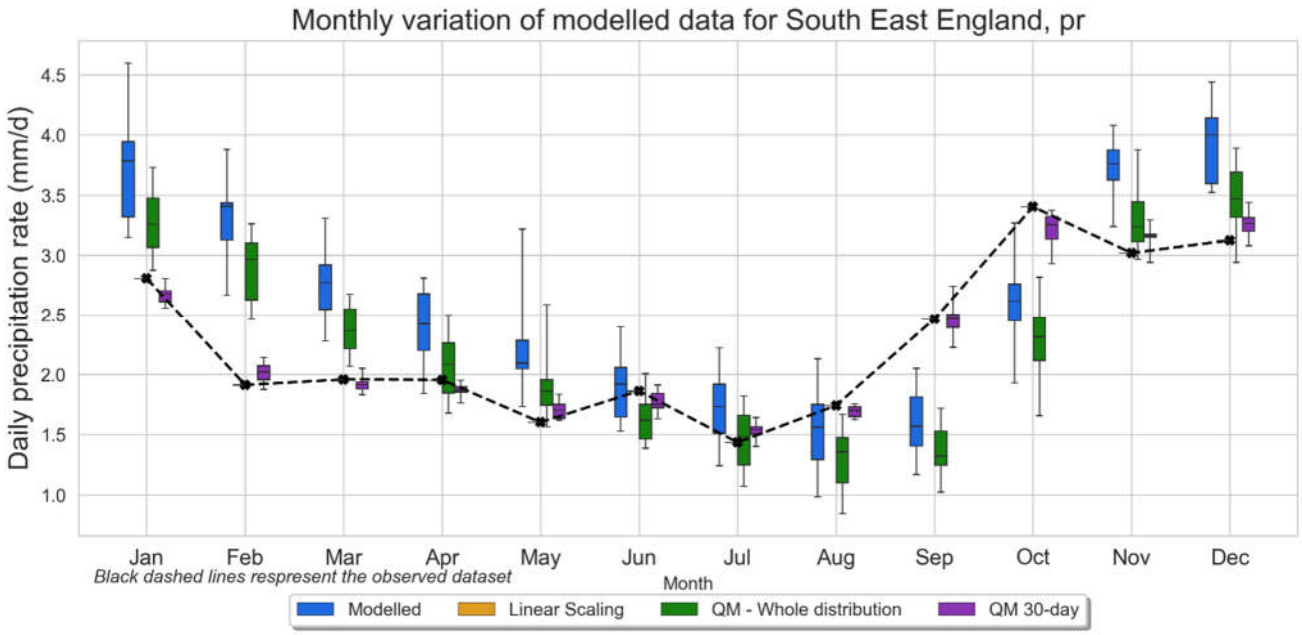

Monthly variation of modelled data for North West England, tas
Mean air temperature (°C)
16
14
12
10
8
6
4
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

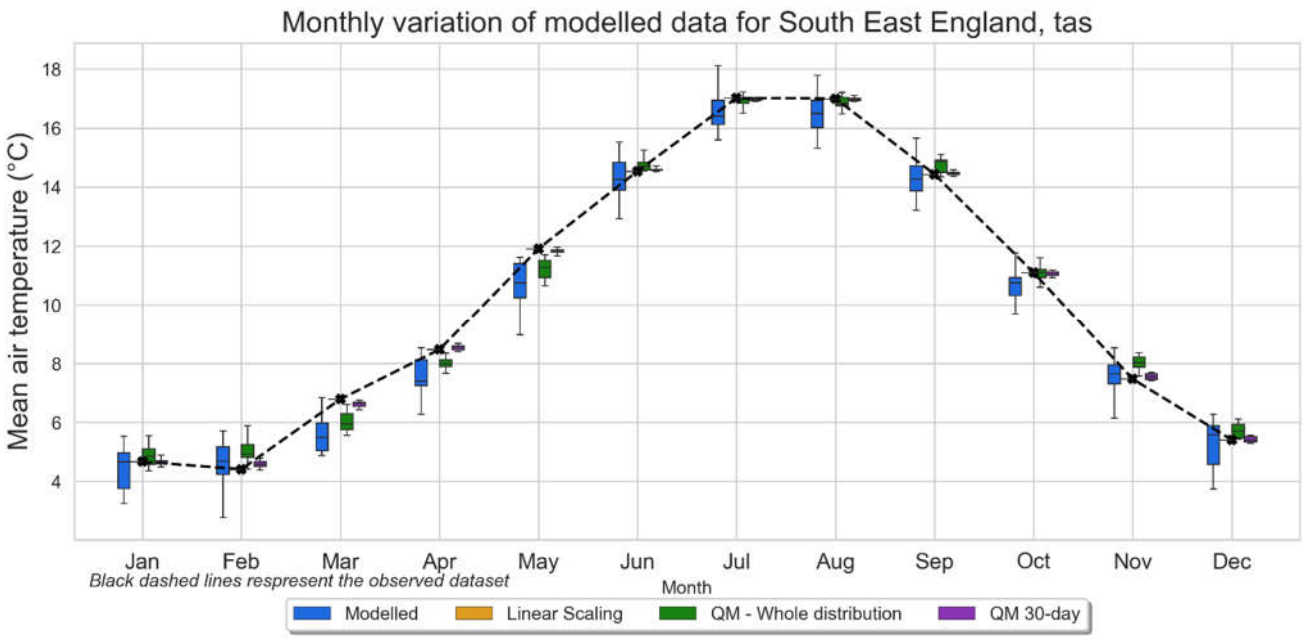

Monthly variation of modelled data for Northumbria, pr
Daily precipitation rate (mm/d)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

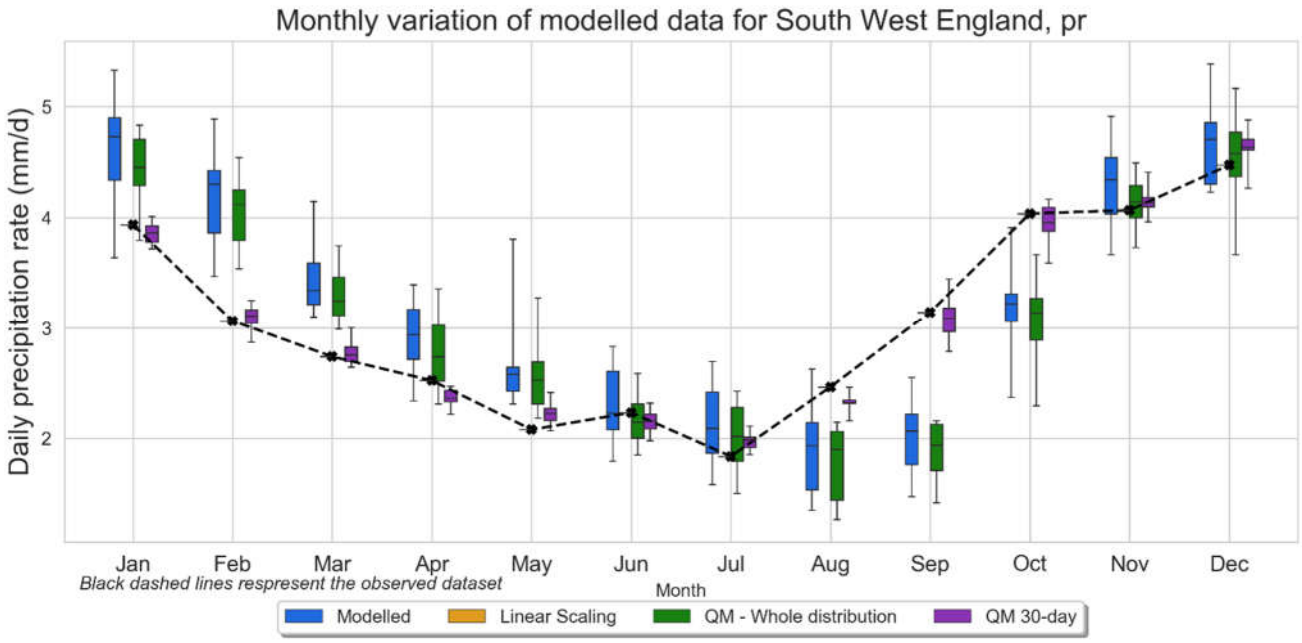

Monthly variation of modelled data for Northumbria, tas
Mean air temperature (°C)
14
12
10
8
6
4
2
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

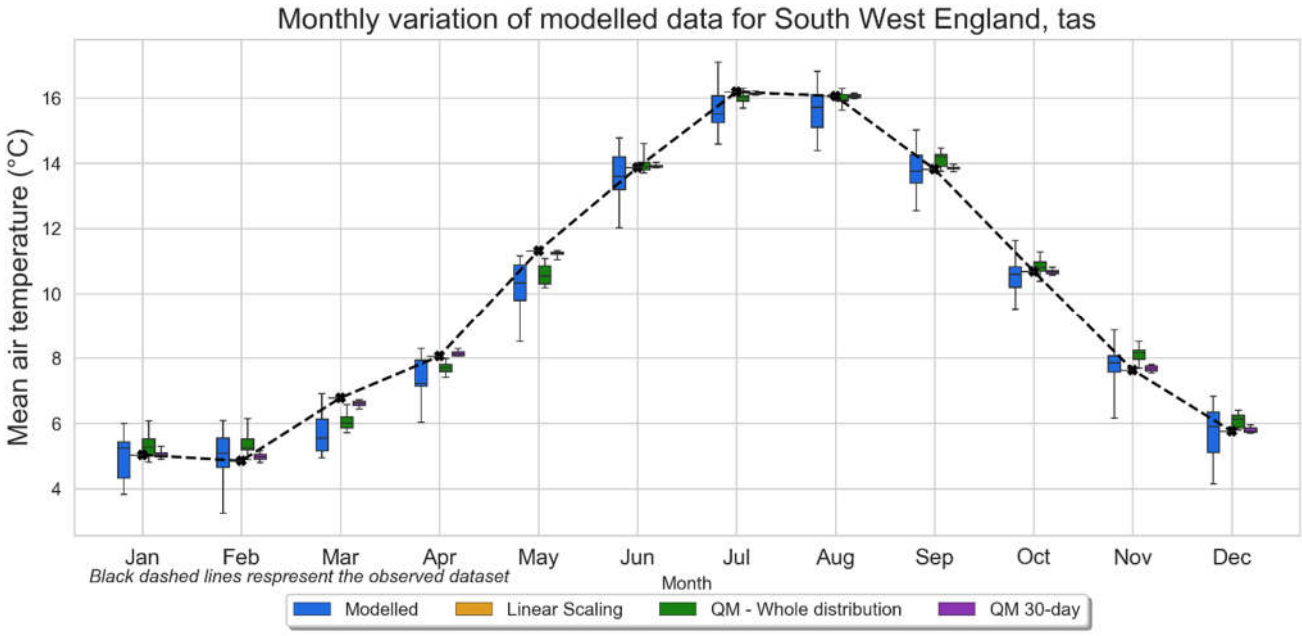

Monthly variation of modelled data for Severn, pr
Daily precipitation rate (mm/d)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

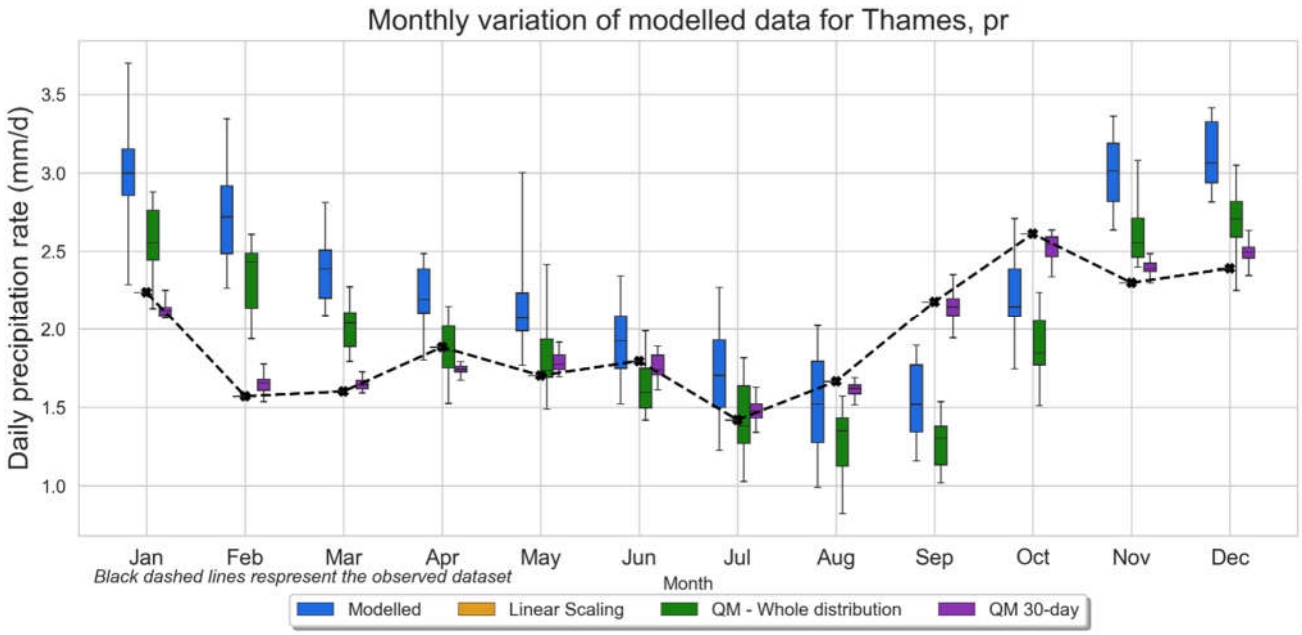

Monthly variation of modelled data for Severn, tas
Mean air temperature (°C)
16
14
12
10
8
6
4
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

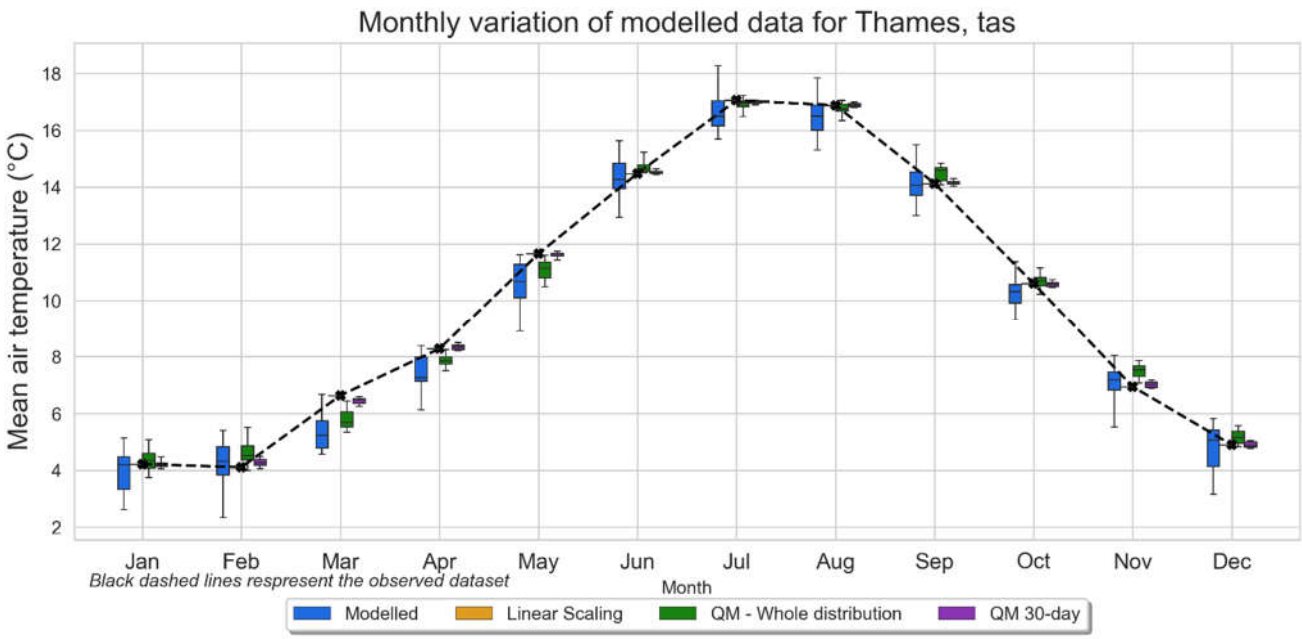

Monthly variation of modelled data for South East England, pr
Daily precipitation rate (mm/d)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

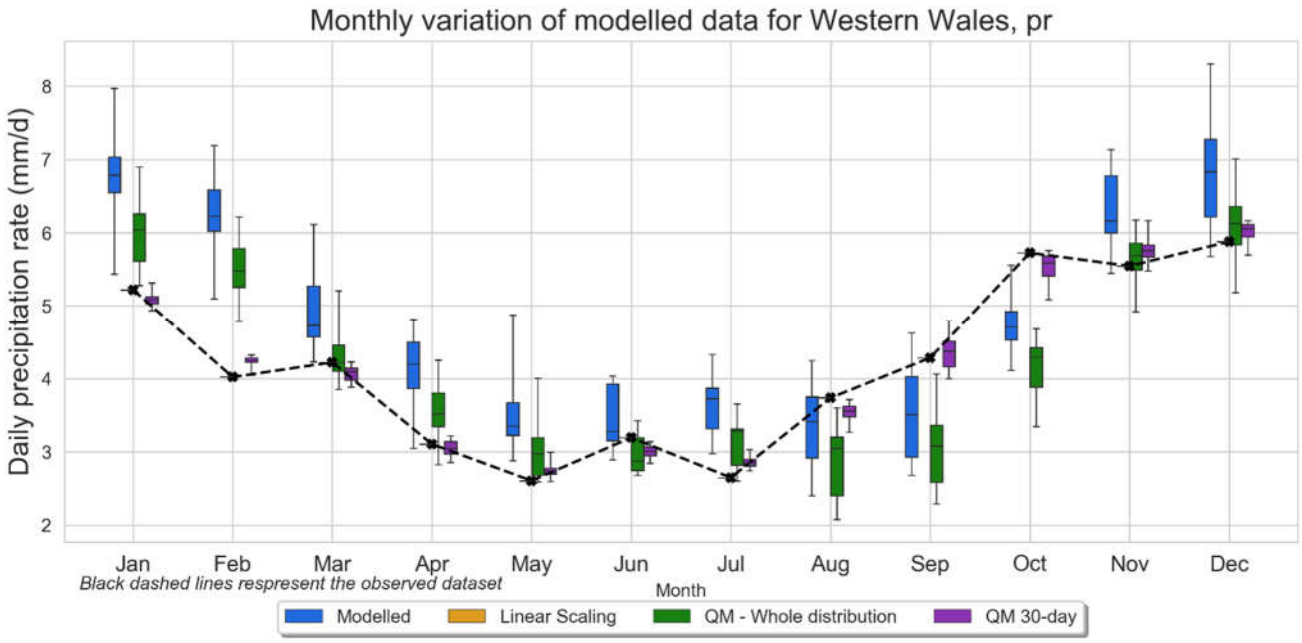

Monthly variation of modelled data for South East England, tas
Mean air temperature (°C)
18
16
14
12
10
8
6
4
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

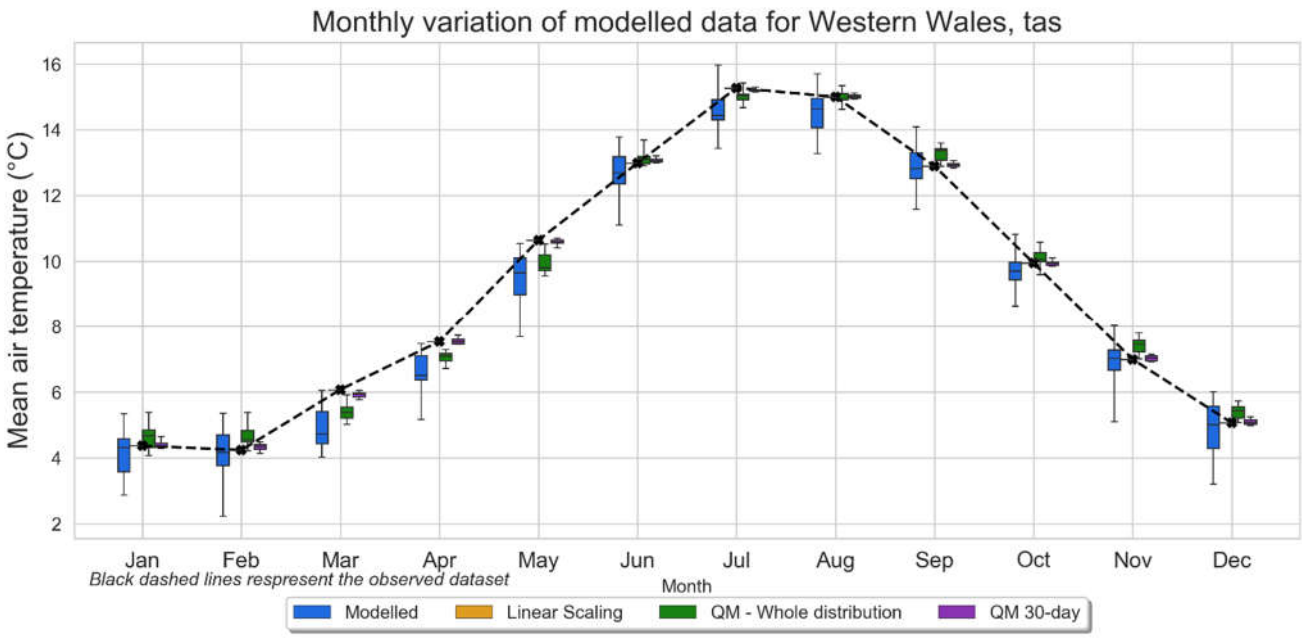

Monthly variation of modelled data for South West England, pr
Daily precipitation rate (mm/d)
5
4
3
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day


Monthly variation of modelled data for South West England, tas
Mean air temperature (°C)
16
14
12
10
8
6
4
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

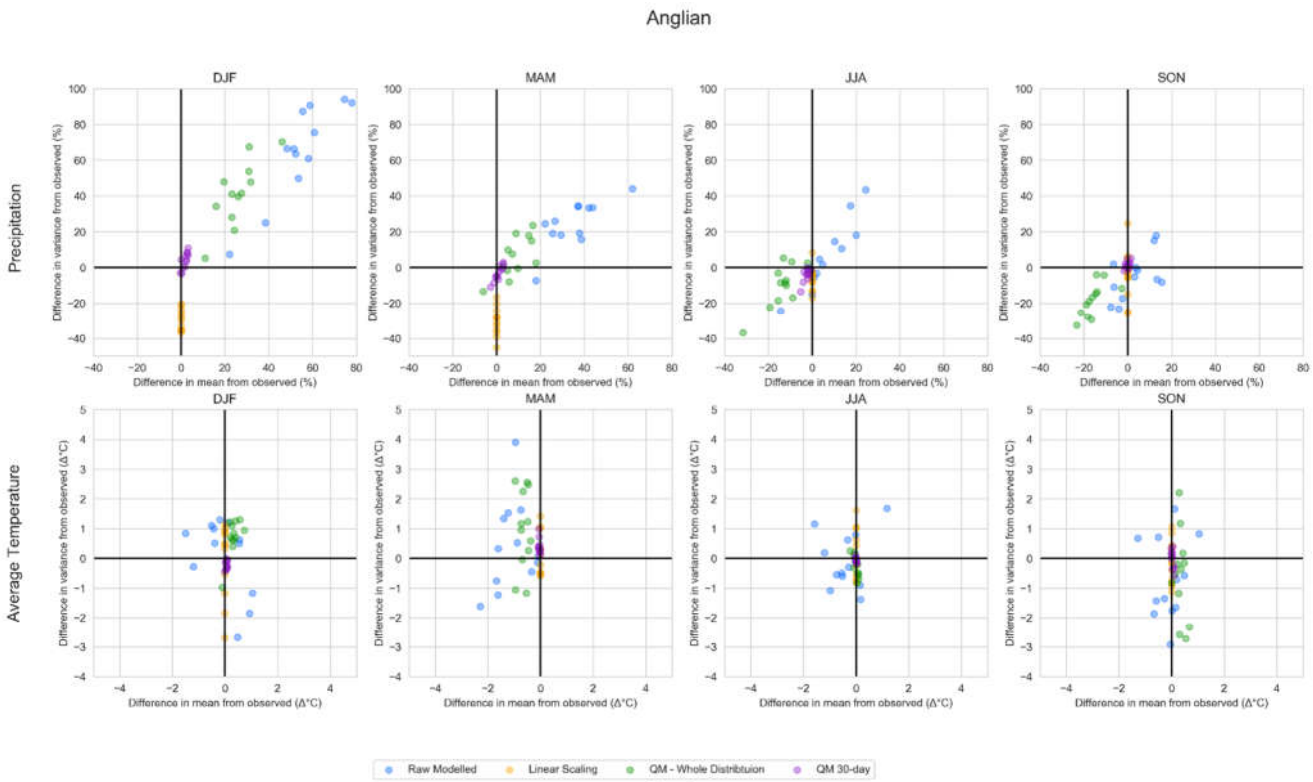

Monthly variation of modelled data for Thames, pr
Daily precipitation rate (mm/d)
3.5
3.0
2.5
2.0
1.5
1.0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day

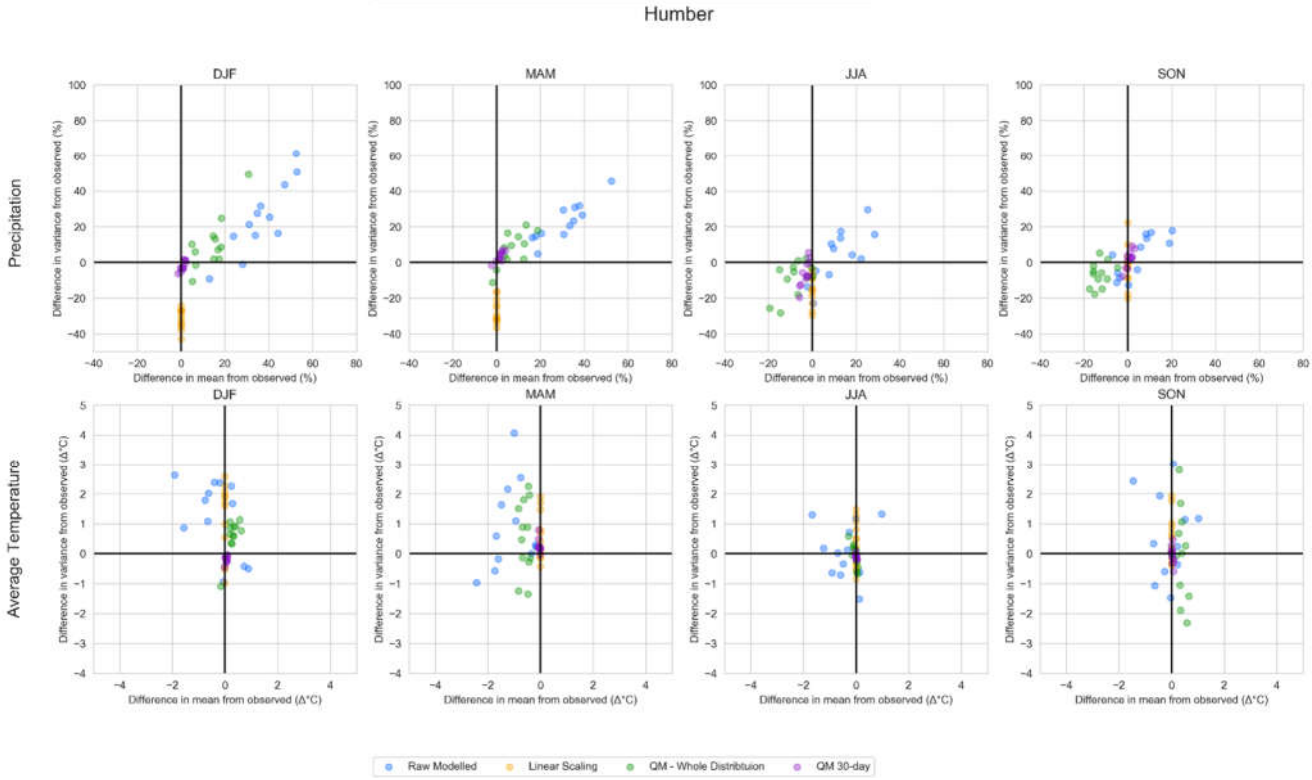

Monthly variation of modelled data for Thames, tas
Mean air temperature (°C)
18
16
14
12
10
8
6
4
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Black dashed lines respresent the observed dataset
Month
Modelled
Linear Scaling
QM - Whole distribution
QM 30-day



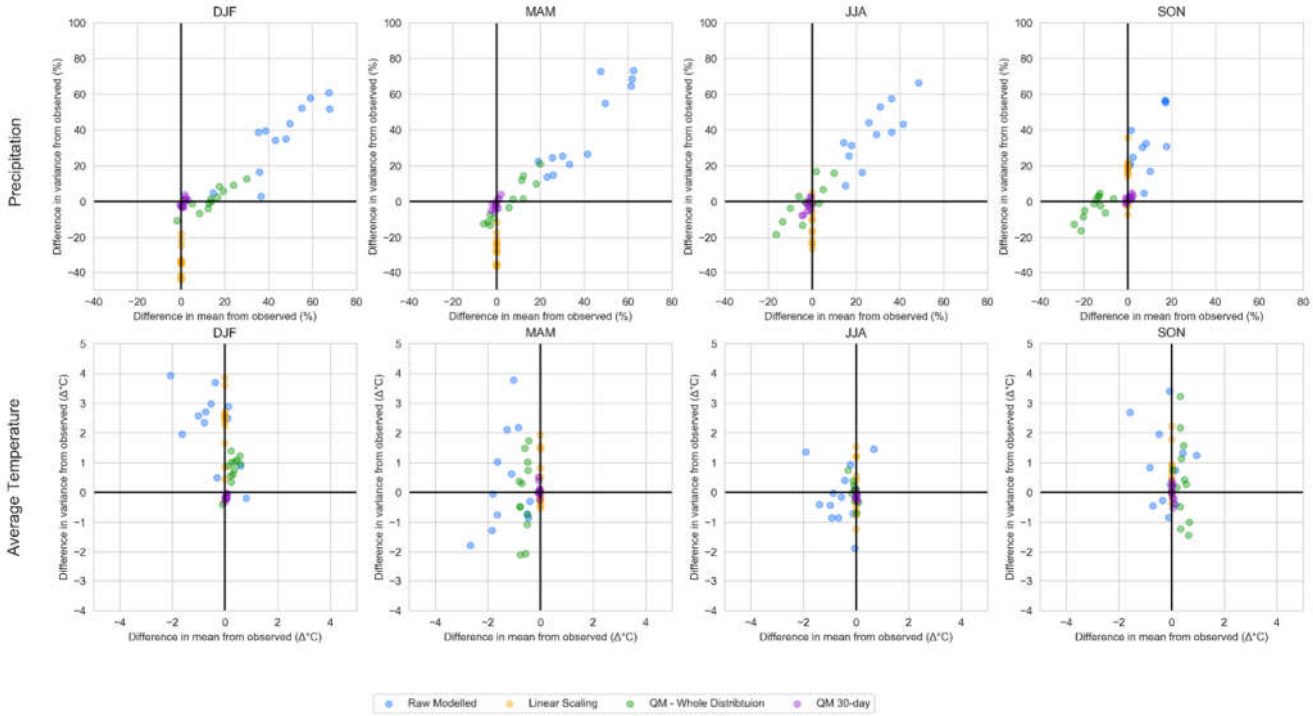


C.13.2. Bias correction: Seasonal scatterplots of means and variances of temperature and precipitation before and after bias correction

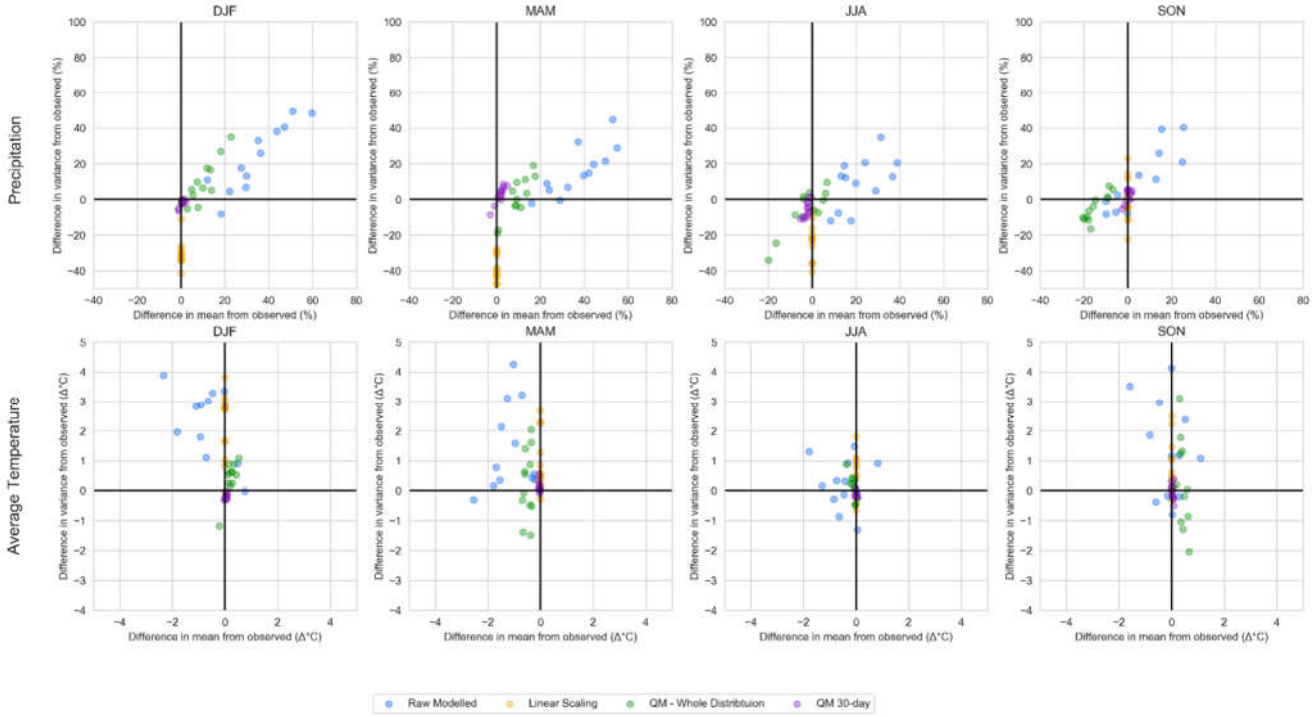

Anglian
DJF
MAM
JJA
SON
Precipitation
Average Temperature
Difference in variance from observed (%)
Difference in mean from observed (%)
Difference in variance from observed (Δ°C)
Difference in mean from observed (Δ°C)
Raw Modelled
Linear Scaling
QM - Whole Distribtuion
QM 30-day


Humber
DJF
MAM
JJA
SON
Precipitation
Average Temperature
Difference in variance from observed (%)
Difference in mean from observed (%)
Difference in variance from observed (Δ°C)
Difference in mean from observed (Δ°C)
Raw Modelled
Linear Scaling
QM - Whole Distribtuion
QM 30-day

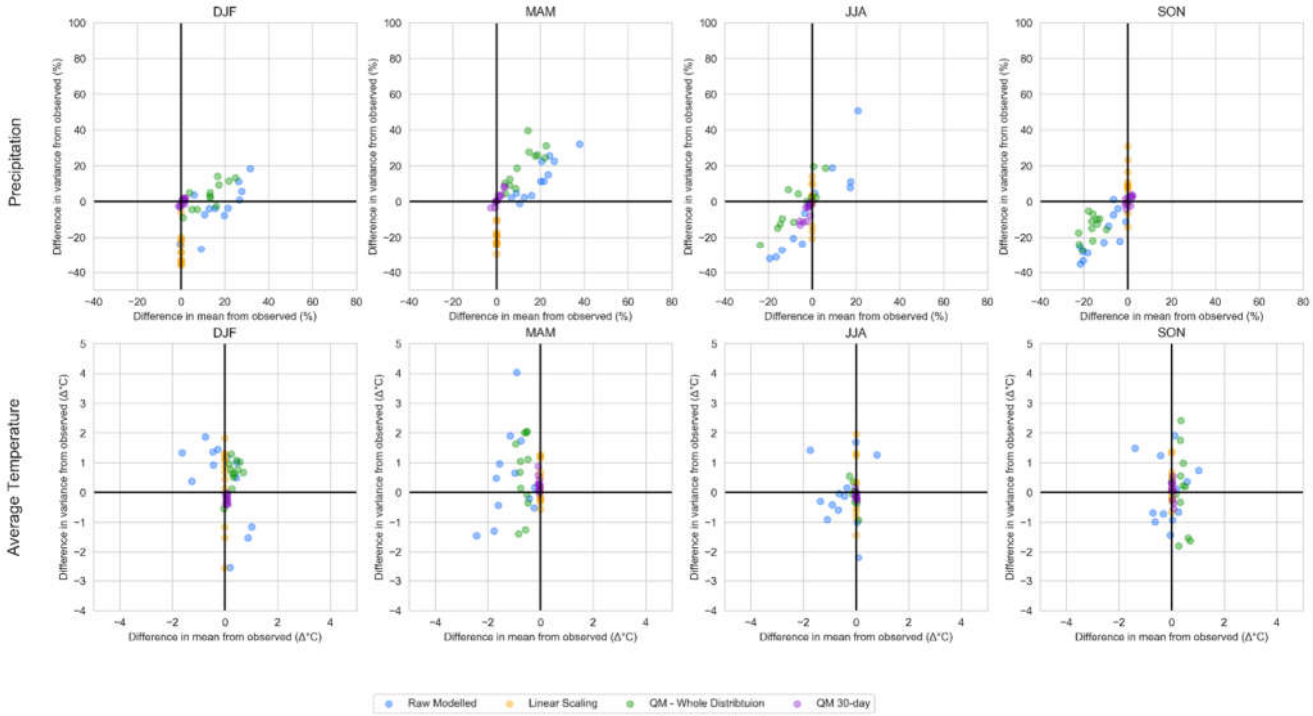
North West England



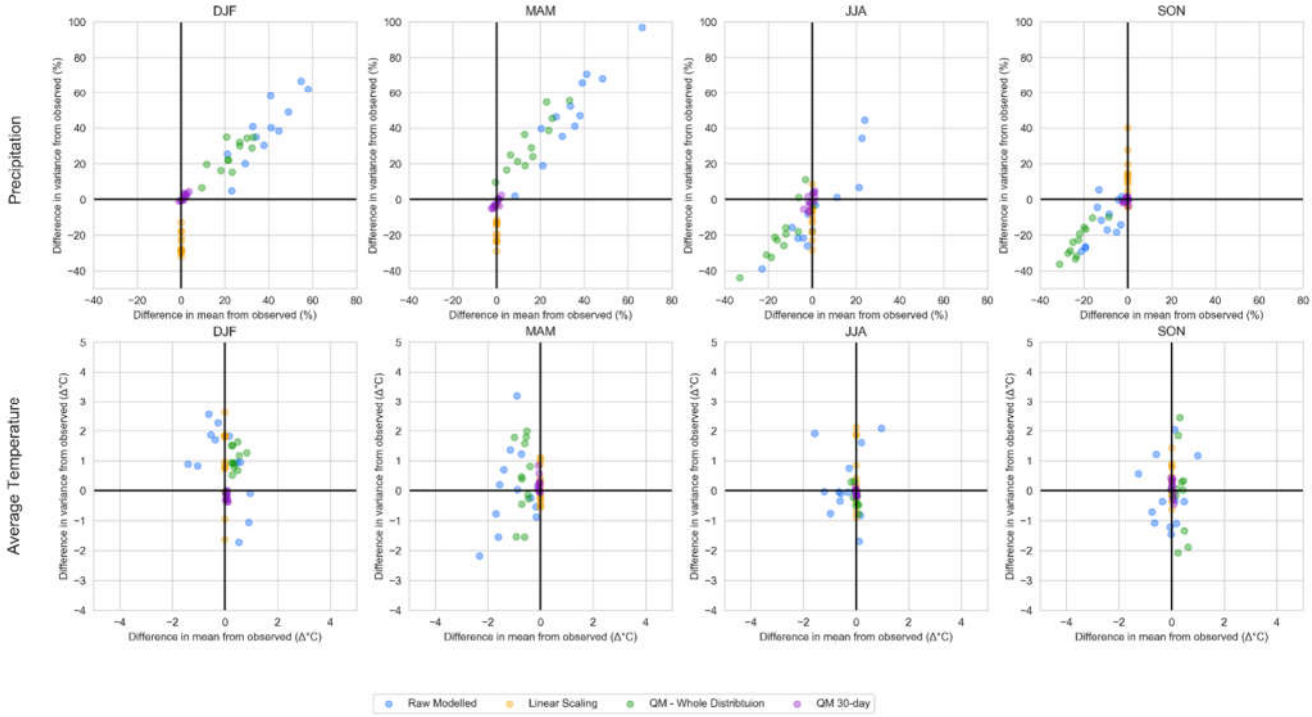
Northumbria



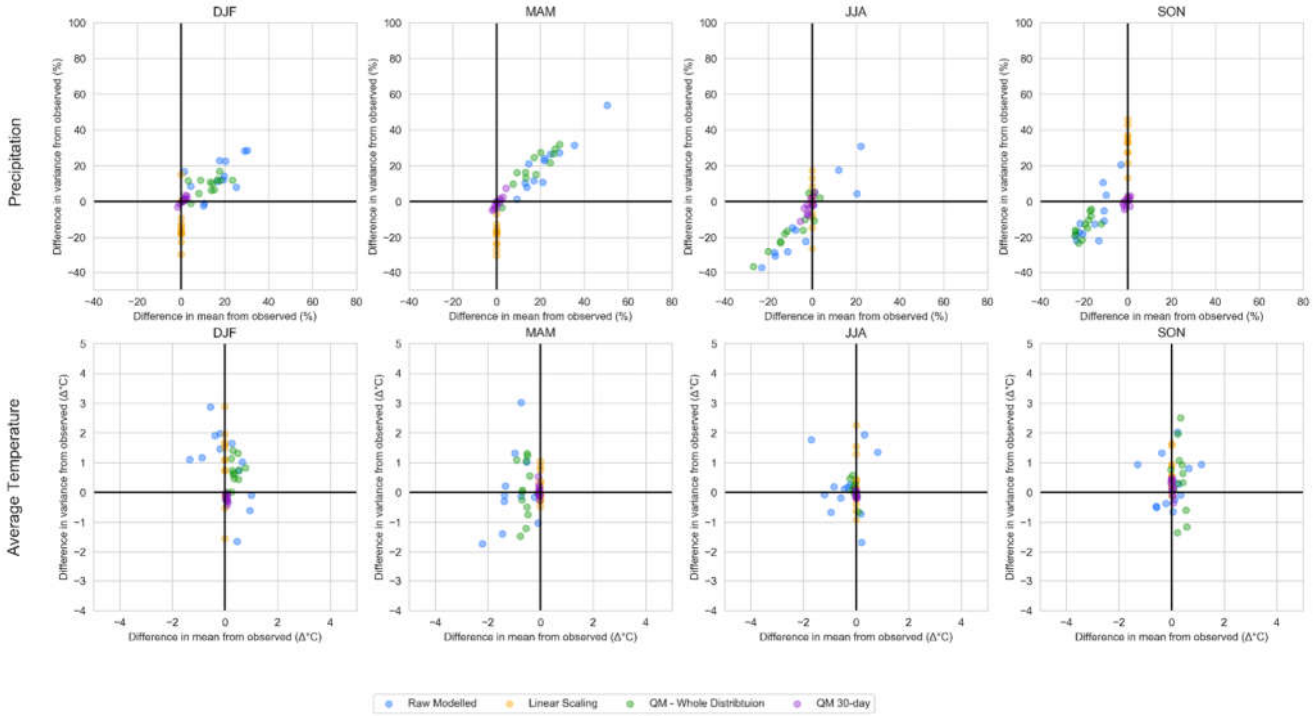
Severn



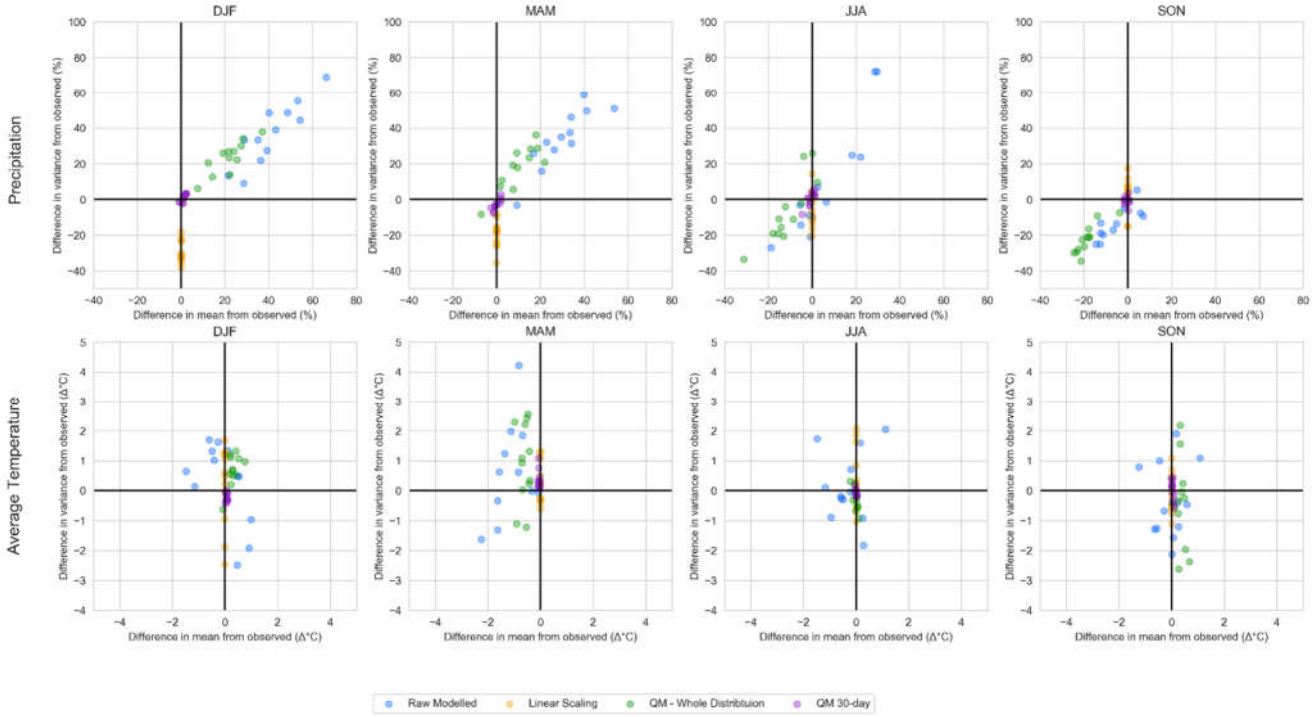
South East England

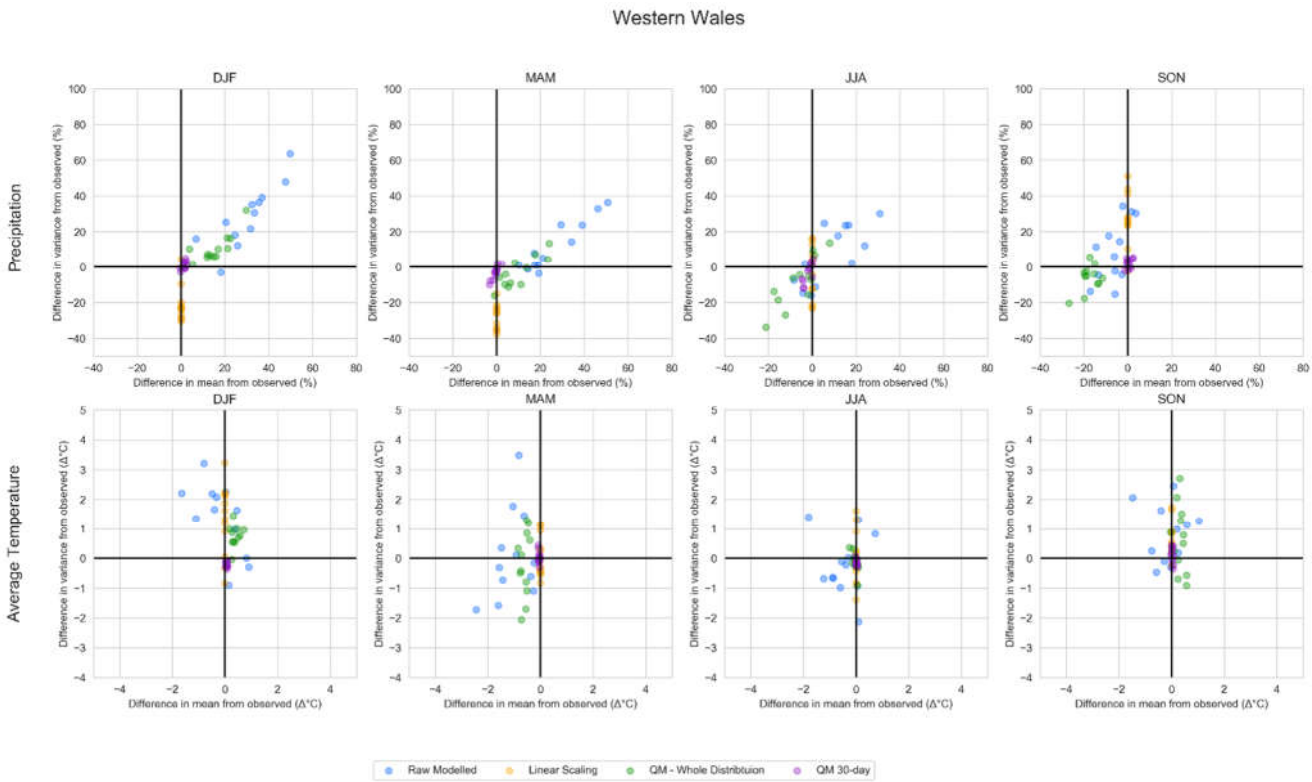


South West England

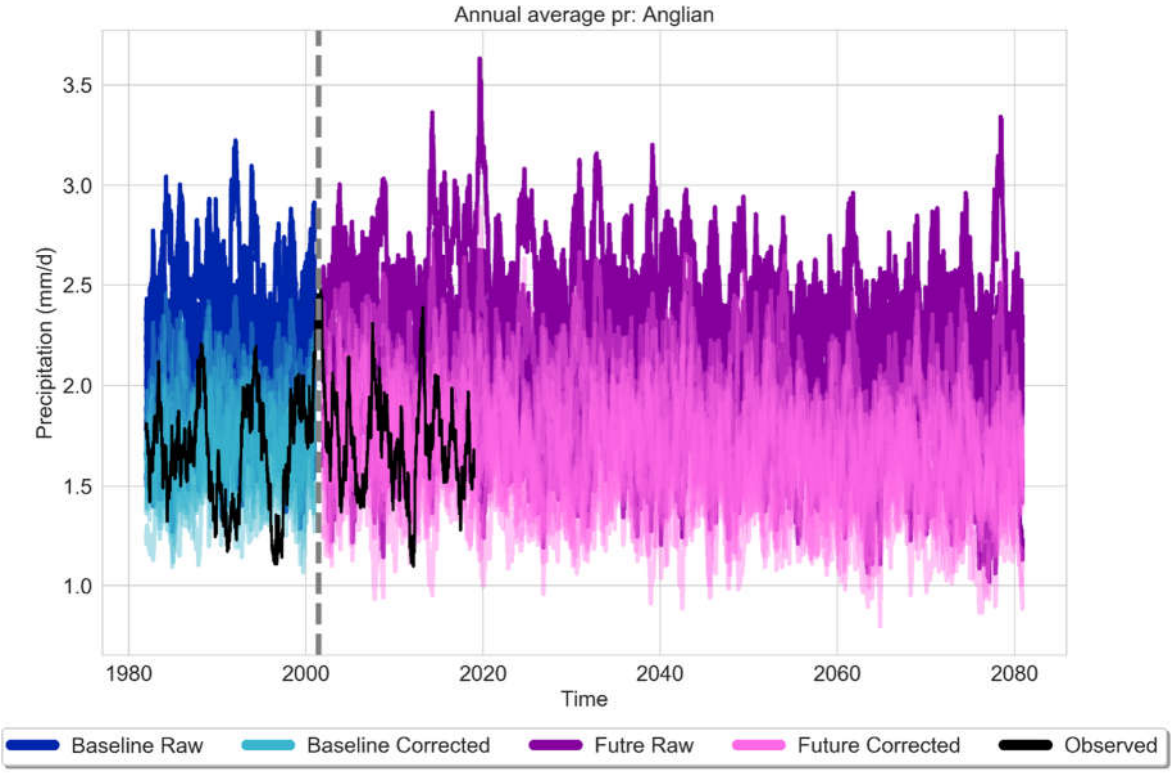


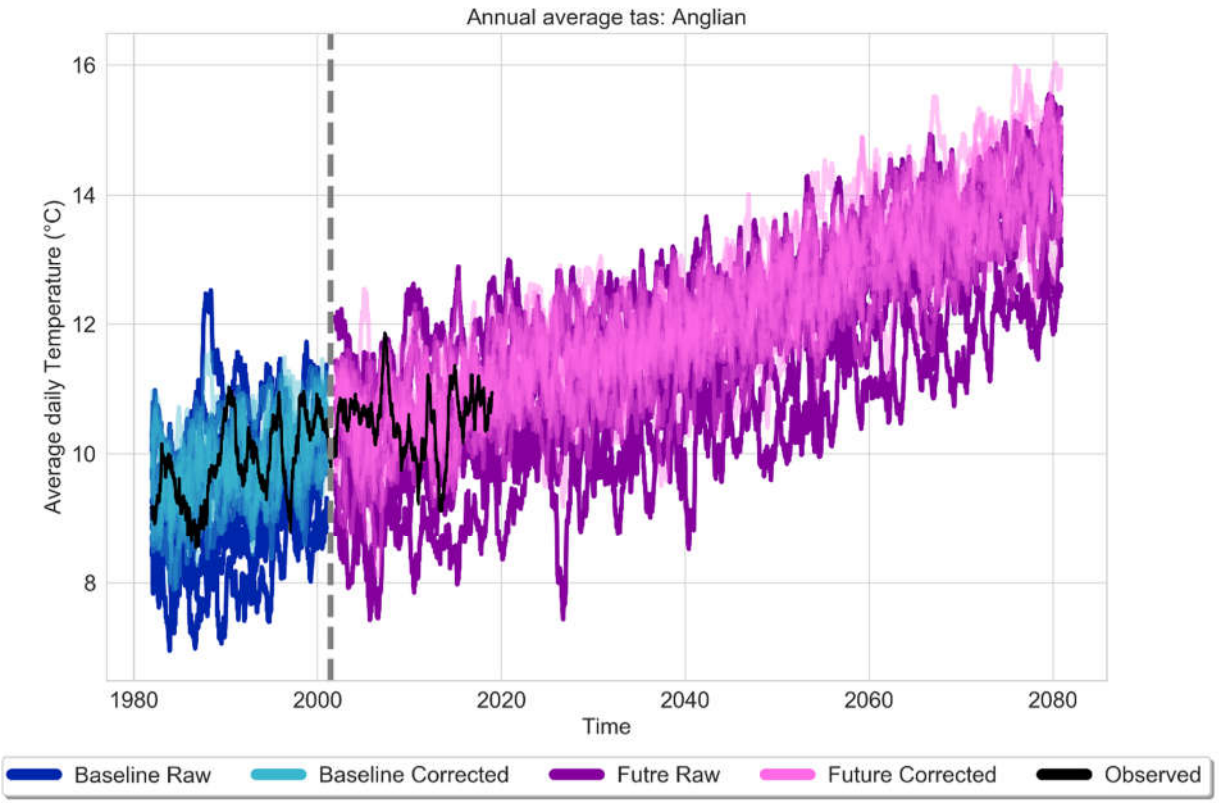
Thames

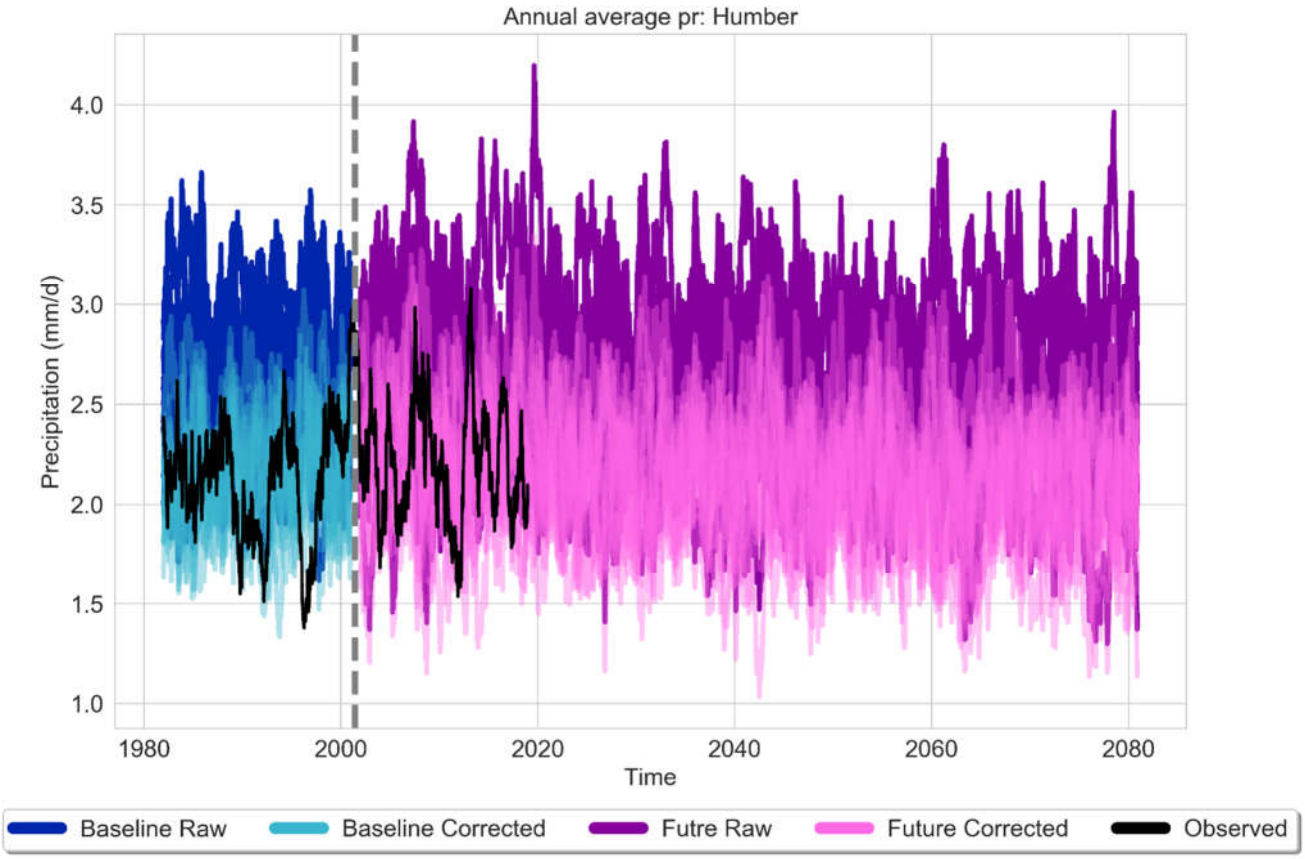


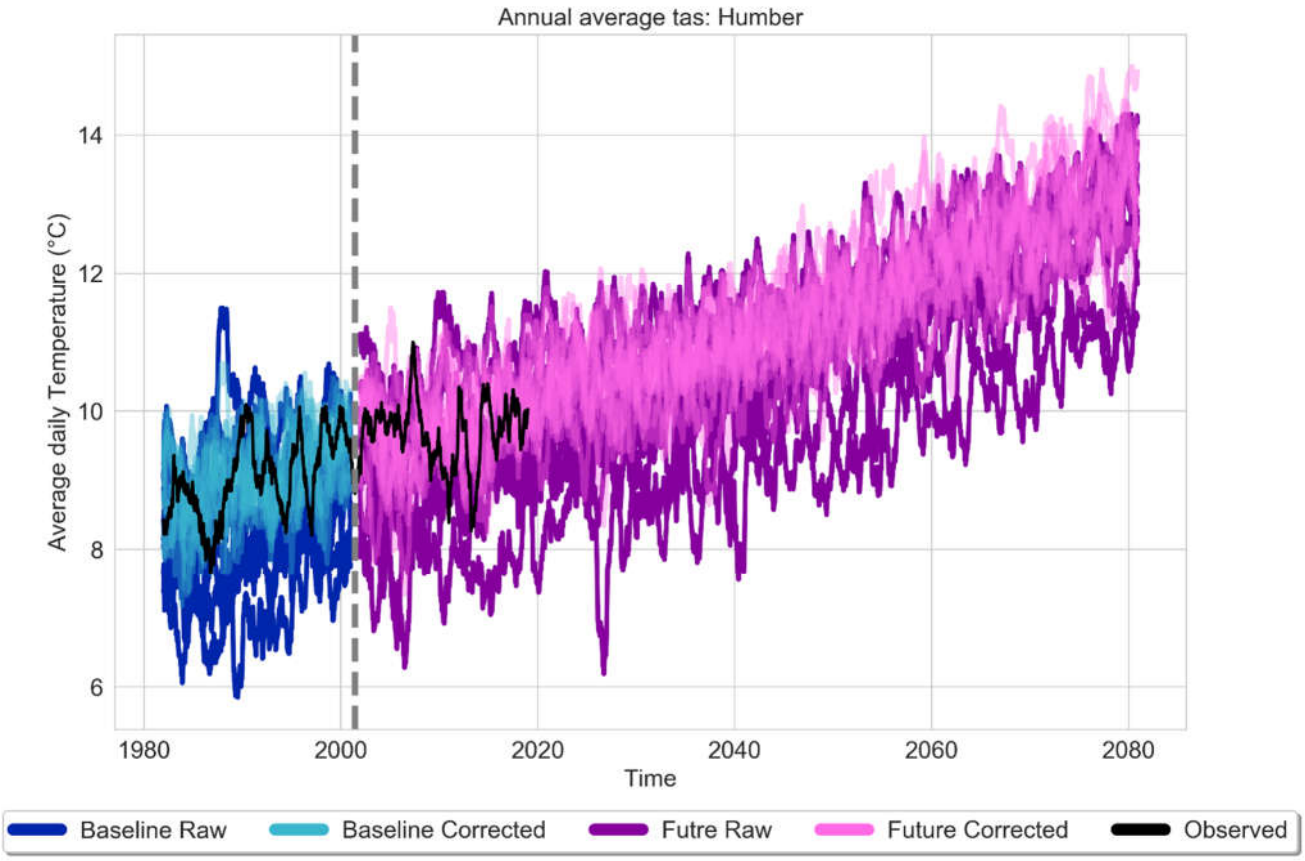


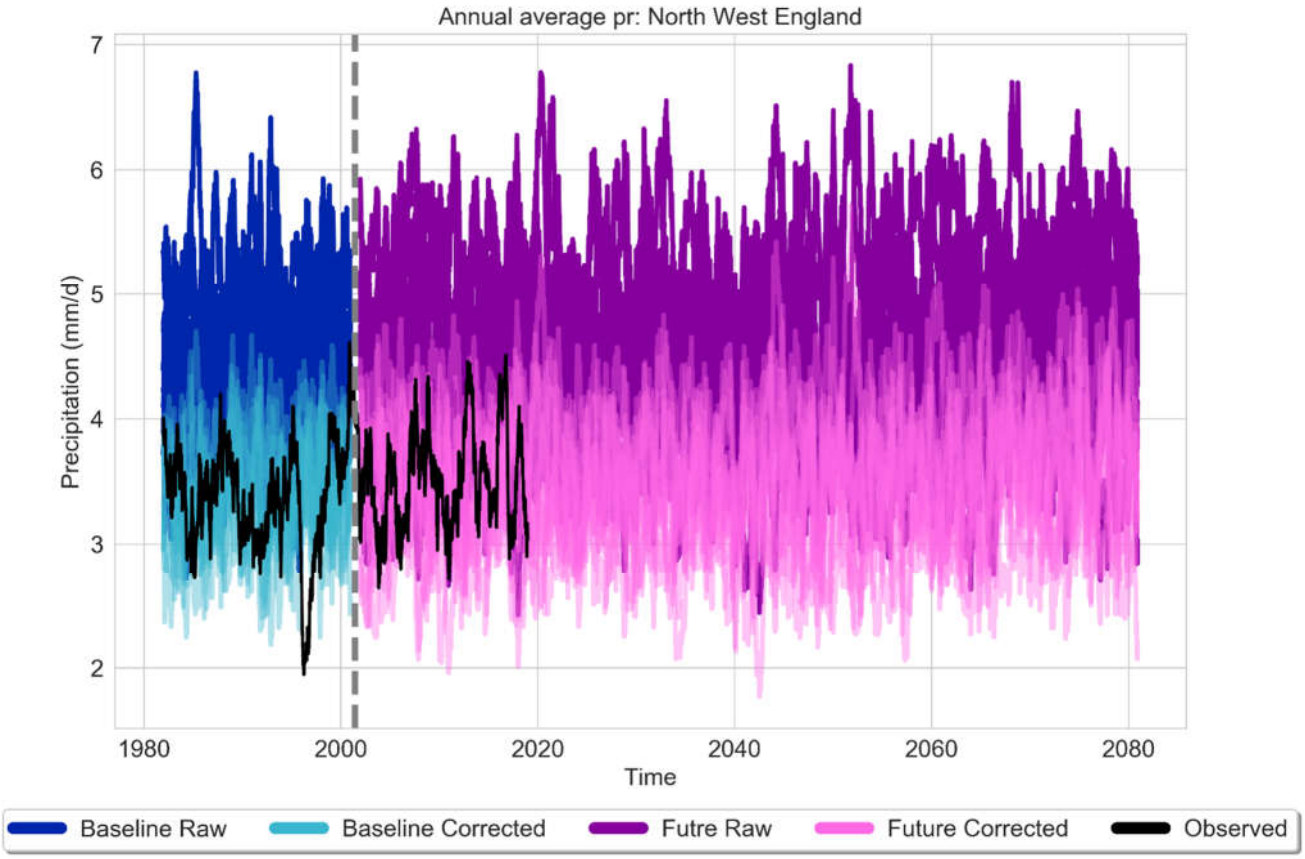
C.13.3. Bias correction: Time series of average temperature and precipitation before and after bias correction

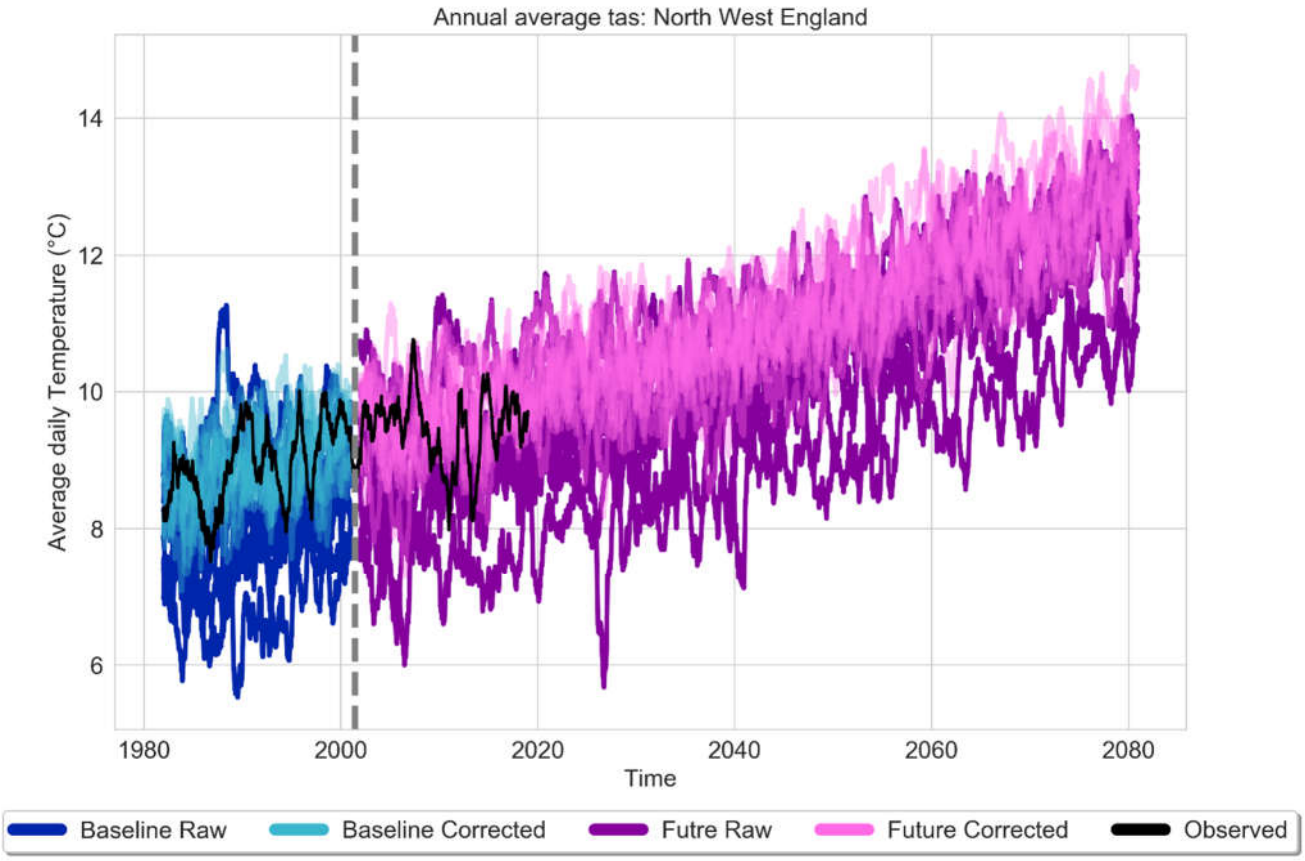

Annual average pr: Anglian
Precipitation (mm/d)
3.5
3.0
2.5
2.0
1.5
1.0
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

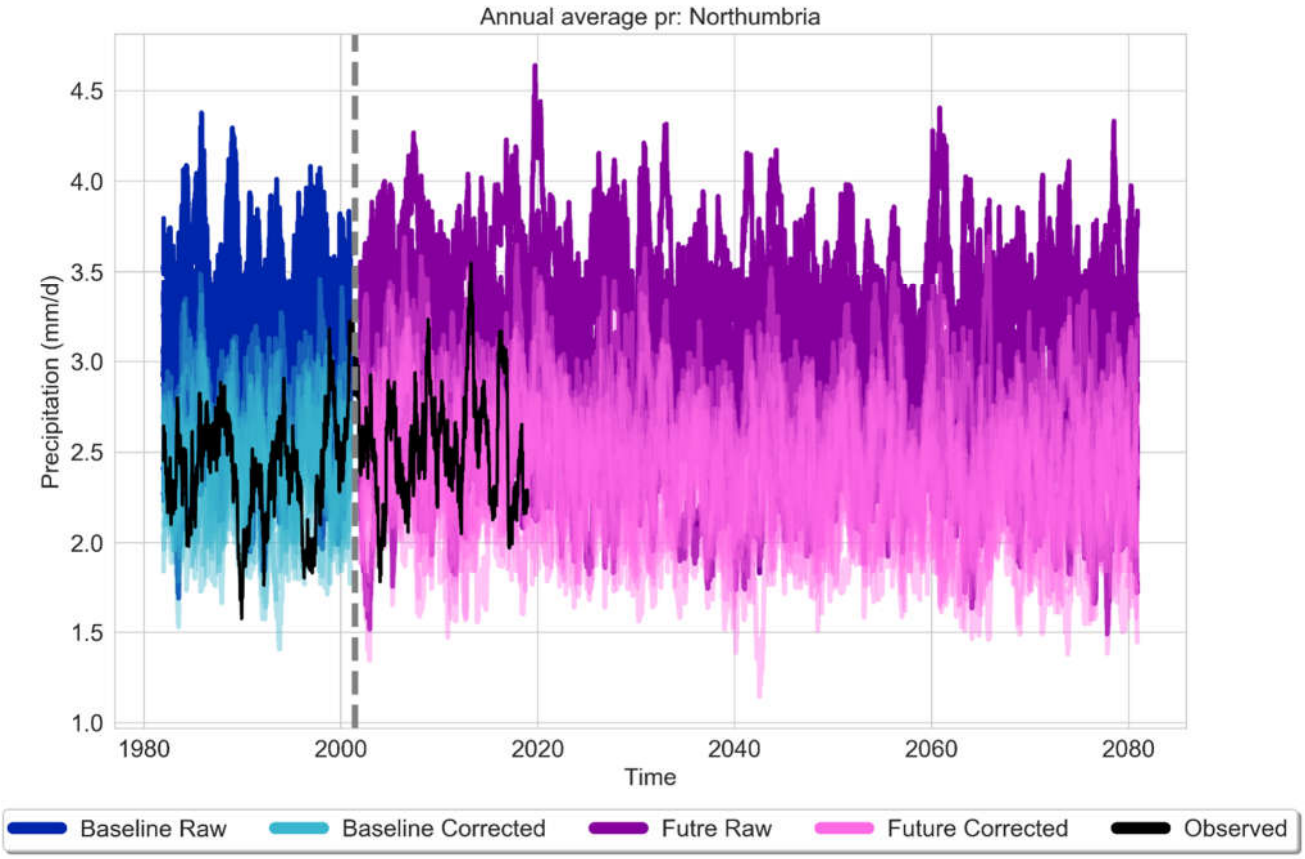

Annual average tas: Anglian
Average daily Temperature (°C)
16
14
12
10
8
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

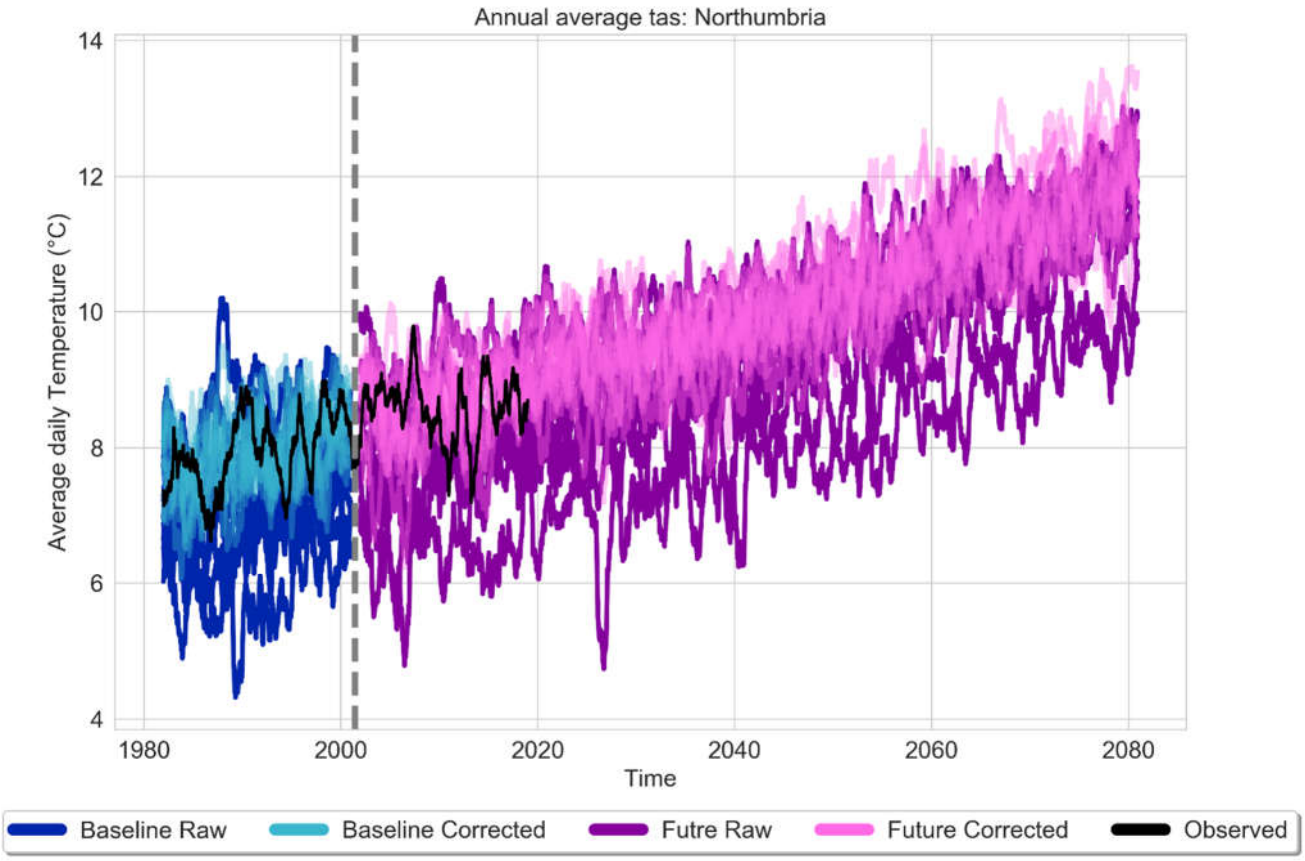

Annual average pr: Humber
Precipitation (mm/d)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

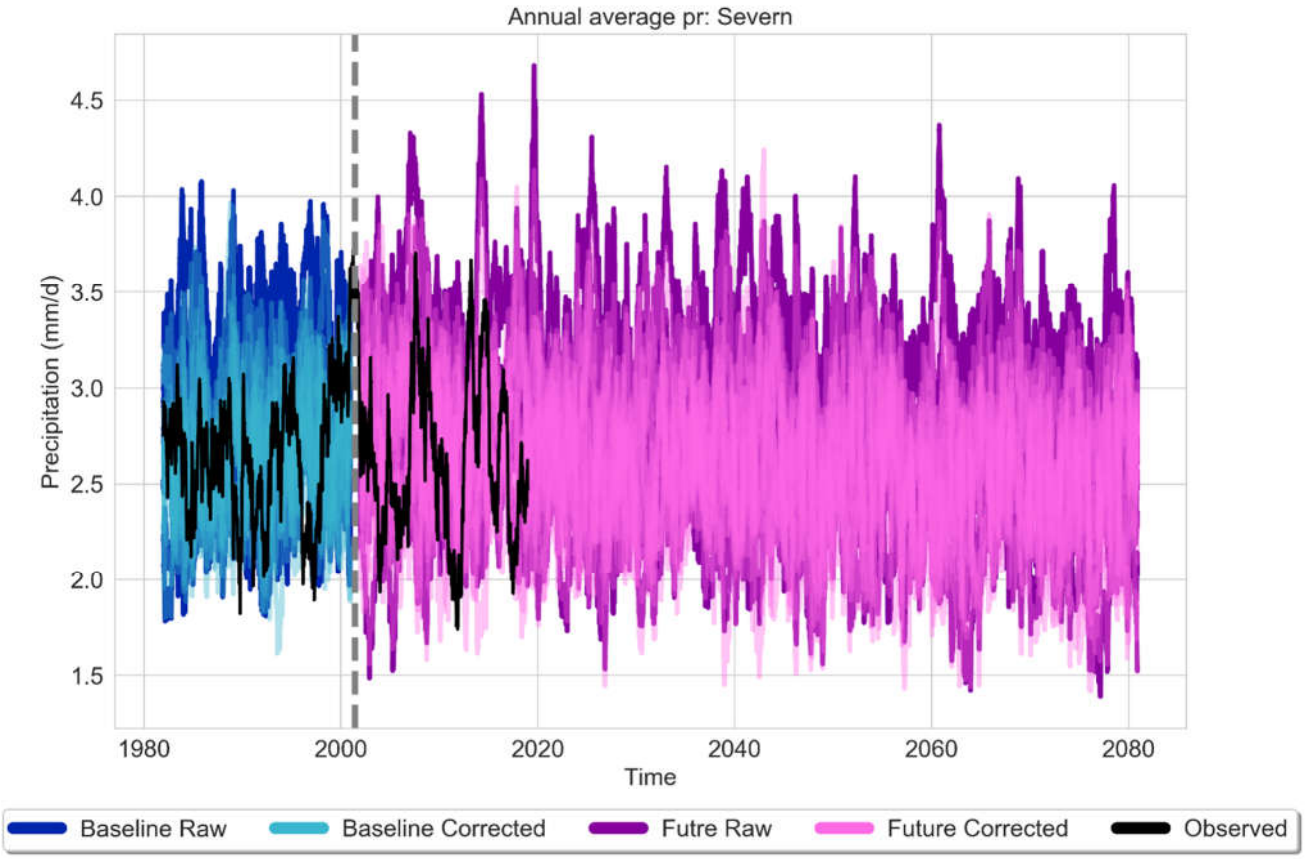

Annual average tas: Humber
Average daily Temperature (°C)
14
12
10
8
6
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

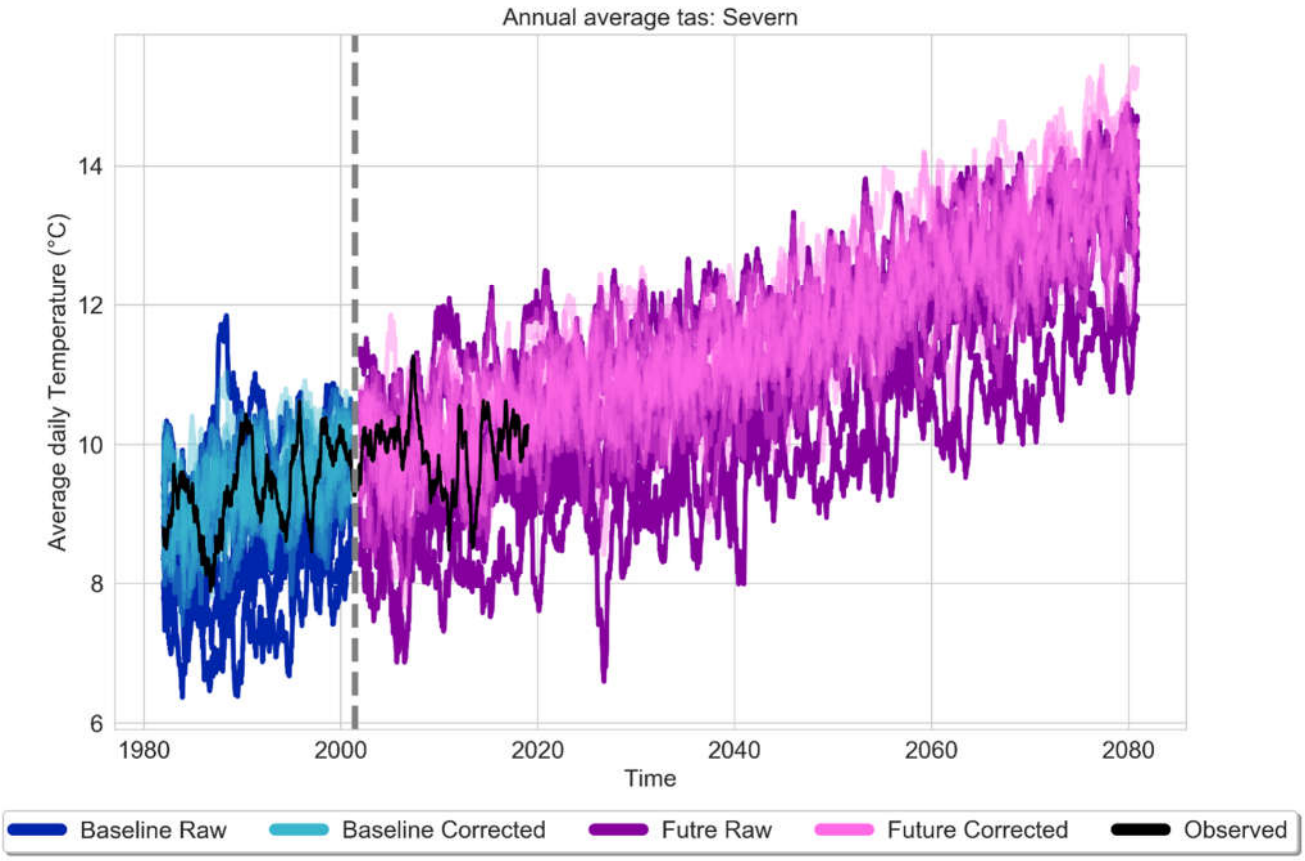

Annual average pr: North West England
Precipitation (mm/d)
7
6
5
4
3
2
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

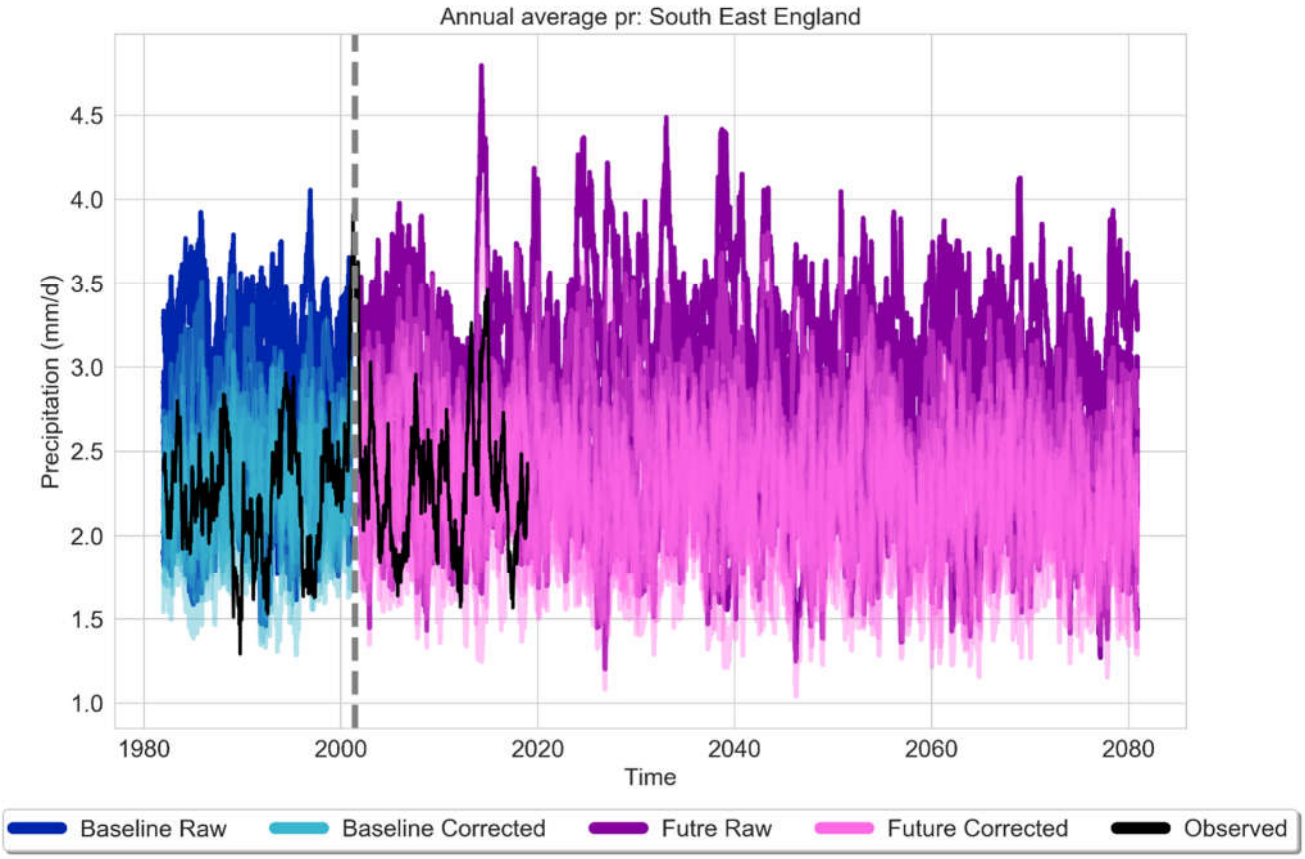

Annual average tas: North West England
Average daily Temperature (°C)
14
12
10
8
6
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

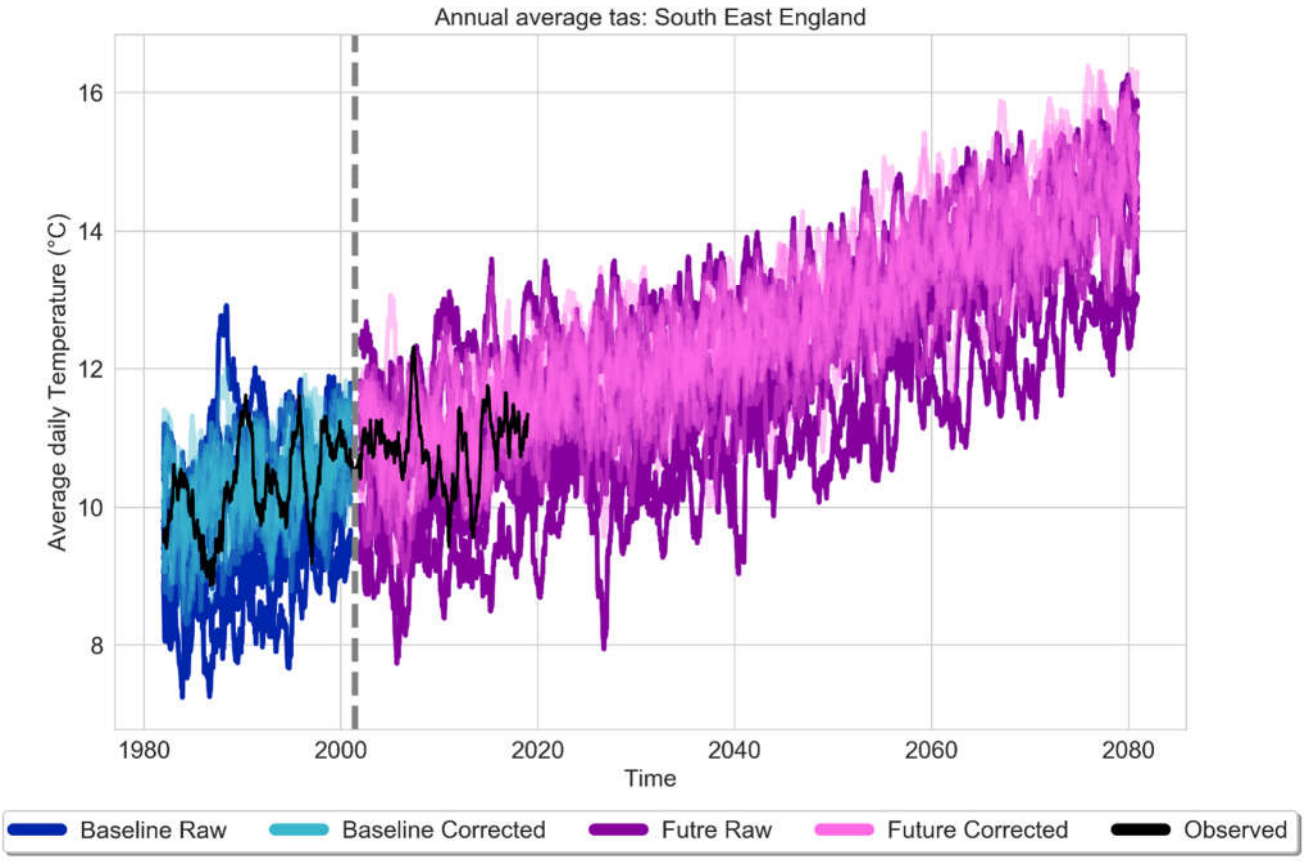

Annual average pr: Northumbria
Precipitation (mm/d)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

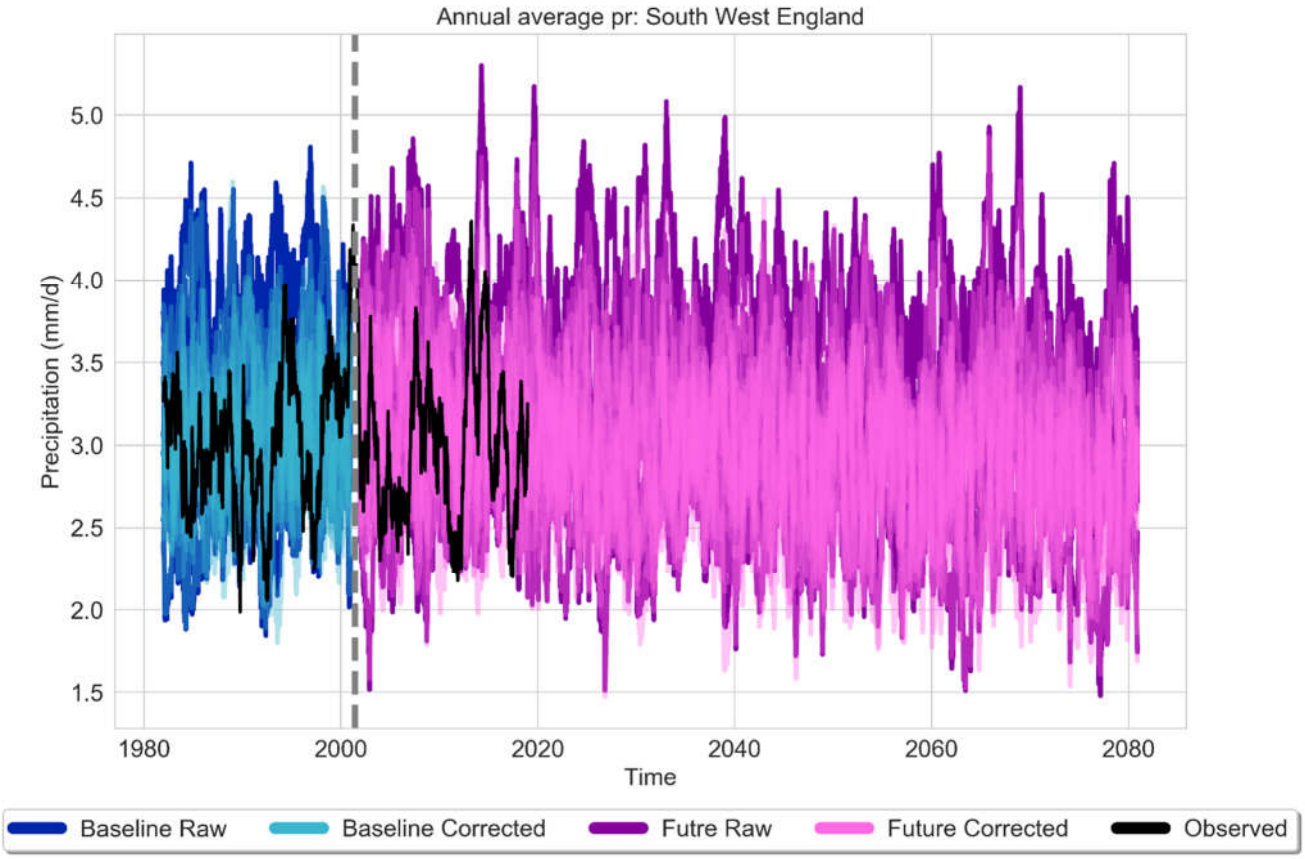

Annual average tas: Northumbria
Average daily Temperature (°C)
14
12
10
8
6
4
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

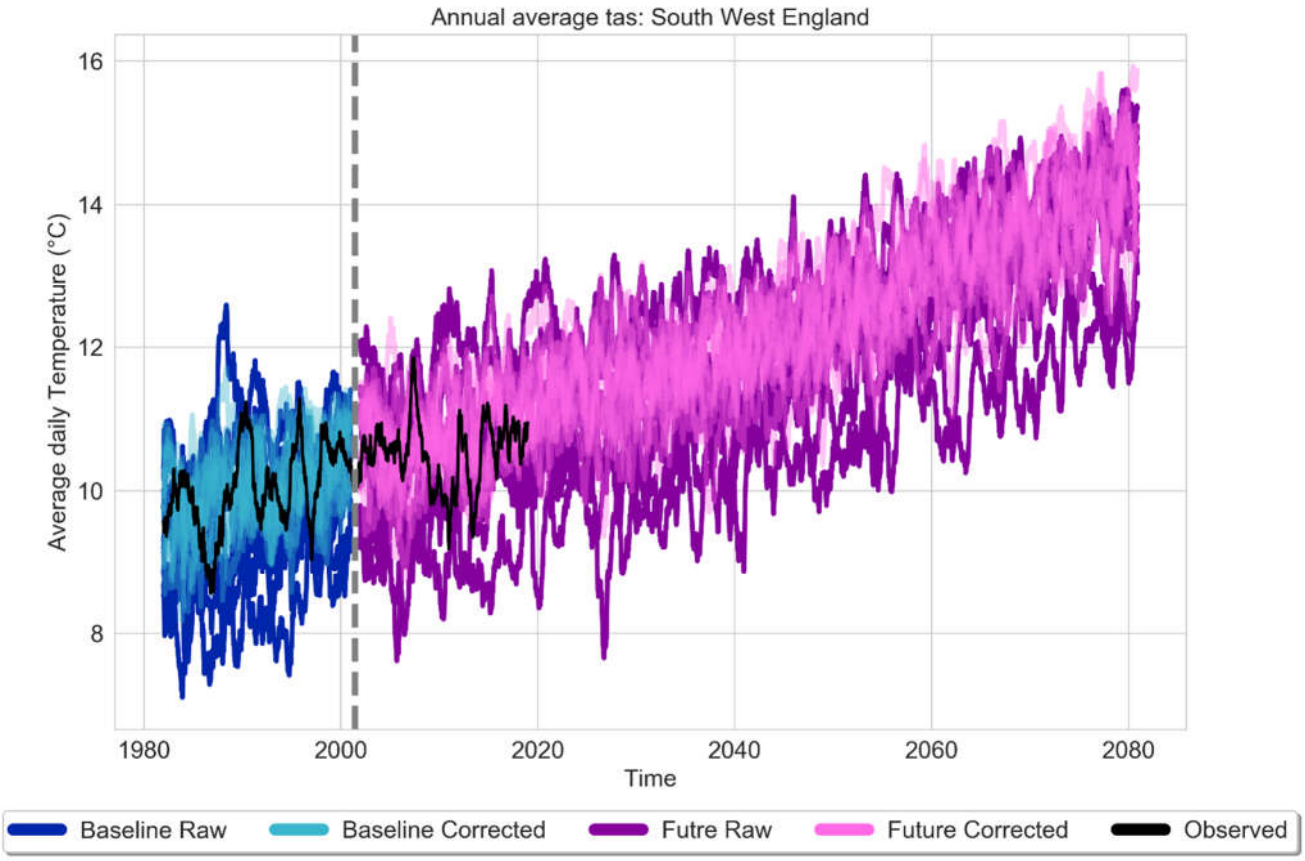

Annual average pr: Severn
Precipitation (mm/d)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

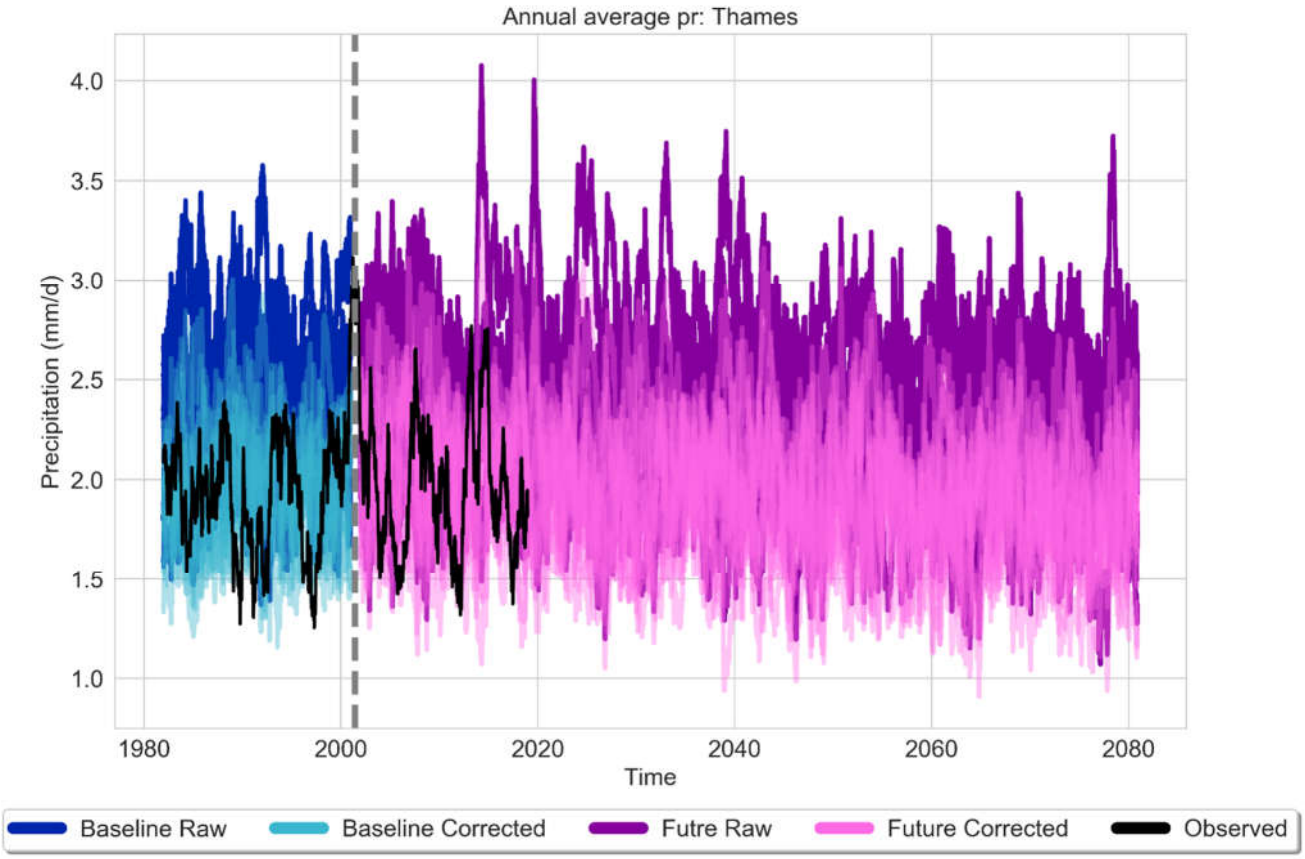

Annual average tas: Severn
Average daily Temperature (°C)
14
12
10
8
6
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

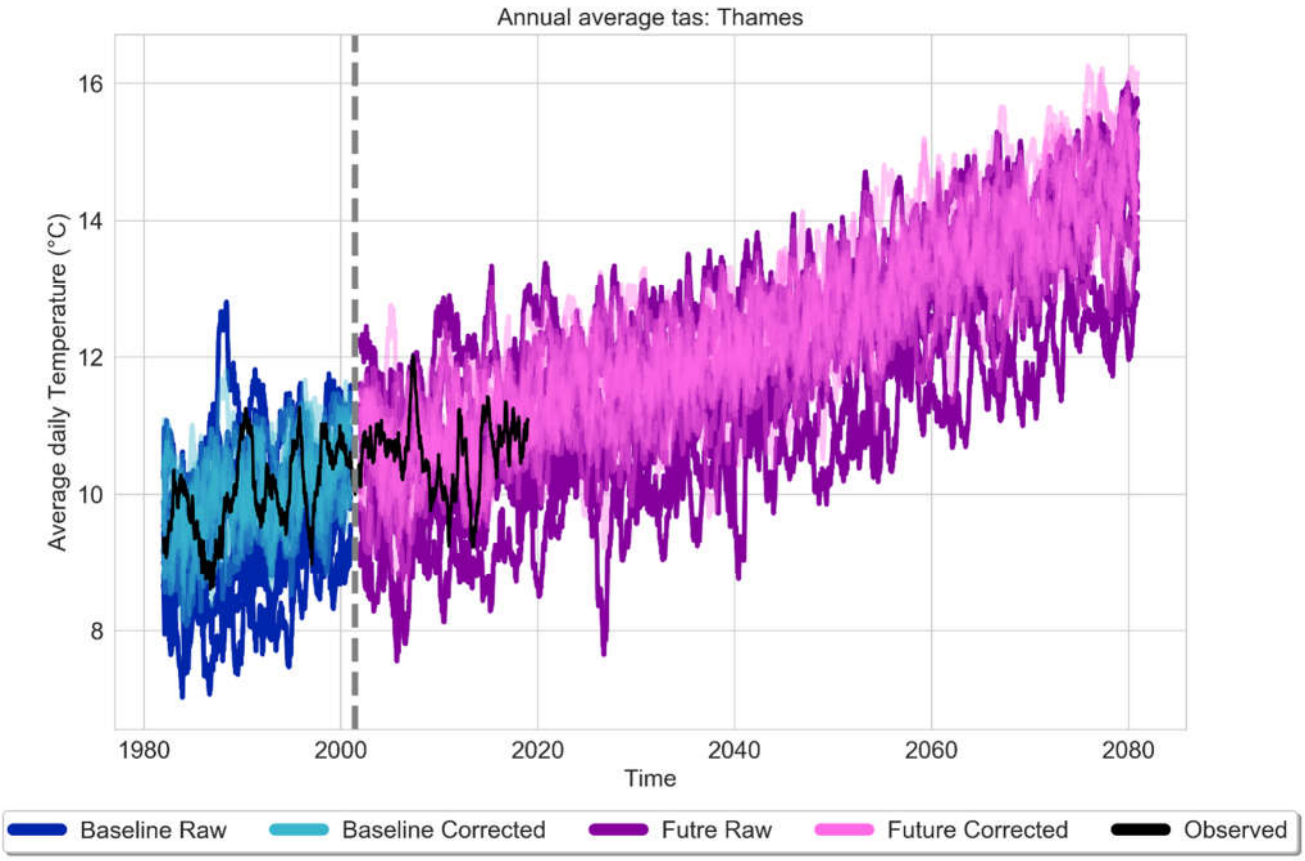

Annual average pr: South East England
Precipitation (mm/d)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

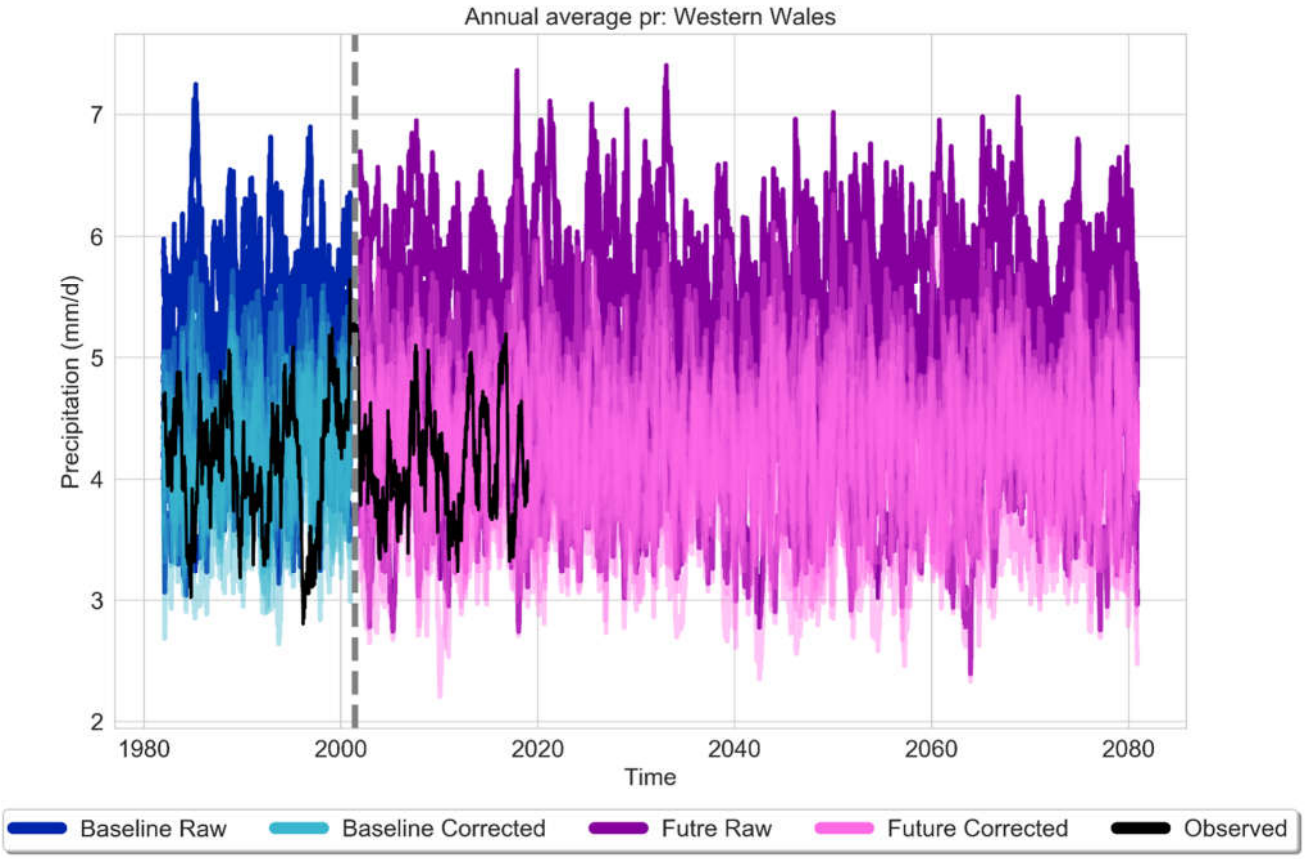

Annual average tas: South East England
Average daily Temperature (°C)
16
14
12
10
8
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

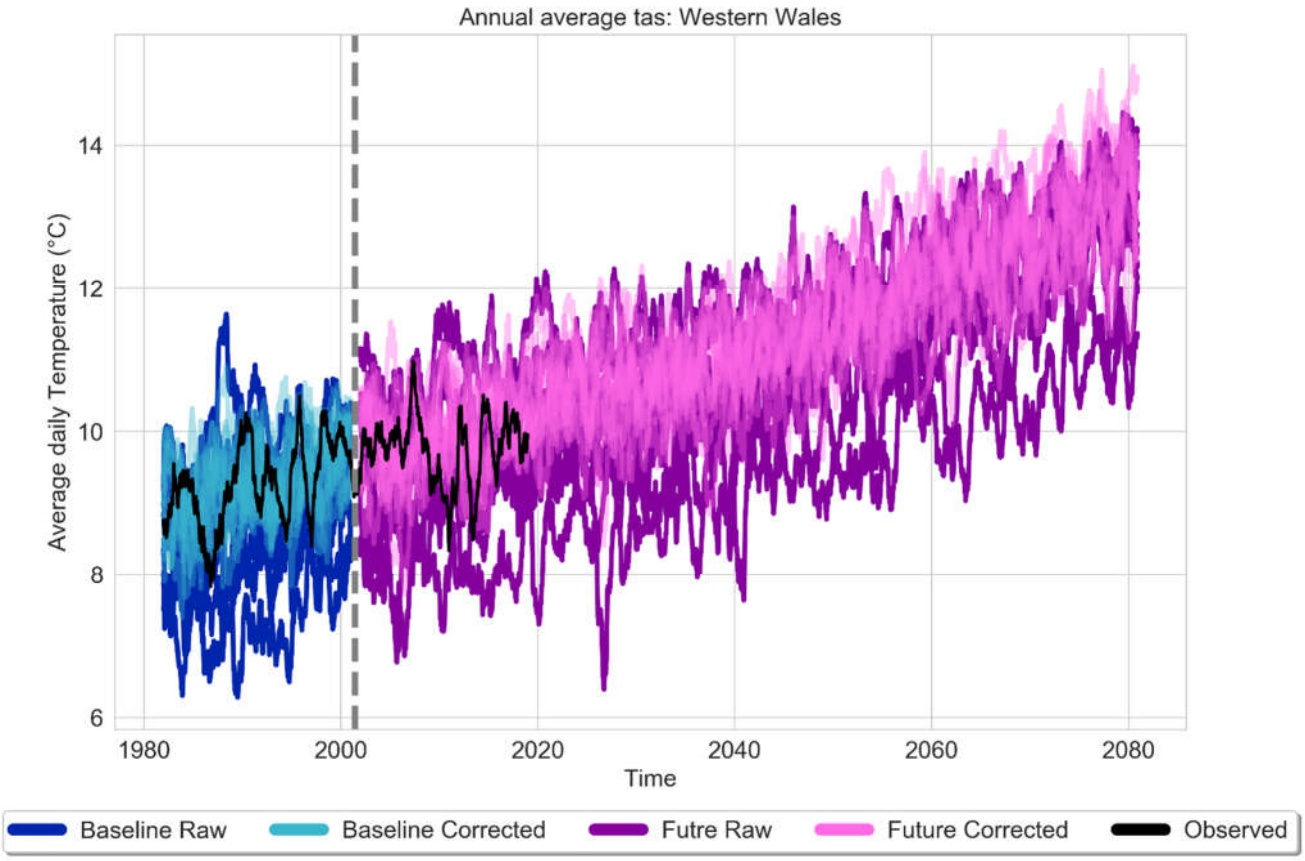

Annual average pr: South West England
Precipitation (mm/d)
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed


Annual average tas: South West England
Average daily Temperature (°C)
16
14
12
10
8
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed


Annual average pr: Thames
Precipitation (mm/d)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

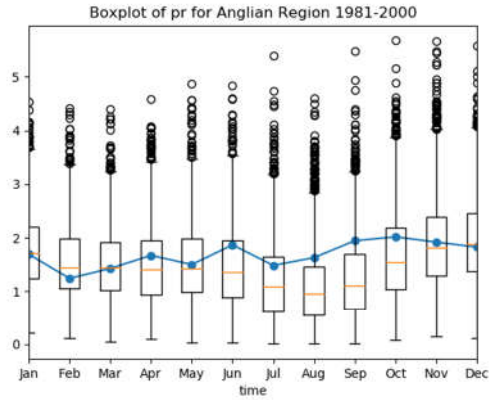

Annual average tas: Thames
Average daily Temperature (°C)
16
14
12
10
8
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

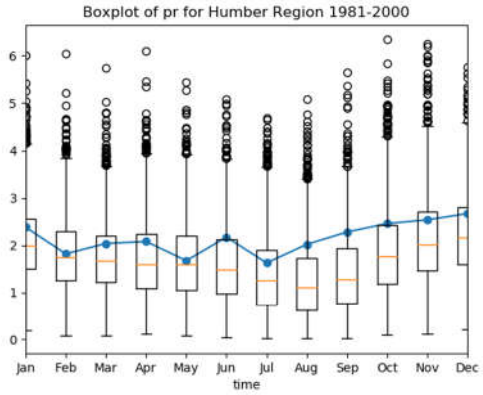

Annual average pr: Western Wales
Precipitation (mm/d)
7
6
5
4
3
2
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

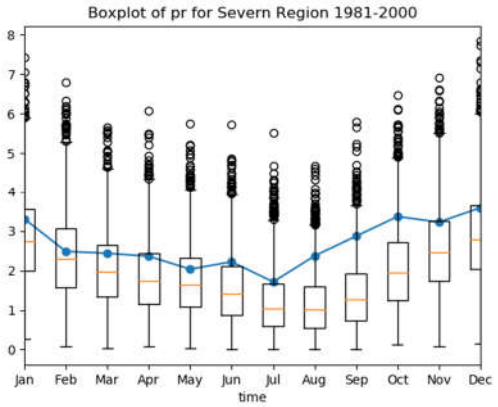

Annual average tas: Western Wales
Average daily Temperature (°C)
14
12
10
8
6
1980
2000
2020
2040
2060
2080
Time
Baseline Raw
Baseline Corrected
Futre Raw
Future Corrected
Observed

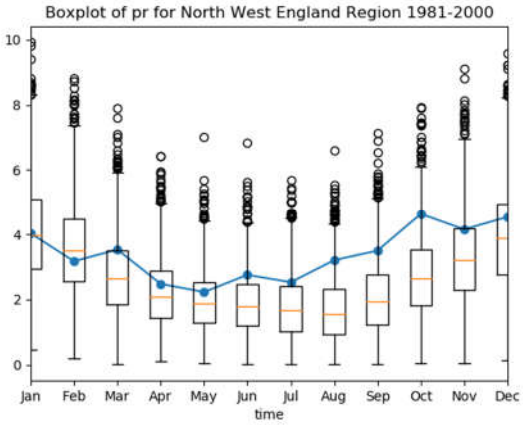
C.14. MaRIUS data sets

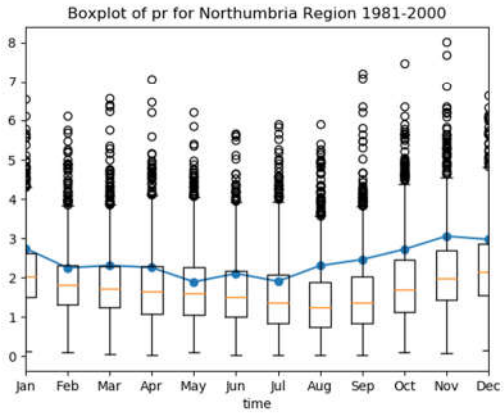
C.14.1. Precipitation (raw)

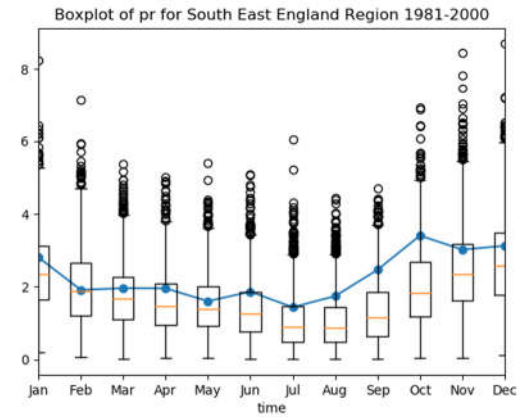


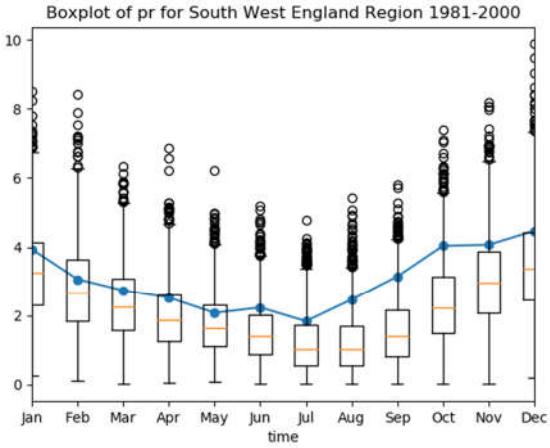


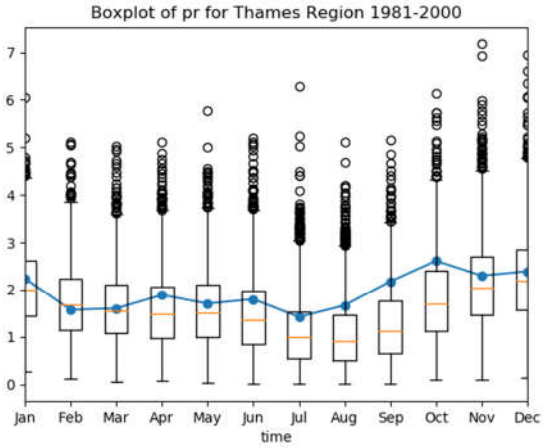









Boxplot of pr for South West England Region 1981-2000
0
2
4
6
8
10
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
time


Boxplot of pr for Thames Region 1981-2000
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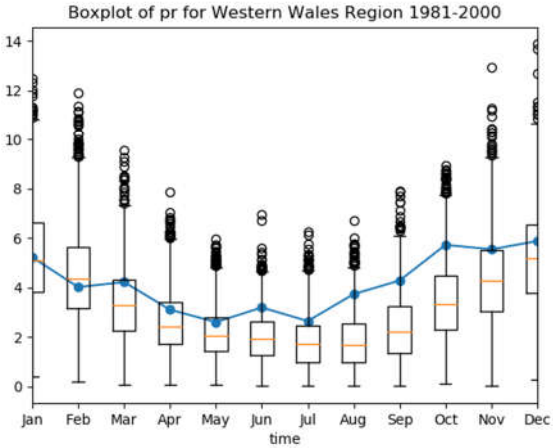
Boxplot of pr for Western Wales Region 1981-2000
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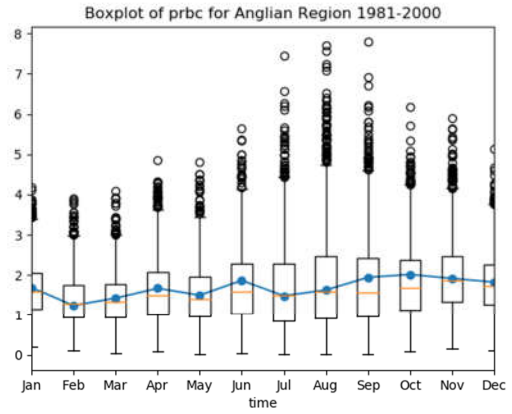
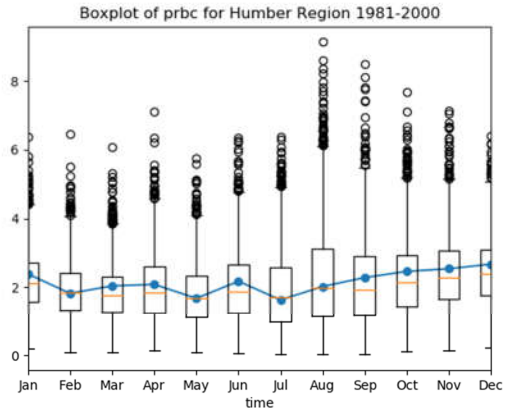
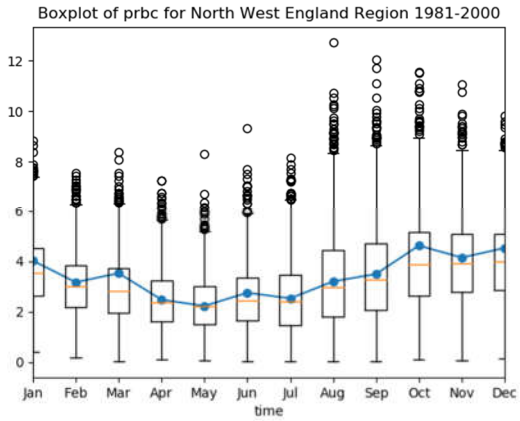
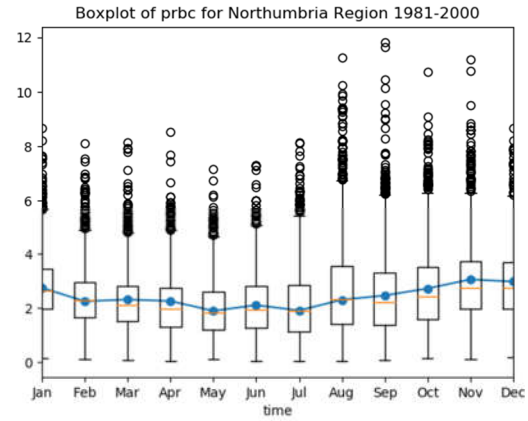
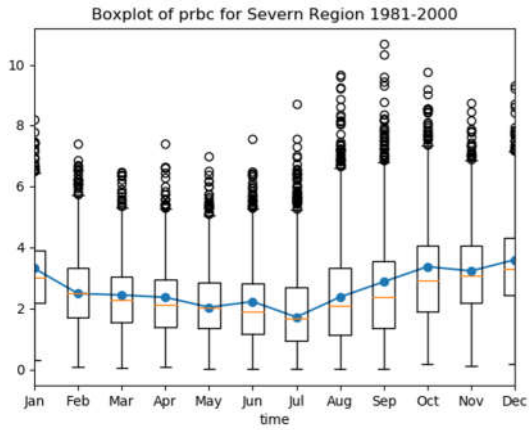
C.14.2. Precipitation (bias-corrected)

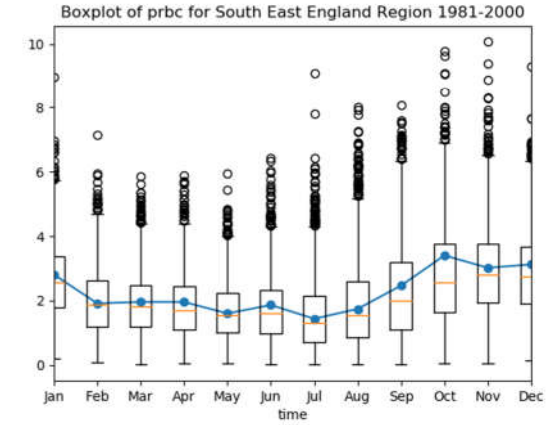


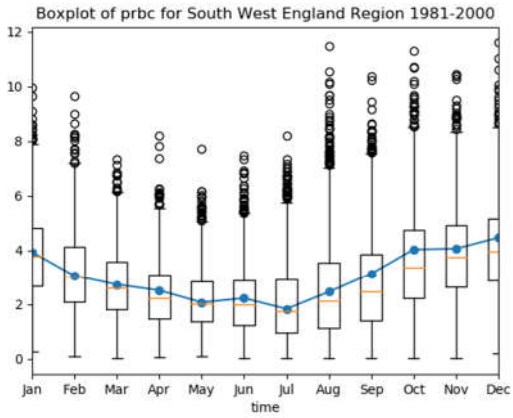











Boxplot of prbc for South West England Region 1981-2000
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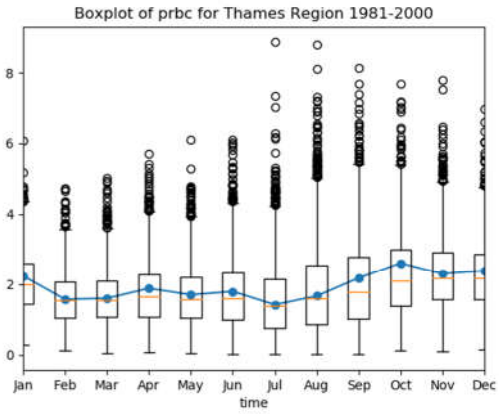
Boxplot of prbc for Thames Region 1981-2000
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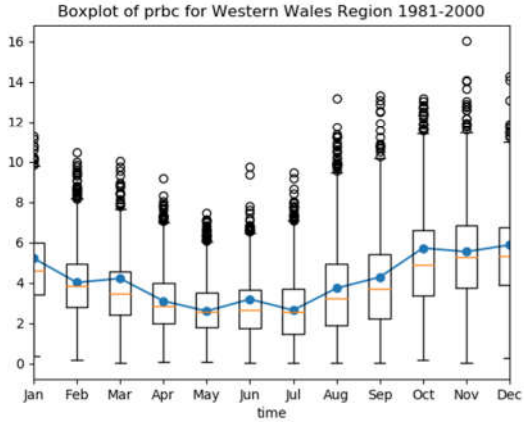
Boxplot of prbc for Western Wales Region 1981-2000
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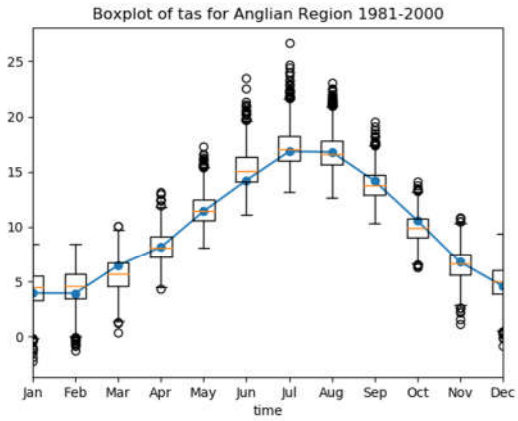
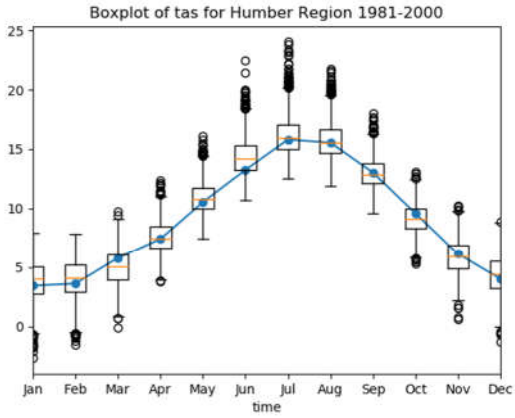
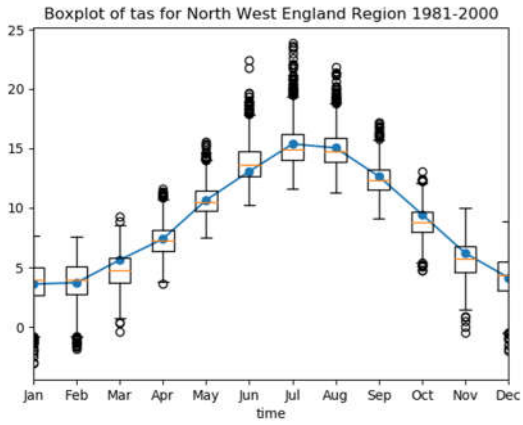
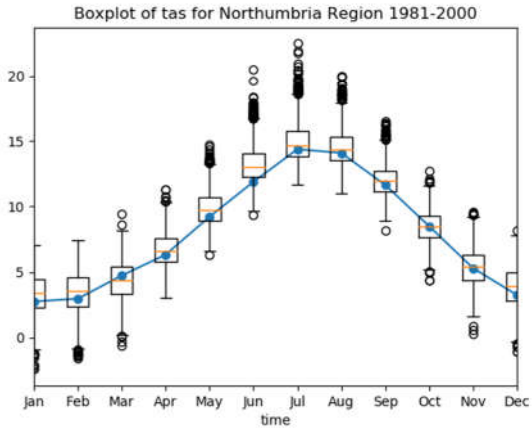
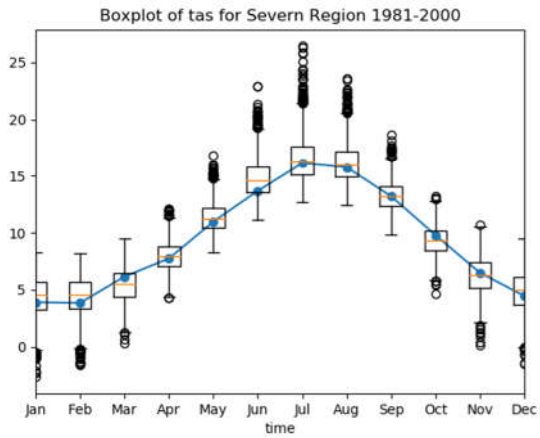
C.14.3. Average temperature (raw)

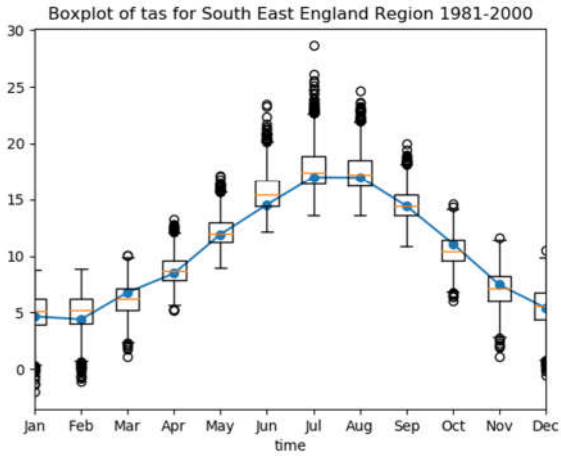


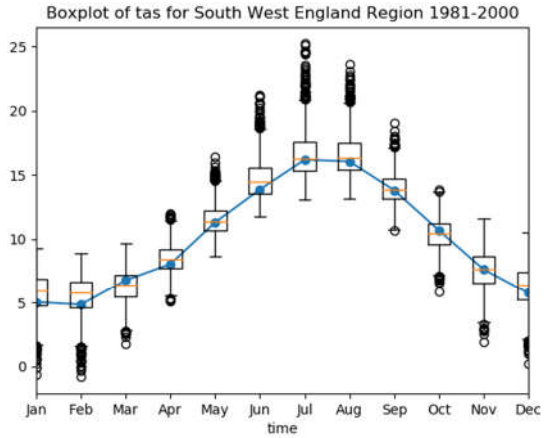











Boxplot of tas for South West England Region 1981-2000
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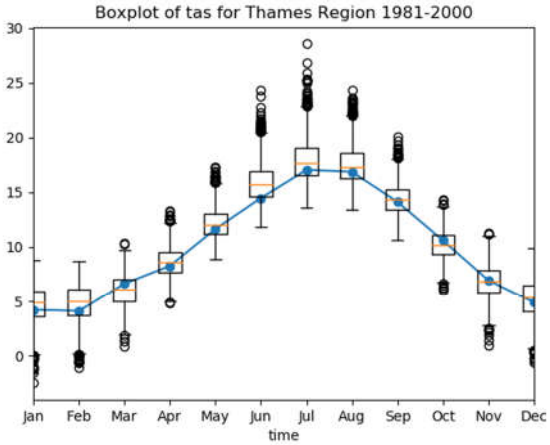
Boxplot of tas for Thames Region 1981-2000
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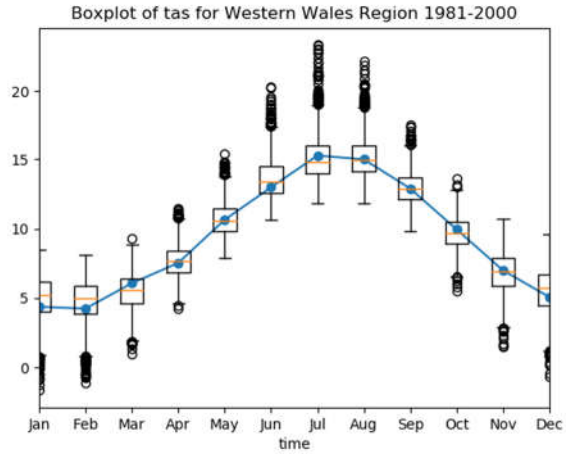
Boxplot of tas for Western Wales Region 1981-2000
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C.15. Bias correction and visualisation codes

A.1.1. Summary of bias correction methods

Method	Description		Pros	Cons	Reference
Delta change	An observed time series is taken, and a model-derived climate change signal is added For precipitation, relative changes rather than absolute changes are applied.		Preserves the observed weather sequence - maintains (linear) interdependencies between variables in space and time.	Climatic variables in the future are expected to have a different spatial and temporal dependence structure than today. Restricted to observed range of anomalies. Unsuitable for extreme events	Maraun (2016)
Linear scaling	Similar to the delta change approach (above) but makes direct use of the simulated time series by subtracting the present day model bias from simulated future time series. Method can be a simple mean bias correction or adjust both mean and variance bias. A modified version also has an additional step which accounts for the number of wet days.		Retains climate change signal Simple method that many have used in the literature. Can be as good as more complex methods (e.g. Shrestha et al, 2013) Simple to code – a useful comparator with other methods.	Assumes time invariant biases.	Fung (2018)
Quantile mapping	CDF-matching	Takes the model output for a future period, finds the corresponding percentile values in the CDF of the model for the training period, and then locates the observed values for the same CDF values of the observations.	Adjusts the entire distribution (i.e. the entire distribution matches the observation distribution for the training period). Corrects the drizzling effect common in many models	Assumes that the historic model distribution applies to the future - the underlying assumption is that the climate distribution does not change much over time (i.e. that the variance and skew are stationary, and that only the mean changes). Results can be sensitive to choice of calibration period.	Maraun (2016) Lafon et al (2013) Gutowski et al, (2003)
	Equidistant CDF-matching (EDCDFm) or QM31	As above, but the difference between the CDFs for the future and historic periods are also considered. The assumption is that for	Incorporates information from the CDF model projection. Explicitly considers changes in the distribution of the	Large number of parameters and danger of over-fitting to short baseline data sets. Extrapolation outside the range of the	Li et al (2010)

Method	Description		Pros	Cons	Reference
		a given percentile, the difference between the modelled and observed distributions applies to the future.	future climate, including the tails of the distribution. Simple to implement	baseline data can be problematic.	
	Trend-preserving	This method combines two steps: Linear scaling approach for the long-term trend Quantile mapping approach for variability	Preserves the long term trend of the modelled data.	To correct data for input to drought models requires variability to be corrected at other timescales (i.e. weekly/monthly time scales as well as daily). Such an extension and testing of the methodology has not been carried out by ISI-MIP (Hempel et al, 2013). More steps involved.	Hempel et al (2013)
	CDF transform	Method implemented by the Climate Data Factory. The assumption is that the model and observational distributions can be inferred by a mathematical function (the "transform") which remains the same for past and future distributions. The transform function is used to derive an "observational future" distribution where CDFm can be implemented	CDF-t does not rely on the stationarity hypothesis: model and observational distributions can evolve and be different. Preserves the raw climate signals.	More steps involved.	Famien et al (2017)
	Scaled Distribution Mapping (SDM)	An extension of the delta change method: multiplies observed values by the ratio of the modelled values (period of interest divided by calibration period) at the same quantiles. More explicitly accounts for the frequency of rain days	Does not rely on the stationarity hypothesis. Outperforms other QDM methods in ability to preserve raw climate model projected changes.	The temporal evolution of climate change might not be captured without further processing e.g. if it is necessary to preserve the climate change signal across a variety of timescales, the SDM must be discretized into smaller blocks (number dependent on how strongly the user wants the bias corrected data	Switanek et al (2017)

Method	Description		Pros	Cons	Reference
		and the likelihood of individual events.		to follow raw modelled temporal evolution of climate change).	

C.15.1. Implemented bias correction methods

For a simple explanation of bias correction, users should refer to Fung (2018) or Navarro-Racines, e*t al.* (2015). For this project we have implemented three bias correction techniques: simple linear bias correction, a basic Quantile Mapping (QM) approach and a more complex method that we are calling QM31 using a 31-day window based on the method referred to as Equidistant CDF mapping (EDCDFm) in the research literature (Li, *et al.*, 2010).

Linear Scaling

To undertake the simple linear bias correction, the following steps were undertaken:

Observed and modelled data for the baseline period of 1981 to 2000 were aggregated from the daily timeseries to a single monthly profile across all years.

Bias correction change factors for each month of the profile were calculated. For temperature the change factors were calculated by subtracting the modelled from the observed data. Whereas for precipitation, factors were calculated by dividing the observed by modelled data.

The relevant bias correction change factor for a given month was then used to correct the daily data of the modelled data for both the baseline period and future periods i.e. the January bias correction factor was applied to all January days.

This method clearly worked well for monthly averages but reduced the seasonal variance in the corrected models, which suggests it is not suitable for looking at period of low rainfall. Therefore, this method was only assessed for the baseline period and not taken any further.

Using the nomenclature of Maraun 2016 the bias for temperatures and precipitation are defined as follows based on the modelled (x) and observed (y) data:

$$\widehat{Bias}(\mu^p) = \bar{x}_i^p - \bar{y}_i^p. \qquad (1)$$

Correspondingly, the relative bias might be estimated as

$$\widehat{Rel.Bias}(\mu^p) = \bar{x}_i^p / \bar{y}_i^p. \qquad (2)$$

Simple mean bias correction for future (f) time series is calculated by subtracting the bias from the raw data or dividing by the bias for rainfall:

$$x^f_{\mathrm{i,corr}} = x^f_{\mathrm{i,raw}} - \widehat{Bias}(\mu^p) = x^f_{\mathrm{i,raw}} - (\bar{x}^f_{\mathrm{i,raw}} - \bar{y}_i^p), \qquad (5)$$

or equivalently for precipitation

$$x^f_{\mathrm{i,corr}} = \frac{x^f_{\mathrm{i,raw}}}{\widehat{Rel.Bias}(\mu^p)} = x^f_{\mathrm{i,raw}} \times \frac{\bar{y}_i^p}{\bar{x}_i^p}. \qquad (6)$$

Quantile mapping

Quantile mapping approaches seek to adjust modelled data considering the distribution of modelled versus observed data rather than using a single annual, seasonal or monthly linear scaling factor (see Fung, 2018; Navarro-Racines *et al.*, 2015). The general principles of QM are to map the values of modelled cumulative distributions to observed distributions at the chosen time scale, typically daily. Therefore, the approach is to simply convert the raw modelled value to a quantile and identify the value associated with the same quantile in

the observed distribution. This simple approach creates a number of challenges related to extrapolation of variables and dealing with special cases related to non-rain days for precipitation.

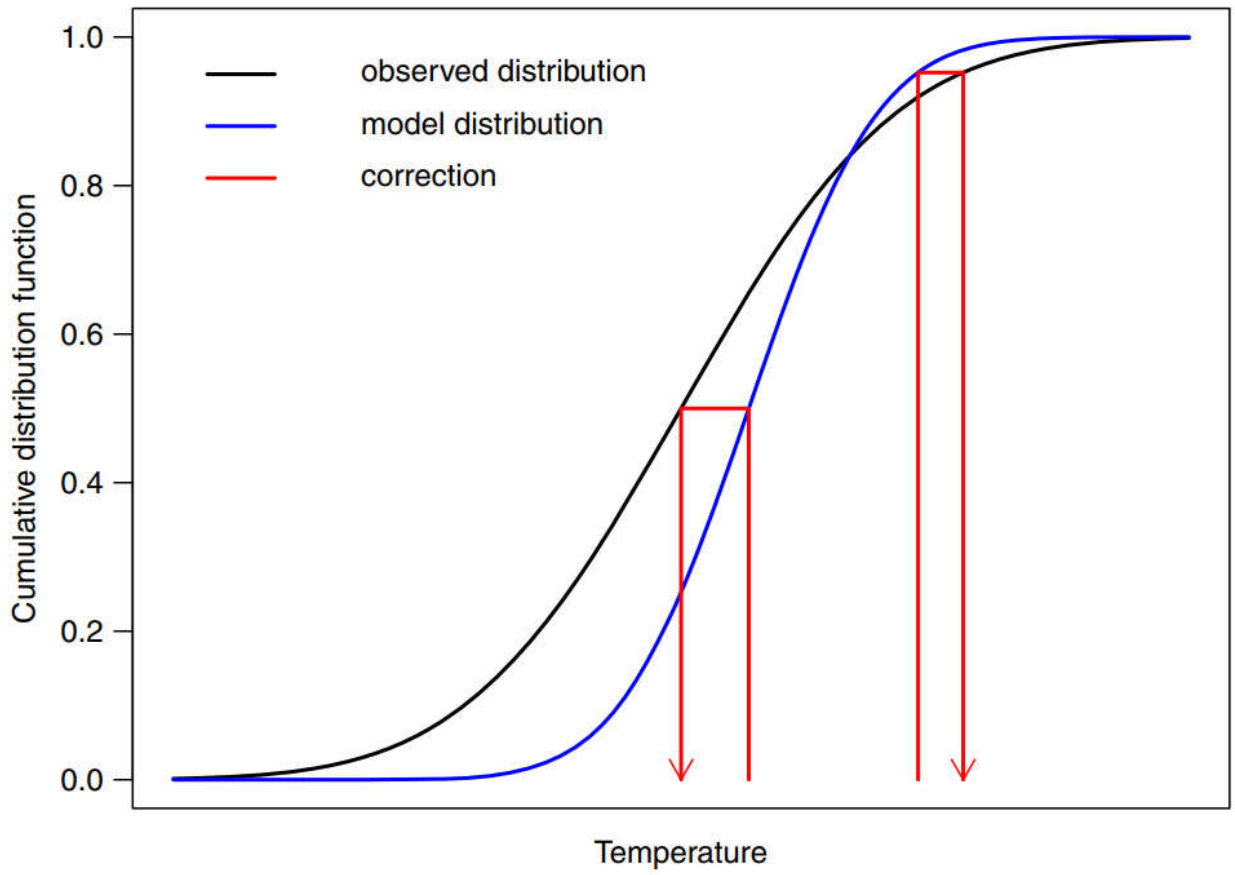
We have tested two methods of QM both on daily data for precipitation and temperature and using percentiles rather than fitting a specific distribution to the daily data sets. The use of percentiles has some disadvantages for the basic QM method, but these overcome on the QM31 approach that works from differences in baseline distributions rather than the direct mapping back the observed data.

QM basic method

Following Maraun (2016), the quantile for a probability α of a distribution D will be denoted as qD(α) and is defined as the value which is exceeded with a probability 1 - α when sampling from the distribution. The corresponding empirical quantile q^D(α) can be obtained by sorting the given time series, say, xi, and then considering the value at position $\alpha \times$ N/100 (also called the rank of the data). The probabilities corresponding to a given quantile qD(α) (i.e. the cumulative distribution function) are written as pD(q) = α . The present-day simulated distribution is replaced by the same quantile of the present-day observed distribution. For future periods the future simulated data is calculated based on relating each raw value to the probability of the simulated present-day distribution and replacing it with the quantile from the present day observed distribution.

$$x^{f}_{\mathrm{i,corr}} = q_{D^p_y}\left(p_{D^p_x}(x^{f}_{\mathrm{i,raw}})\right). \qquad (7)$$

In other words to bias correct model values for a future period, we first find the corresponding percentile values for in the cumulative distribution function (CDF) of the model for the simulated present day (control period 1981-2000 in our case) and then locate the observed values for the same CDF values of the present-day observations, as illustrated below.



QM31 method

This method is based on Equidistant CDF mapping based on Li et al (2010). Here the equation is written using the same definitions as above, from Maraun (2016):

$$x_{i,corr}^{f} = x_{i,raw}^{f} + qD_{y}^{p}(PD_{x}^{f}(x_{i,raw}^{f})) - qD_{x}^{p}(PD_{x}^{f}(x_{i,raw}^{f}))$$

This variation of quantile mapping was chosen because it incorporates the use of both the observed and modelled empirical CDFs without assuming a direct correlation. The assumption here is that for a given percentile, the difference between the observed and modelled data for the baseline period also applies in the future. The main difference between basic QM and equidistant CDF matching (EDCDFm) is that changes in the distribution of variables in the future are more explicitly considered in the EDCDFm method.

Error! Reference source not found. shows how raw future modelled output was corrected using raw modelled baseline data and observations for temperature. First, the ECDF distributions were generated for the observed data (black solid line) and raw modelled data (dark-blue dashed line) in the baseline period. Next, the percentile position of each future raw data point was determined (the red lines in **Error! Reference source not found.** show that the 70th percentile is located for a temperature of 15°C in the raw future data). The difference between the baseline raw data and the baseline observations at this percentile is used to adjust the future raw data (red arrows in Figure 3 show a decrease of ~1°C for data at the 70th percentile). When adjusting temperature, the adjustment made is an additive shift, but when precipitation is adjusted the adjustment is relative.

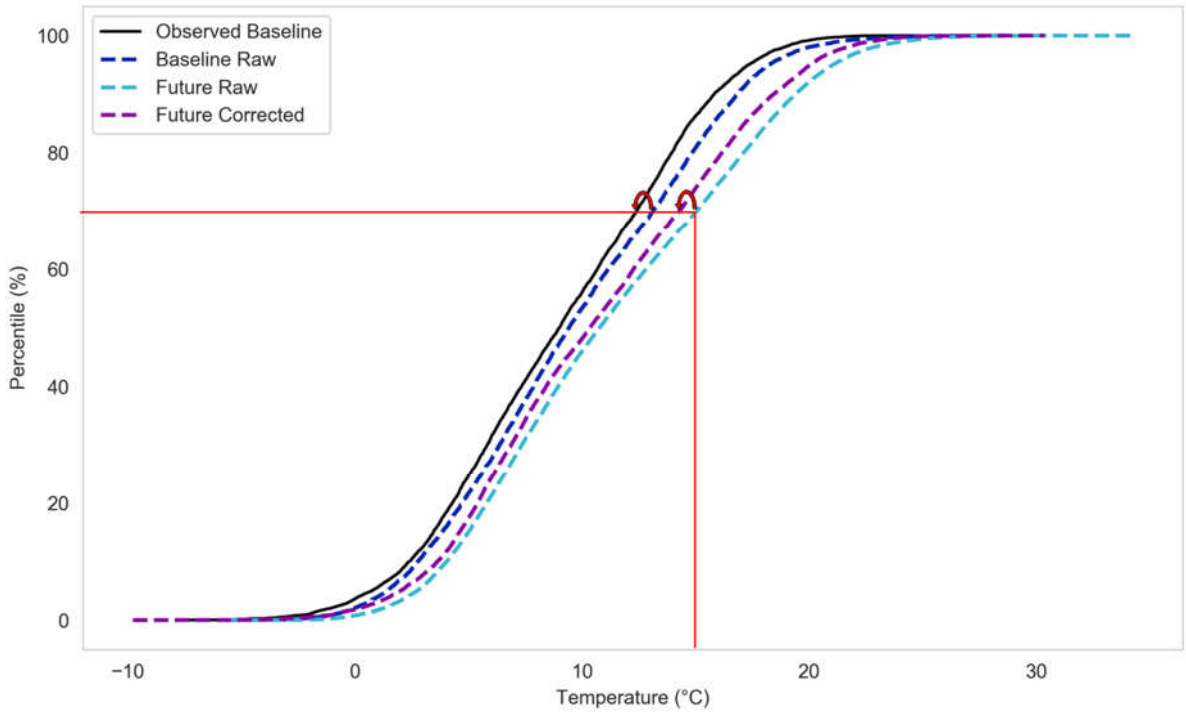


Figure 23 EDCDFm methodology applied to RCM 15 temperature outputs over the Humber river basin for demonstrative purposes. for temperature. Red lines show how a data point of 15°C in the RAW future data is bias-corrected to 14°C using information from the baseline observed and baseline raw model distribution (see text for details).

It was clear that UKCP data has large monthly bias for precipitation therefore, we used one ECDF for each day of the year (365 ECDFs), where each ECDF is made up of data from a 30 day rolling window about the day in question (see Thrasher, 2012 and the PyCAT library in Python). For example, to correct a value on the 32nd day of the year (1st Feb), an ECDF containing a distribution of all days from day 17 to day 47 across all years in

the baseline period is constructed to determine the percentile of the value on the 32nd day. In the case of a leap year (366 days), the last day of the year shared the same ECDF as the last day of a 365-day year.

A.1.2. Dealing with 360-day model years

RCMs operate on a 30-day month and 360 day year, so assumptions are needed to turn these data to a standard calendar year. In our analysis (i) the non-calendar dates in February are removed from the 360-day format (30th Feb and 29th Feb for a non-leap year) and (ii) missing calendar dates are then added to year (31st of Jan, March etc.). Temperature infilled to this added date is a linear interpolation between the day before and after. For precipitation it is assumed to be a dry day.

C.16. Peer review comments

Reviewer	Main comment	Response (Action)
Rob Wilby (3/3/20)	#1. The recent questioning of the credibility of RCP8.5 is acknowledged. This combined with the hot-dry end changes in the Hadley models suggests that these scenarios can only really be used for precautionary testing of options.	Agreed. The EA are yet to release guidance on choice of RCPs and on climate change in general, but we anticipate that most companies will use UKCP probabilistic factors to perturb WG outputs. Focus on use for stress testing and in cases when companies want to look a transient time series.
	#2. Mention of the typical confidence intervals of the gridded observations is needed – the past is probabilistic too! So bias correction to imperfect baseline data should be recognized.	Added one additional Met Office paper and will seek clarification on magnitude of uncertainties
	#3. The report is virtually silent about PET yet this is clearly a key ingredient for water planning. How is PET to be bias corrected? At the constituent variable or as a post-processing stage of bias correction? This may also depend on the choice of PET equation…	Based on selection of available PET data using a sampling method that aims to retain correlation with precipitation. Any PET formulae can be used, and the expectation is to work with whatever companies are using for their hydrological modelling.
	#4. Note that all bias correction is problematic when extrapolating outside the range of the baseline data.	Add commentary in Appendix D when validation work is completed.
	#5. What about the 2.2 km UKCP18 product – explain why this has been excluded.	Added a sentence on this. It can be used for planning and may have some advantages for uplands and small basins. However, it was out of scope because it was not included in our proposal.
	#6. Why not apply a statistical downscaling algorithm to fit the RCM output to the observations? This was done in UKCP09. At very least, this should be listed as an option in Appendix D.	Further information will be added as an alternative method in the next draft.
	#7. What if any cross-validation testing has been applied to the QM31 technique given that this is a massively parameterised approach? Some demo cross-validation results would really test the method.	We aim to validate for the 2001-2017 period (includes droughts, cold snaps and heatwaves) and 1961-1980 (includes 76 drought)
	#8. The report would benefit from a section that checks the QM31 skill at replicating PDFs of multi-season precipitation totals, as this will be a key basis for credible multiple-season extreme drought analysis further down the line…	To be addressed when the climate change work is joined up with the stochastics work.

	#9. Has Met Office offered any explanation for the cold bias in their model runs? It would be good to provide some physical insight so users of the outputs can judge whether bias correction is credible, especially if there is a systemic issue with the climate models.	SDW to discuss with Met Office
	#10. Is there any update on new H++ outputs that are relevant to this report?	SDW to discuss with the Met Office
	#11 More work to be done in testing the various BC procedures using the types of drought diagnostic that will be applied further down the line. For instance, how would they all fare at reproducing the 20-year return period SPI-36, or the 100-year estimate of the SPEI-60? Maybe, this type of analysis falls out of the scope of the present report but, if planned, should be sign-posted at the end of the document.	As per comment 8.

Appendix D. Case studies

D.1. WRSE – Western Rother

WRSE regional group recommended Western Rother catchment, at Hardham, as their case study location. This catchment is important to the WRSE region, as Pulborough, one of the Southern Water's strategic surface water abstractions, lies immediately upstream of the flow gauge, and there are a number of irrigators in the Western Rother catchment. Southern Water's 2019 Drought Plan also identifies an import from Portsmouth Water near to the Pulborough source as a supply-side drought option.

D.1.1. Stochastic Drought Generation

The monthly rainfall data were randomly sampled from 1000 replicates to 400, 48-year long runs, resulting in a total of 19,200 years' worth of stochastic data. The Q-Q (quantile-quantile) plots in Figure 5-24 presents the stochastic (both before and after the random sampling) and observed rainfall data, over 3 consecutive hydrological years; the red dots along the red line are observations prior to 1950. As shown, the sampling does not have a discernible impact on the range and mean suggesting it is representative of the full stochastic dataset. The sampled monthly rainfall dataset was used to produce the daily rainfall and PET datasets using the daily resampling process.

One of the stochastic rainfall sites in the WRSE stochastic weather generator is Hardham rainfall gauge site. Therefore, this site's data was assumed to represent the Western Rother catchment's climatology and taken directly into the hydrological catchment model, with no further catchment averaging or transposing required.

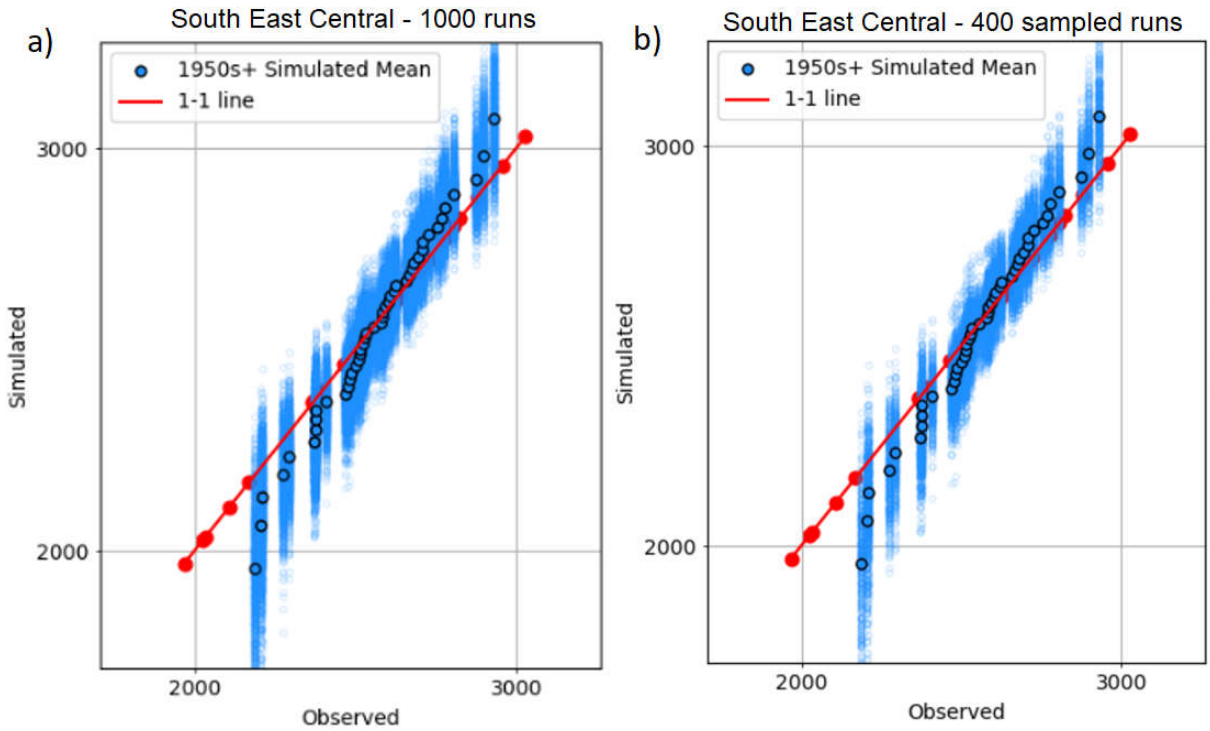


Figure 5-24 - Q-Q plots for South East Central WRSE sub-regional rainfall (3 hydrological years). (a) 1000 runs before random sampling, (b) 400 runs after random sampling.

D.1.2. Hydrological modelling

Southern Water has an existing, calibrated Catchmod rainfall-runoff model for the Western Rother catchment at Hardham. Catchmod model was not calibrated based on HadUK data. However, as shown in

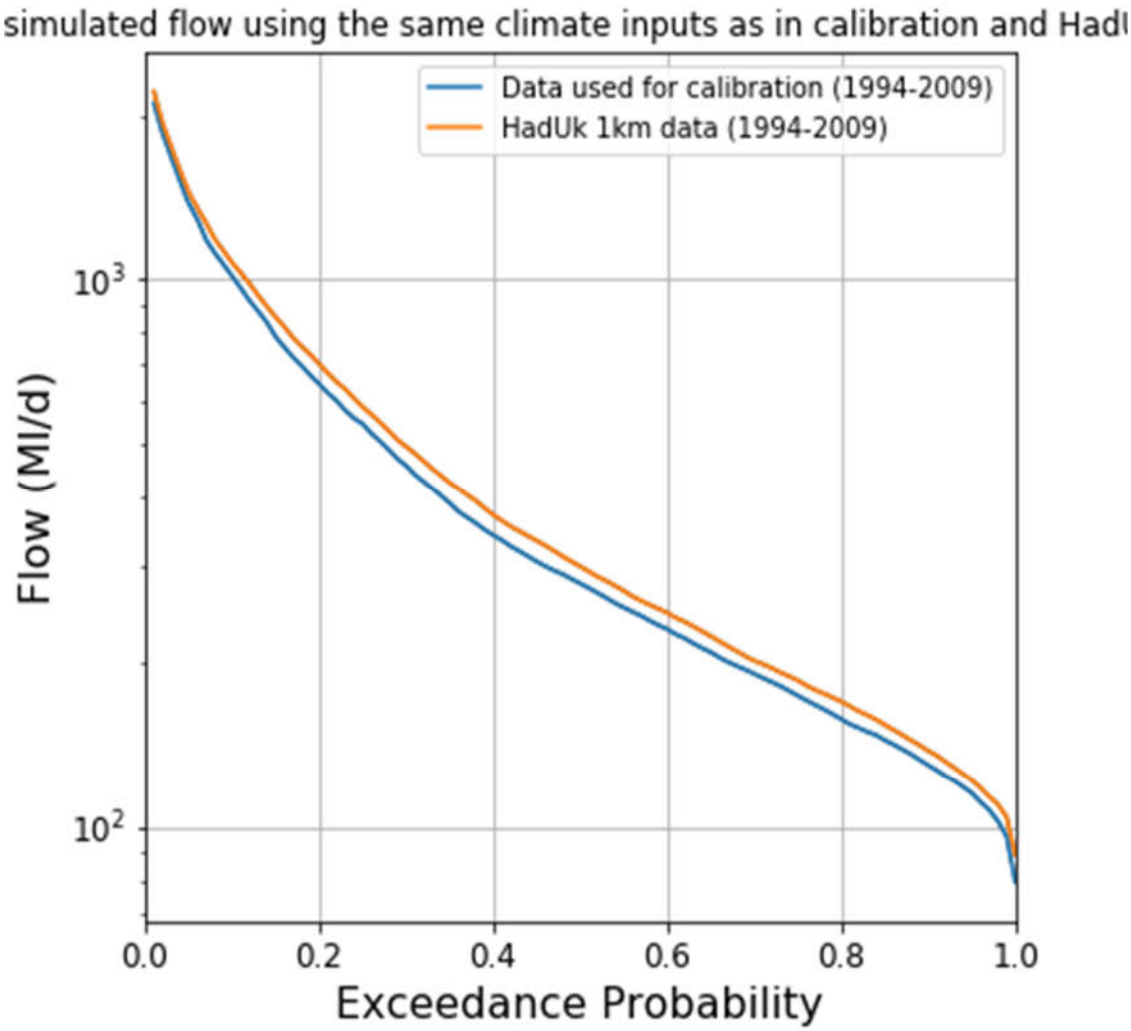


Figure 5-25, the flows derived using the same input data used for Catchmod's calibration are similar to the simulated flows derived using HadUK data as input[39] For this reason, no further calibration of the Western Rother Catchmod model was undertaken.

[39] HadUK 1 km precipitation data averaged over the catchment was used, and PET was derived using the Oudin formula based on HadUK 1 km maximum and minimum temperature averaged over the catchment. The average between maximum and minimum temperature was used.

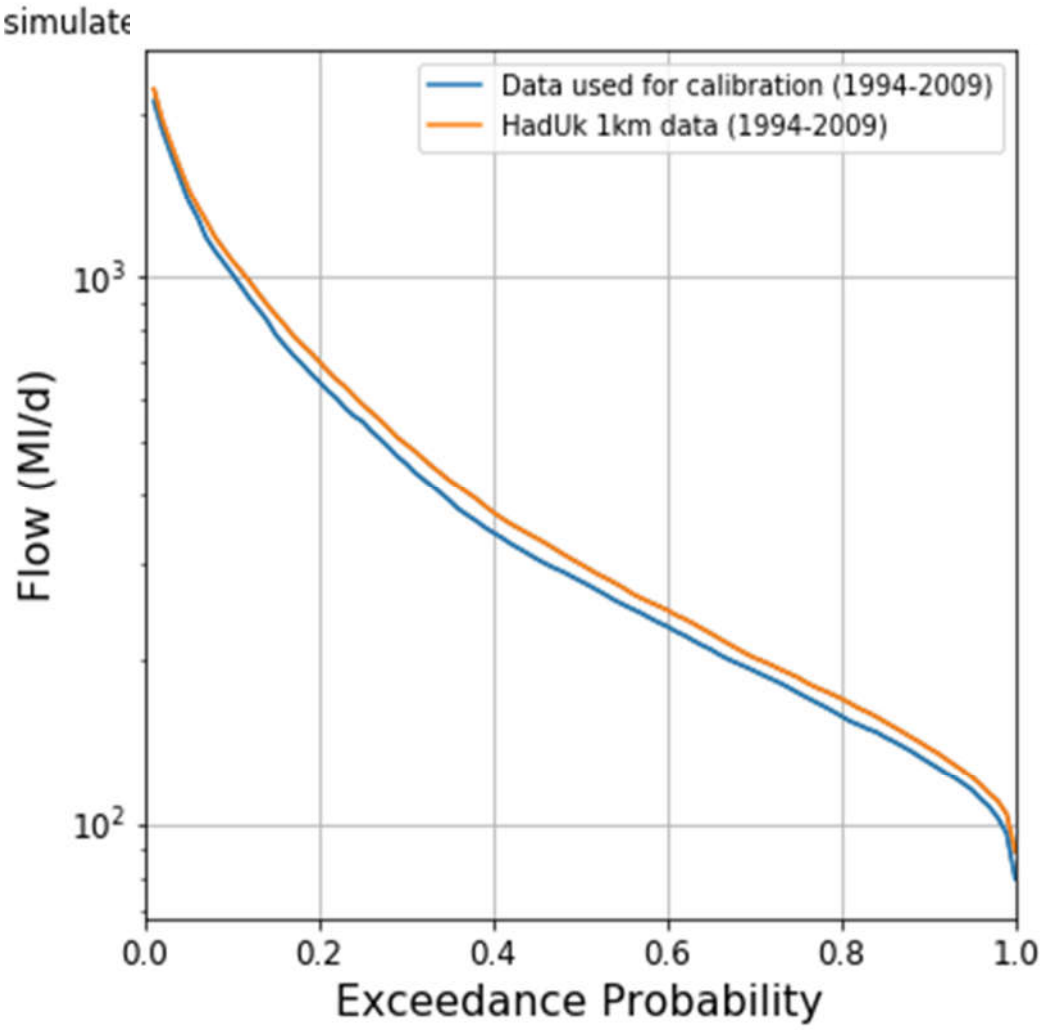


Figure 5-25 – Simulated flows using the same data used by the water company to calibrate Catchment and using HadUK data

This model was used to simulate flow based on the stochastic precipitation (P) and PET data. Figure 5-26 presents flow duration curves (FDC) for the sampled 400 stochastic data timeseries against the simulated flow using HadUK data There is noticeable variability between the 400 FDCs; the difference is greatest at higher exceedance probabilities, associated with low flows This shows that the FDCs for HadUK data lies within the range of stochastic flow series' FDCs, however its position within the range does vary at different exceedance probabilities. For example, between 80% and 95% exceedance probabilities (equivalent to low to very low flows), the HadUK FDC lies very close to the lowest stochastic FDCs.

The differences between flows modelled using the observed HadUK data and the 400 stochastic datasets are also presented in Figure 5-27. The median extreme low flows (95% exceedance probability) are less extreme than those produced from the HadUK data (+4%), however, as shown the stochastic data provides a large range of flows to test the Hardham system. The variability/range in the 400 stochastic replicates increases as the exceedance probability increases (as flows decrease).

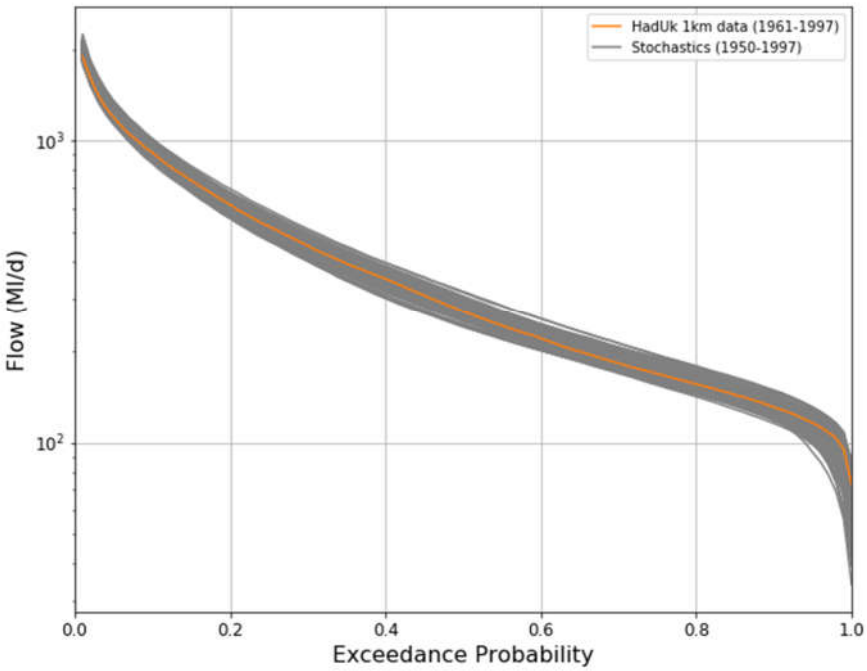


Figure 5-26 - Hardham flow duration curves for stochastically generated flow

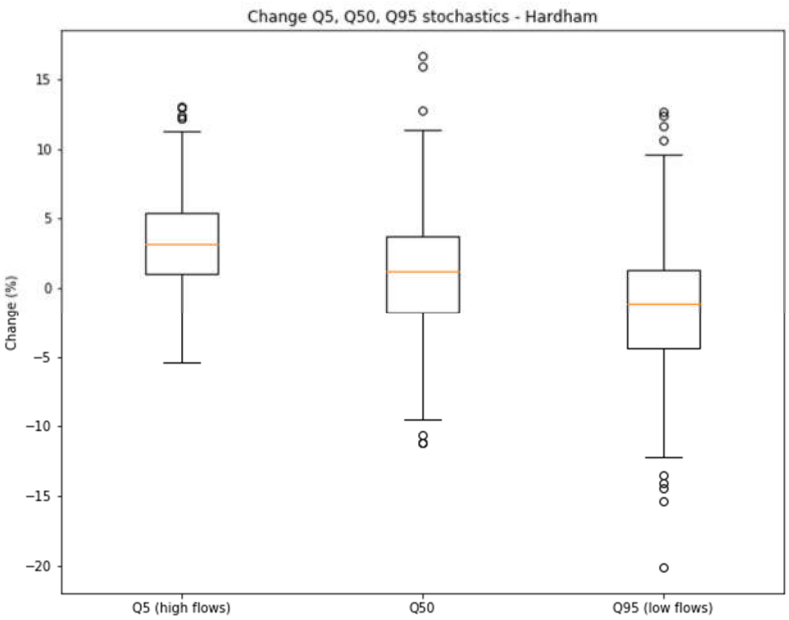


Figure 5-27 - Percentage differences between flows at Hardham calculated using observed HadUK and those calculated using stochastic weather data (Q5: extreme high flows, Q50: median flows, Q95: extreme low flows)

D.1.3. Climate change scenarios

To consider the vulnerability of regional water resources to climate change, companies are likely to either perturb the stochastic time series with climate change factors or run future climate change time series through their system. There are a number of UKCP18 products that could be used for perturbing the stochastic data. As part of this project we have provided processed climate change products for each region and all river basins requested by regional groups.

To compare the impact of choice of climate model on river flows at Hardham, climate change factors were applied to the HadUK baseline (1981-2000) data. The climate change data tested is presented in Table 5-8.

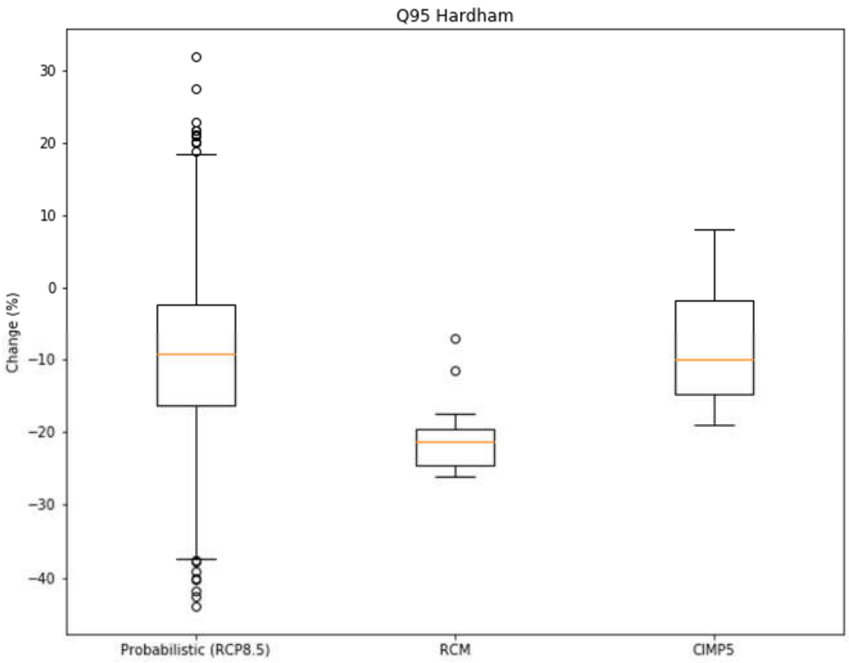
Table 5-8 - Climate change datasets applied in Hardham case study

Data set	Further detail	Application
UKCP18 RCM (bias-corrected) factors – RCP8.5	12 bias corrected RCM RCP8.5. P, T and PET change factors to apply to stochastic data sets, to create stochastics *plus* climate change. Factors for the 2060-2080 period.	Climate change risk assessment.
UKCP probabilistic – RCP8.5	3000 climate change factors for P and T for the 2060-2080 period. Factors produced for the whole England and Wales area.	The 3000 factors provide a broader context to the 13 RCM data sets.
UKCP probabilistic – A1B scenario	3000 climate change factors for P and T for the 2060-2080 period. Factors produced for the whole England and Wales area.	The 3000 factors provide a broader context to the 13 RCM data sets. The A1B scenario was commonly adopted for climate change planning when UKCP09 data was used. It has been reproduced in UKCP18 for comparison with the new pathways approach.
UKCP Global Coupled Model Inter-comparison Project (CMIP5) – RCP8.5	13 climate change factors for P and T for RCP8.5 for the 2060-2080 period. Factors produced for the whole England and Wales area.	CMIP5 data provide a broader context and wider range of possible outcomes.

The section below presents a summary of the percentage change in flows, with climate change under RCP8.5, in the Western Rother at Hardham for the probabilistic, RCM and CMIP5 projections. As shown, all climate models project lower flows in the future as a result of climate change. The probabilistic data cover the full range of uncertainty captured by both the bias corrected RCMs and the CMIP5 projections.

The probabilistic projections suggest the change in flow could range from no change to a maximum decrease of approximately 75%, with an approximate median decrease of 37%. The RCM and CMIP5 provide fewer climate model ensembles than the probabilistic which is reflected in the smaller variability of projected flow changes. The RCM and CMIP5 median flow decreases are noticeably different, 55% and 30% respectively. This indicates that the bias-corrected RCM change factors project a more severe impact on river flows under future climate change than the probabilistic projections however, this lies within the range of results projected by the 3000 probabilistic projections.

The comparison of flows at Hardham under different climate change models suggests that any analysis undertaken with RCM data should be contextualised within the range of uncertainty projected by the probabilistic projections.



D.2. WRE – River Ouse

Water Resources East (WRE) recommended producing a case study on the Great Ouse catchment to Offord, where water is abstracted to supply Grafham Water, as shown in Figure 5-28. This forms part of Anglian Water's integrated Ruthamford network, which consists of Rutland, Grafham and Pitsford Water reservoirs and supplies major towns and cities within the region, including Milton Keynes and Peterborough. The network is also of regional strategic importance, as the reservoirs supply other WRE water companies; water is transferred from Grafham to Affinity Water and from Rutland to Severn Trent Water.

In the previous round of regional planning, WRE used a stochastic weather generator (Atkins, 2018). As part of this project several improvements have been made; the aim of this case study is to test the updated stochastic weather generator, and in particular, the inclusion of additional climate drivers.

Stochastic drought generator improvements

During WRE Phase 1, Atkins worked with Met Office and the East Atlantic Index (EAI) was added to the climate drivers in the stochastic weather generator. As part of this study two additional teleconnections have also been added to the stochastic weather generator, the East Atlantic-West Russian Pattern (EA-WR) and the Scandinavian Pattern (SCAN).

The availability and quality of teleconnection data for EA-WR and SCAN prior to 1950 is significantly poorer than that in the second half of the century. So as explained in the main report, the length of the output time series from the generator is 48 years (1950-1997), compared to 91 years (1900-1990), as produced using the previous stochastic weather generator in WRE Phase 1.

To enable comparison to the previous work, the stochastic data generated for this case study is for the same points as before, using HadUK 1km precipitation and MORECS PET data. The main differences are:

- The stochastic model (including the updated bias correction process) and length of output time series, and
- The use of HadUK 1km rather than CEH GEAR rainfall.

Therefore, in order to identify how changes made to the stochastic weather generation process affect climate and river flow outputs, this case study has two different strands of work:

1. Pinpointing the effect of the new climate drivers on stochastic monthly rainfall generation. In this strand, the only aspect of the stochastic weather generation process that differs between the two model runs is the range of teleconnections (and hence the number and length of each run).
2. Comparing the previous stochastic weather outputs to the new outputs, including how these influence river flow. In this strand, various aspects of the stochastic weather generator have changed, as well as the inclusion of additional teleconnections.

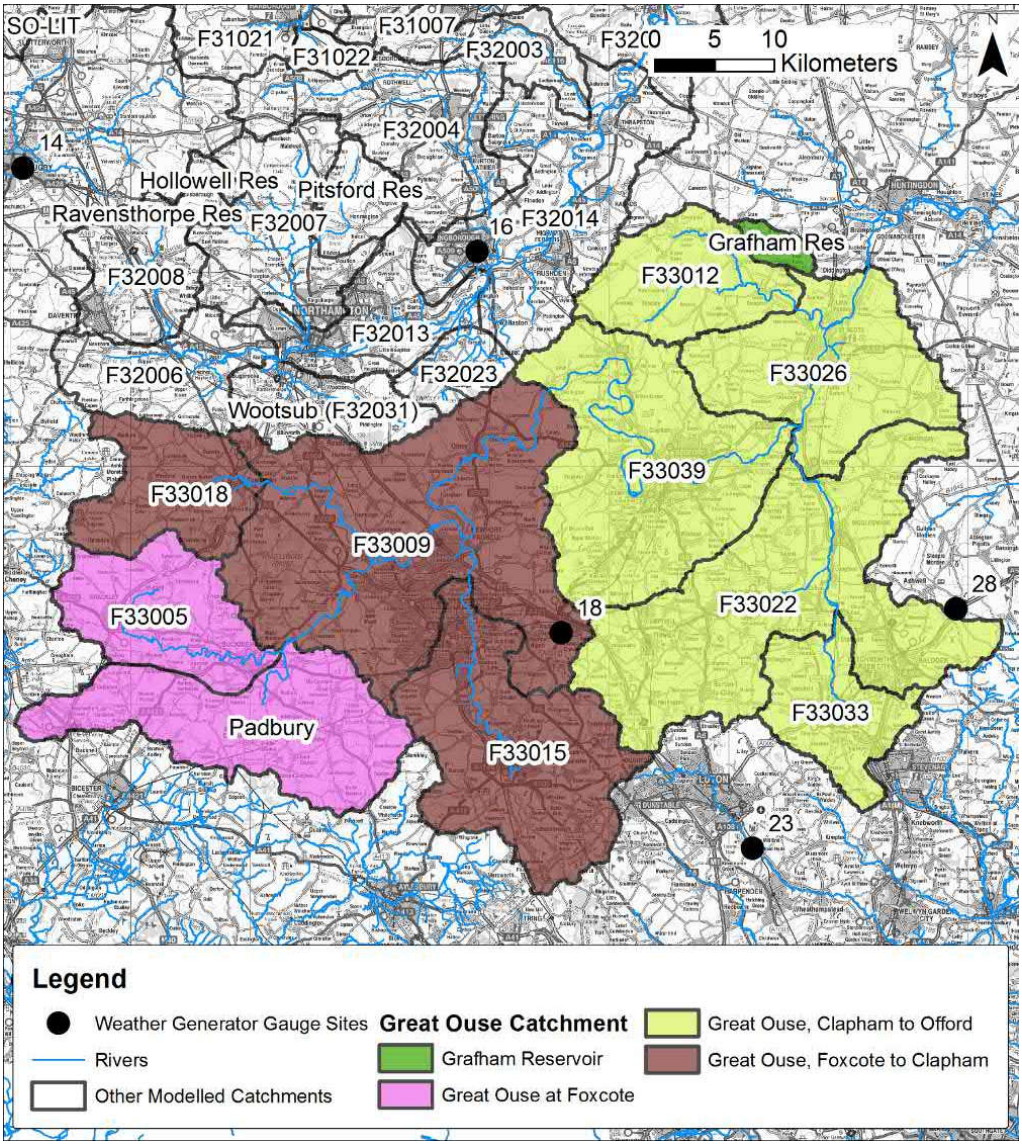


Figure 5-28 - Great Ouse to Offord catchment

The effect of additional climate drivers

The two stochastic weather generator models were run:

Model	Historical years	Teleconnections
20th Century	1900 – 1997	Main effects and interactions between: • Month factor • North Atlantic Oscillation • Sea Surface Temperature • Atlantic Multi-decadal Oscillation • East Atlantic Index

1950s	1950 – 1997	• Main effects and interactions between: • Month factor • North Atlantic Oscillation • Sea Surface Temperature • Atlantic Multidecadal Oscillation • East Atlantic • East Atlantic West Russia • Scandinavia

The raw outputs of the first stage of the stochastic weather generator have been compared; these are the pre-bias correction monthly rainfall datasets.

The new (1950-1997, referred to as the 1950s+ model) and previous (1900-1997, referred to as the 20th century model) were run through the stochastic weather generator. All other factors were kept constant and the HadUK observed data was used. The HadUK observed data indicates that the first half of the 20th century was drier than the second, hence the 1950s model does not contain some of the key droughts in the 20th century. However, the new stochastic generator using the shorter period performed as well as, or marginally better, against the observed data. For example, the percentile plot in Figure 5-29 shows that the 1950s+ model lies closer to the observed data than the 20th century model.

In many cases where the lowest historical record in the 20th Century was not represented in the 1950s model, the lowest rainfall totals for the 1950s model appeared lower against their equivalent lowest observed value, for example, as presented in Figure 5-29. This effectively covers the range that would have been represented within the 20th century model. Therefore, this indicates using a shorter period of observed data does not prevent the stochastic weather generator from producing very extreme low rainfall patterns, thus supporting the use of the 1950s+ model and that including additional climate drivers improves the stochastic climate datasets.

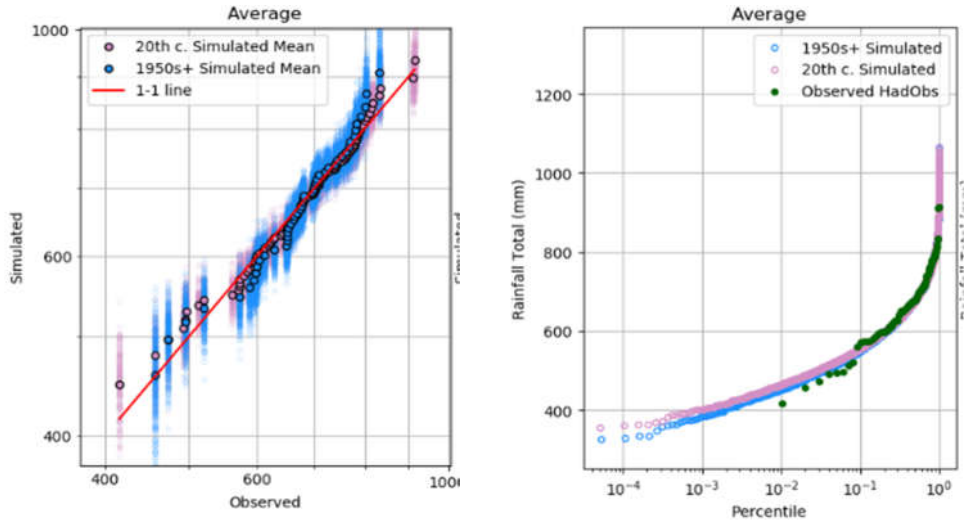


Figure 5-29 - Q-Q (left) and percentile (right) plots for WRE region comparing stochastic monthly rainfall produced using 20th century and 1950s+ periods

The effect of input data

Figure 5-30 presents a comparison of the two input weather datasets; this indicates that the average and range of rainfall values that were used in the new (HadUK) and old (GEAR) stochastic weather generator are very similar. For example, the median monthly rainfall across the region is 51.8 mm from the HadUK dataset and 51.4 mm from the GEAR dataset. This suggests that the choice of input climate dataset has a limited impact on

the stochastic weather datasets, and that much of the difference would arise from the other updates to the stochastic weather generator model.

The new WRE stochastic weather generator produces 1000, 48-year long series of monthly rainfall data. The bias correction process has also been updated in the new stochastic weather generator, to limit the adjustment as much as possible and ground it in probabilistic methods. This is explained in more detail within the main report. The new bias correction technique was applied at a sub-regional scale to improve the fit between simulated and HadUK observed monthly rainfall; this includes HadUK observations prior to 1950, to somewhat account for the more extreme droughts observed in the first half of the 20th century. Figure 5-31 shows the sub-regional stochastic and observed rainfall for the hydrological year; the Central and South sub-regions are the focus of this case study, as the five gauges used for the Great Ouse catchment sit within these regions. This is comparable to Figure 5-32, the same plot produced in the previous WRE regional planning phase (Atkins, 2018). The differences indicate that the new stochastic weather generator achieves its aim of reducing the extent of bias correction, which is particularly evident in the Central region.

The Q-Q (quantile-quantile) plot in Figure 5-33 presents the range and mean of the stochastic data, along with the observed total rainfall over 3 consecutive hydrological years; the red dots indicate observations prior to 1950. While the lowest ranked simulated data for both South and Central sub-regions deviate from the observed, the range covered by the simulated data takes account of the lowest observed point in the record prior to 1950. This indicates that the stochastic dataset includes droughts of magnitudes exceeding those in the historical record.

The monthly rainfall data was randomly sampled from 1000 to 400, 48-year long runs. The sampled dataset was used to produce the daily rainfall and PET datasets using the daily resampling process. This was of equivalent length to the daily rainfall and PET datasets previously produced using the former weather generator adopted by Anglian Water in PR19.

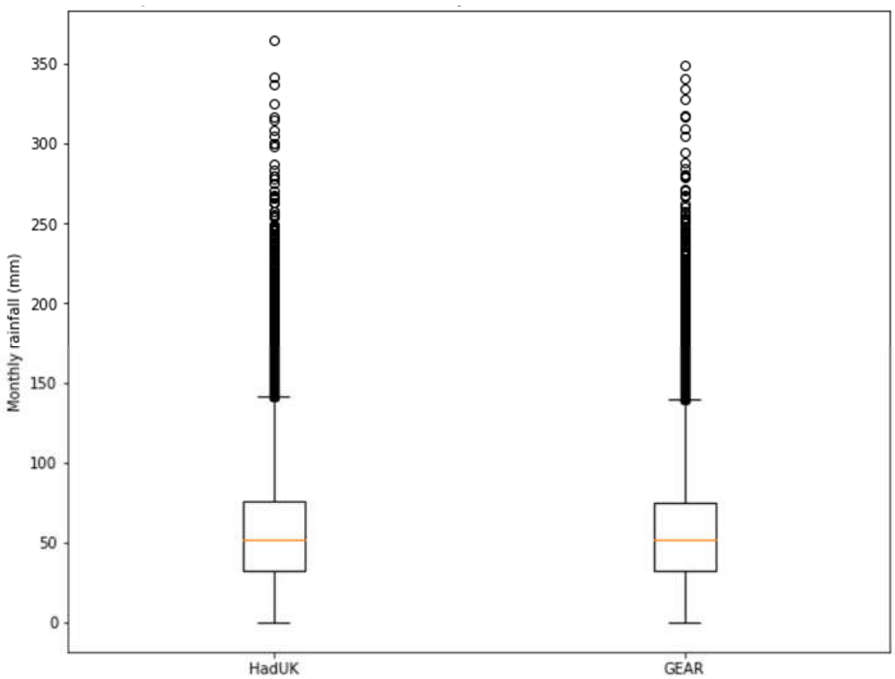


Figure 5-30 - Comparison of HadUK (1900-1997) and GEAR (1900-1990) monthly rainfall data across all WRE stochastic sites

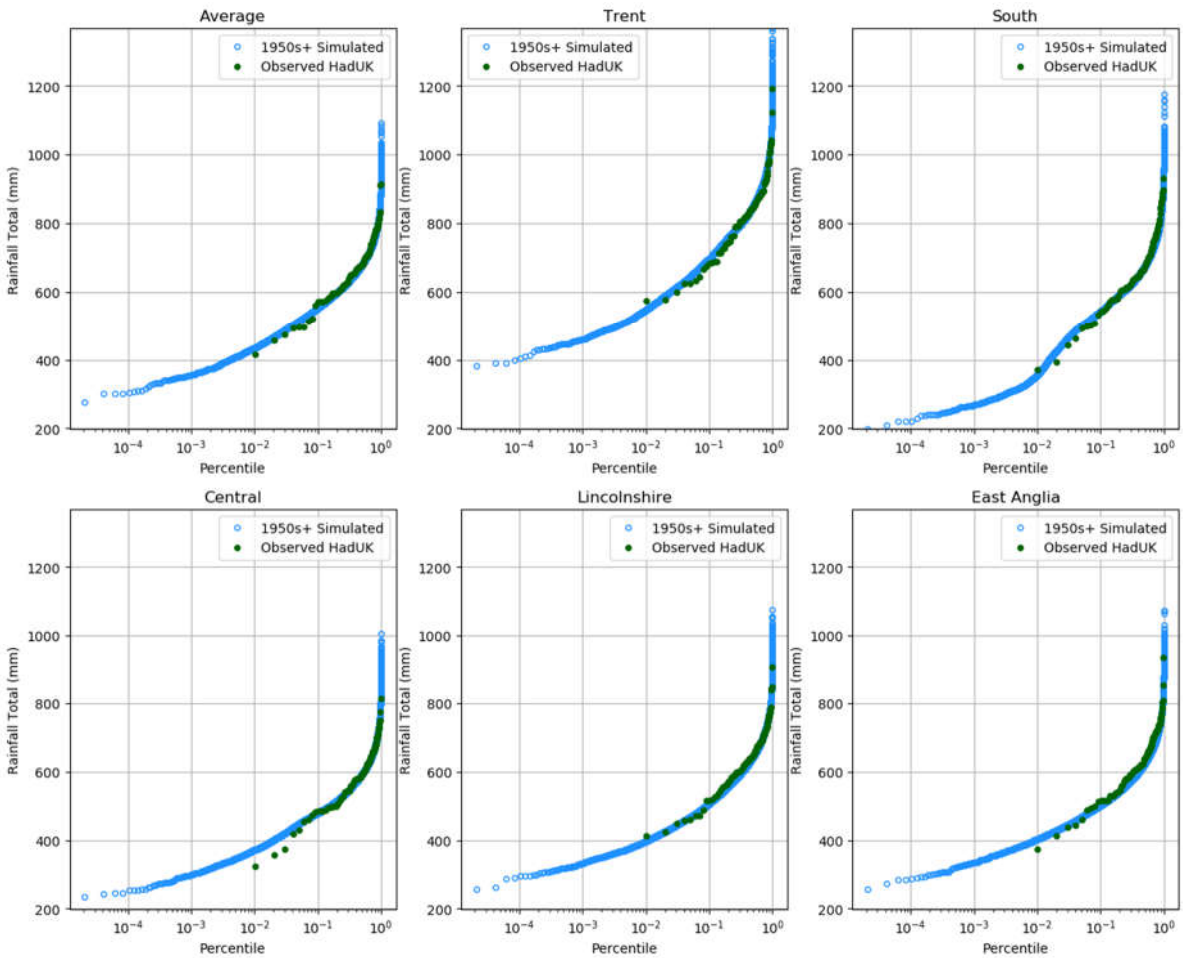


Figure 5-31 - Updated WRE total sub-regional rainfall for hydrological year

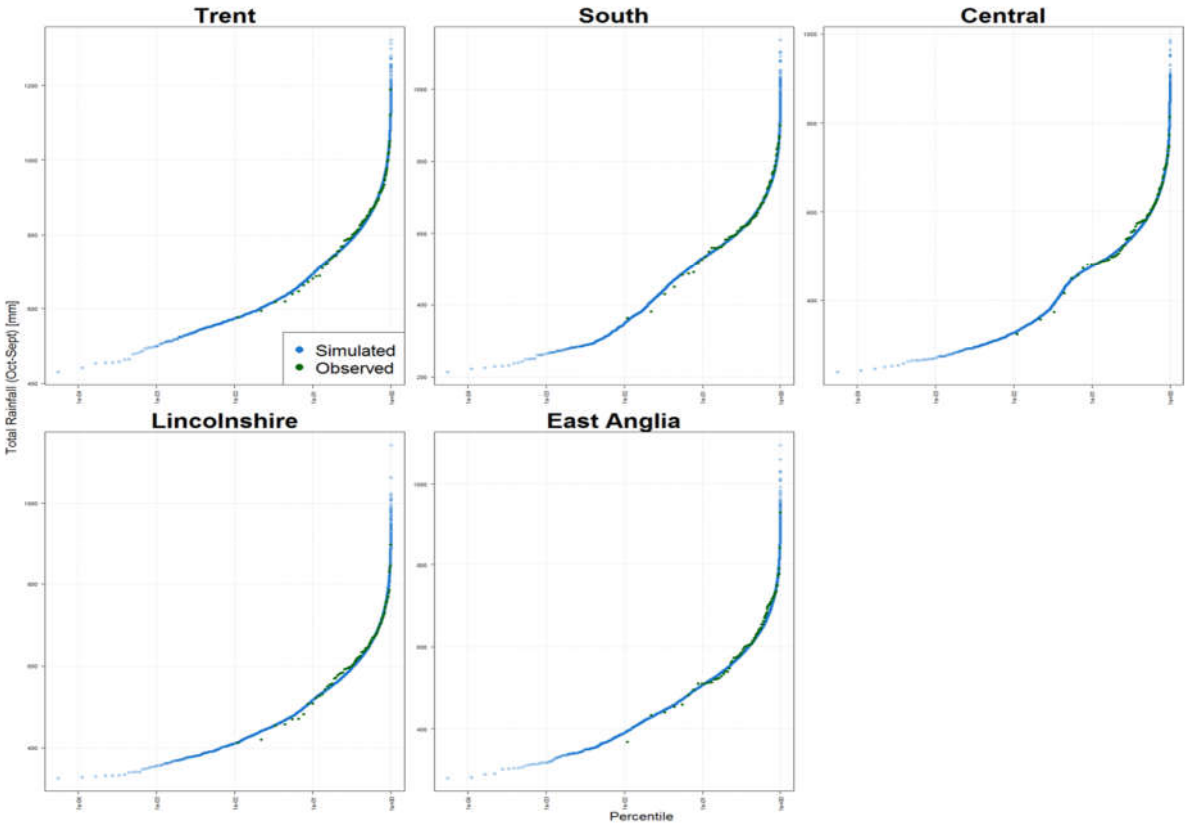


Figure 5-32 - WRE total sub-regional rainfall for hydrological year produced using previous stochastic weather generator [1]

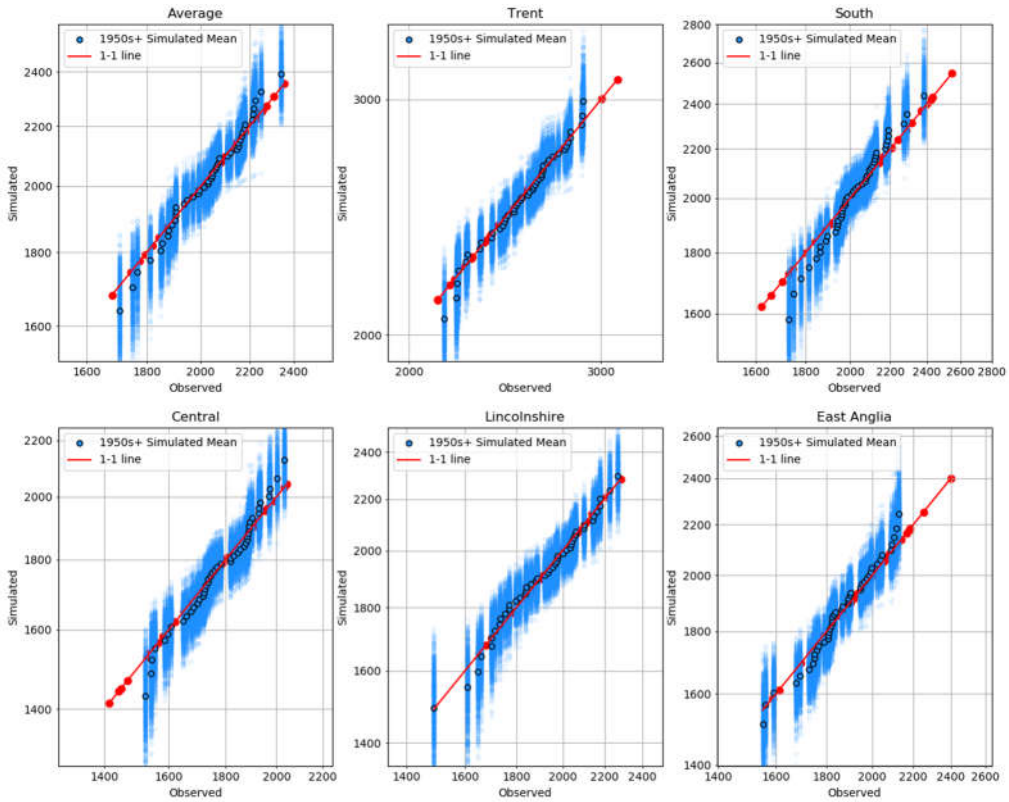


Figure 5-33 - Q-Q plot for WRE sub-regional rainfall (3 hydrological years)

Impact on flows

Hydrological modelling for the Great Ouse catchment was undertaken using the Stanford Watershed Model (SWM). Both the new and old stochastic weather datasets were used to model river flows at Offord, as well as historic rainfall (GEAR) and PET time series. The catchment was split into 11 sub-catchments, with one rainfall site and PET square assigned to each sub-catchment; the rainfall data was then scaled to the catchments using pre-defined factors, as in WRE Phase 1. (Atkins, 2018).

The flow duration curves for river flow at Offord derived using the historic and stochastic climate datasets are presented in Figure 5-34. Figure 5-35 presents flow series for Q50, Q70 and Q95, comparing the new and old stochastic flow, as well as historic flow data at Offord. The historic flow data presented shows that flows in the 1950-1997 period are higher than in the 1918-1990 and 1918-2015 periods, particularly for the extreme low flows. For the Q95 flow percentile (extreme low flows), the median flow across the 400 stochastic runs is higher for the new stochastic dataset than for the old stochastic dataset (approximately 200 Ml/d compared to 195 Ml/d). However, the range of flows is greater for the new stochastics, and the lower whisker extends further, with a minimum flow of approximately 145 Ml/d, compared to approximately 165 Ml/d for the old stochastics dataset. Therefore, the new stochastic data provides a greater range of low flows to test the WRE system; this should be taken into consideration when defining design droughts.

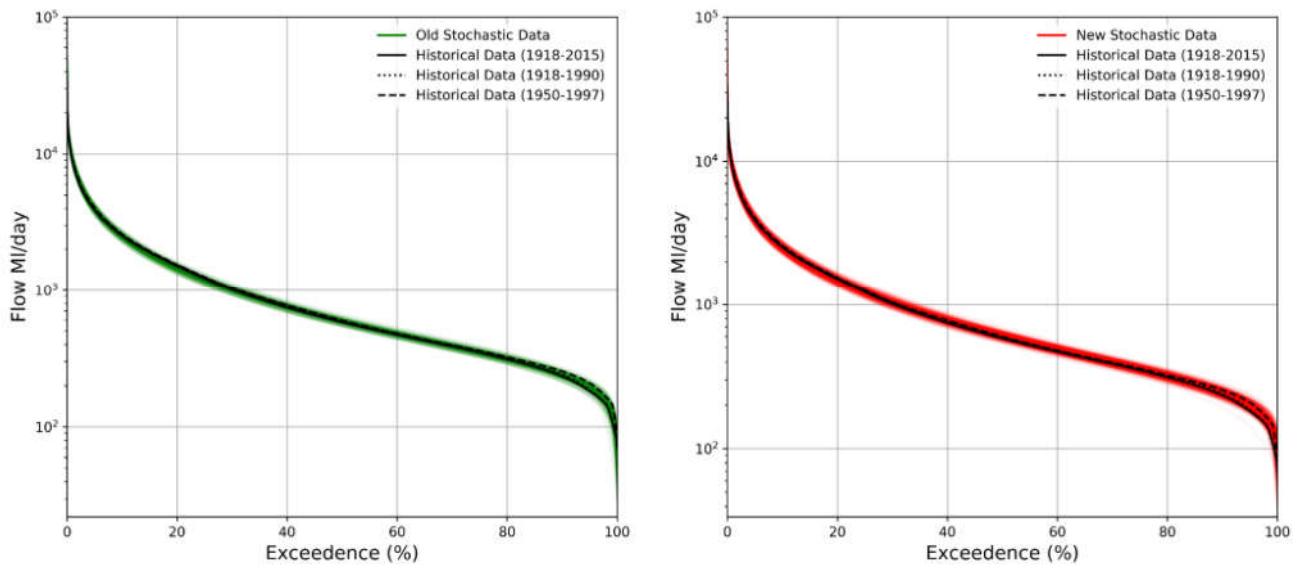


Figure 5-34 - Flow duration curves for stochastic series compared against historical data

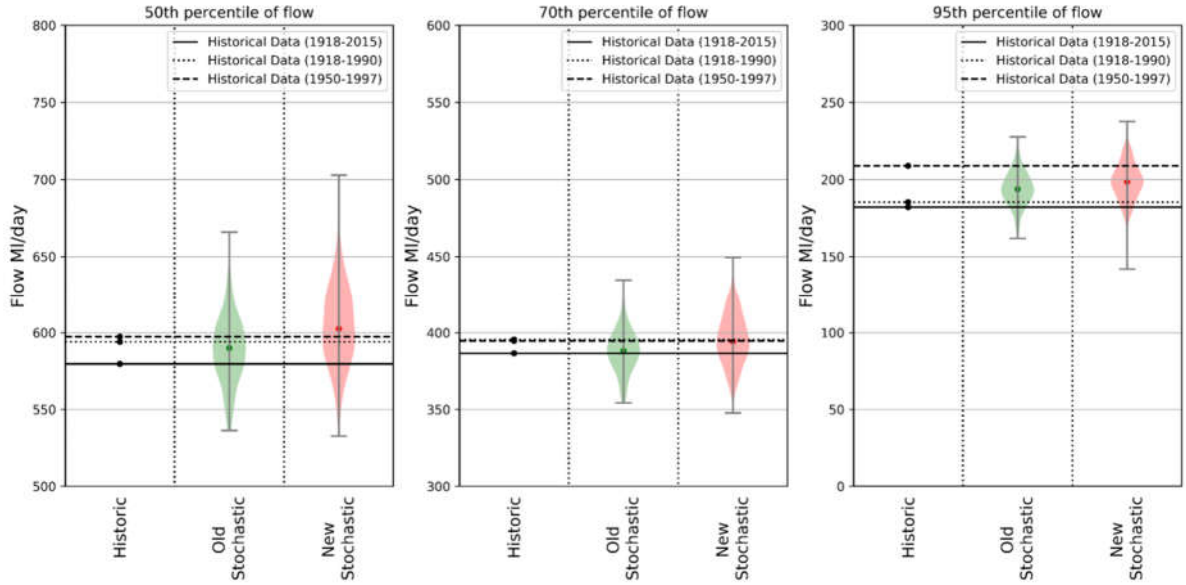


Figure 5-35 - Flow statistics for stochastic series compared against historical data

D.3. WRW

To follow.

D.4. WCWRG –Ashton Farm and Wimbleball

D.4.1. Introduction

West Country Regional Group recommended the Ashton Farm and Wimbleball catchments as their case study locations. Ashton Farm is a groundwater catchment comprising of Dorset Chalk. Wimbleball is a surface water catchment located on Exmoor and faces a number of pressures as it is an area of intense agriculture and is an important water supply for many parts of Devon and Somerset.

For this case study the stochastic generated flows were perturbed by climate change model projections from a range of UKCP18 products to compare the impact on groundwater levels and help inform regional groups decisions around which product/s to apply for their assessment of future drought under climate change.

D.4.2. Hydrological modelling

Table XX summarises the climate data that was applied to the stochastic data for hydrological modelling for this case study. UKCP18 projections are based on Representative Concentration Pathways (RCPs) rather than the Special Report on Emissions Scenarios (SRES) used in UKCP09. However, UKCP18 provides projections for A1B to enable direct comparison.

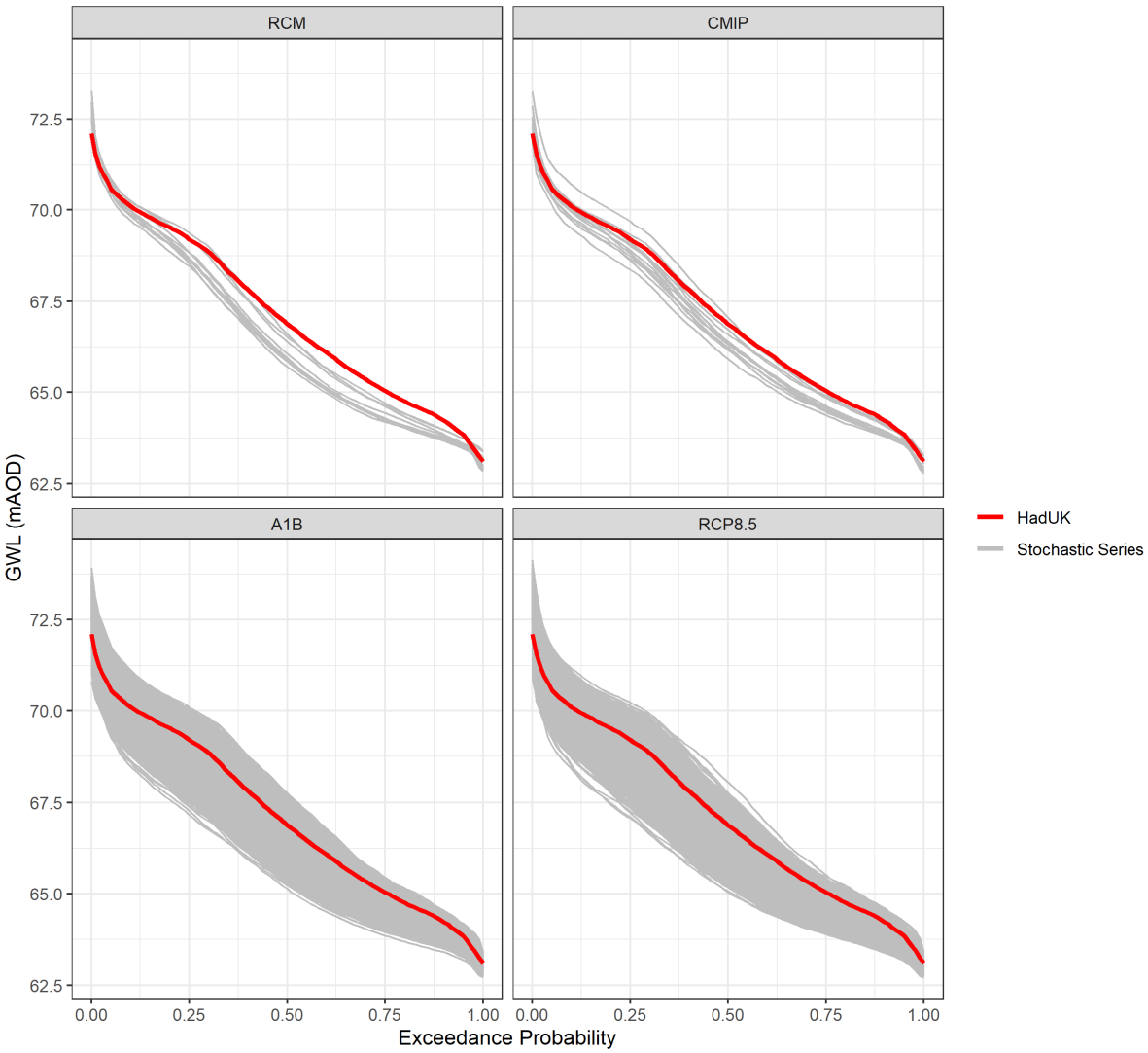
Table 5-9 - Climate change datasets applied in WCWRG case study

Data set	Further detail	Application
UKCP18 RCM (bias-corrected) factors – RCP8.5	12 bias corrected RCM RCP8.5. P, T and PET change factors to apply to stochastic data sets, to create stochastics *plus* climate change. Factors for the 2060-2080 period.	Climate change risk assessment.
UKCP probabilistic – RCP8.5	3000 climate change factors for P and T for the 2060-2080 period. Factors produced for the whole England and Wales area.	The 3000 factors provide a broader context to the 13 RCM data sets.

UKCP probabilistic – A1B scenario	3000 climate change factors for P and T for the 2060-2080 period. Factors produced for the whole England and Wales area.	The 3000 factors provide a broader context to the 13 RCM data sets. The A1B scenario was commonly adopted for climate change planning when UKCP09 data was used. It has been reproduced in UKCP18 for comparison with the new pathways approach.
UKCP Global Coupled Model Inter-comparison Project (CMIP5) – RCP8.5	13 climate change factors for P and T for RCP8.5 for the 2060-2080 period. Factors produced for the whole England and Wales area.	CMIP5 data provide a broader context and wider range of possible outcomes.

Figure X and Figure X show that for all climate models, groundwater levels at Ashton Farm are projected to decrease, relative to the HadUK 1981-2000 baseline period, for both Q50 and Q95. Probabilistic projections for both A1B and RCP8.5 were modelled. The results suggest that probabilistic projections for RCP8.5 and A1B predict similar future groundwater levels (median changes of less than +/- 1%) with a slightly greater range of future groundwater levels projected under RCP8.5.

The RCM projections, under RCP8.5, project greater decreases in median groundwater levels than the probabilistic projections with -1.5% decrease in Q50 levels. However, as expected, the range of projected changes for the 12 RCMs and 13 CMIP5 models are narrower than projected by the 3000 probabilistic predictions for all flows (Q). This suggests that to understand the full range of potential future groundwater levels the RCMs should be contextualised within the full range of probabilistic projections.


RCM
CMIP
A1B
RCP8.5
GWL (mAOD)
72.5
70.0
67.5
65.0
62.5
0.00
0.25
0.50
0.75
1.00
Exceedance Probability
HadUK
Stochastic Series

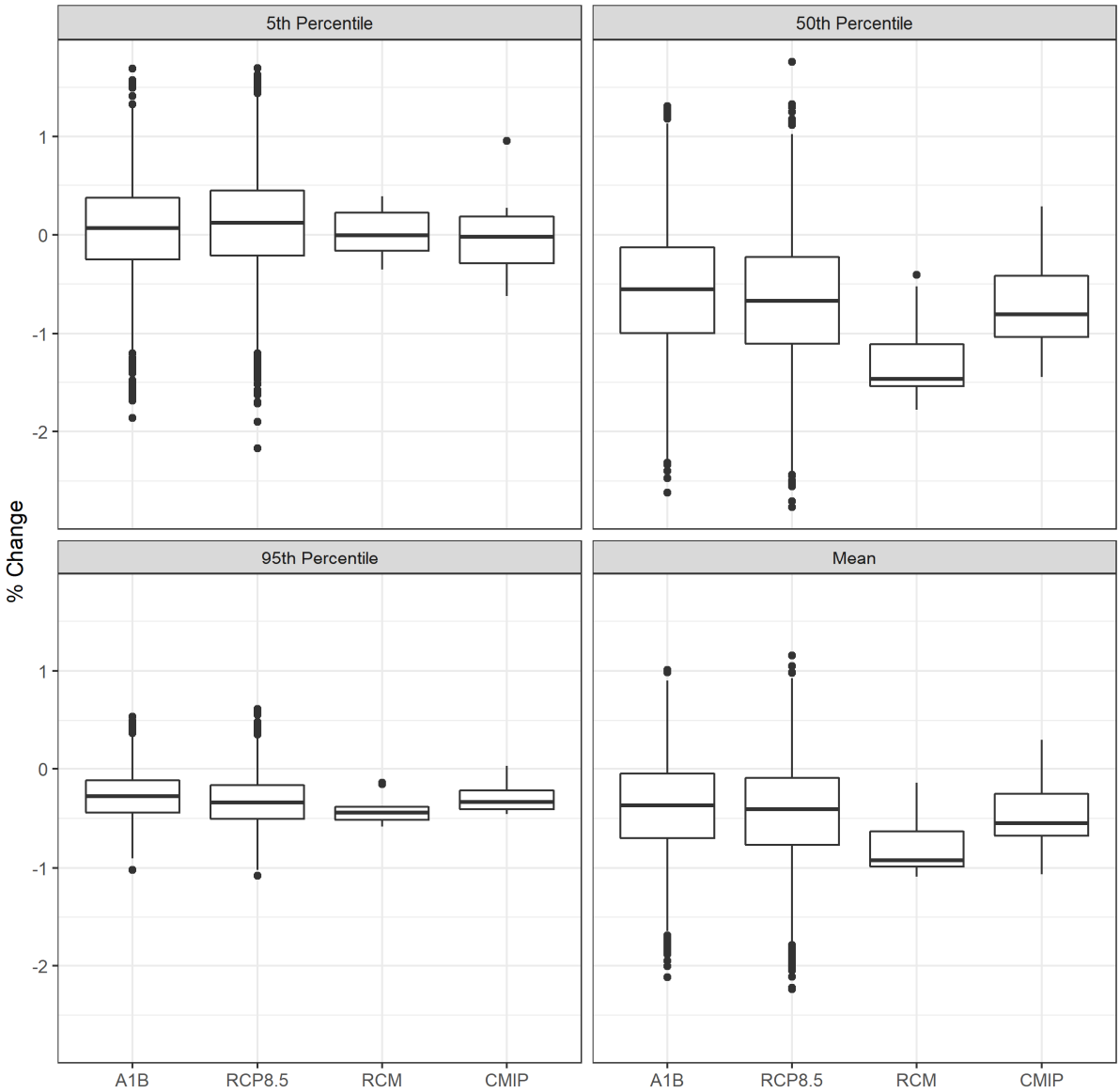
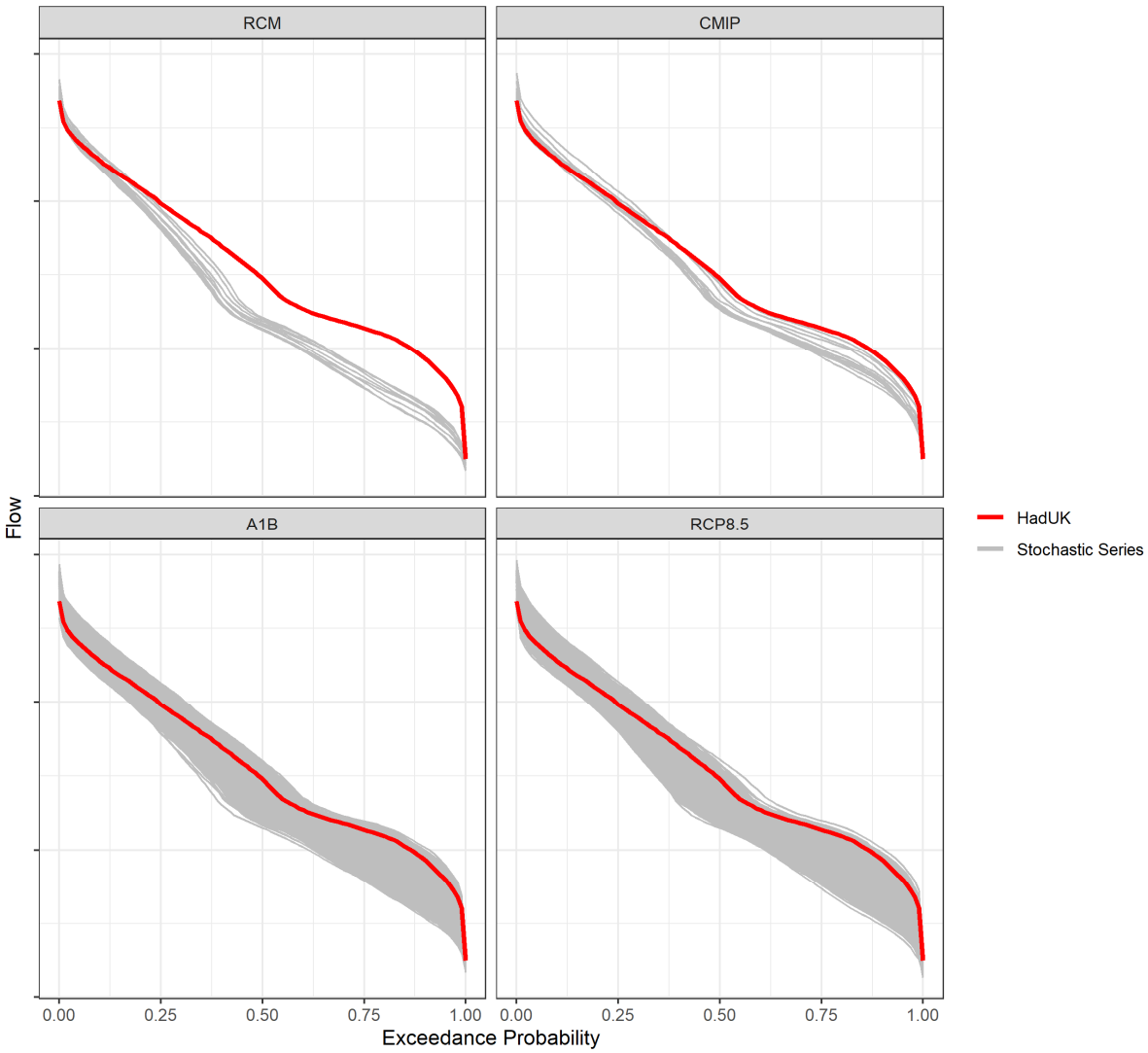
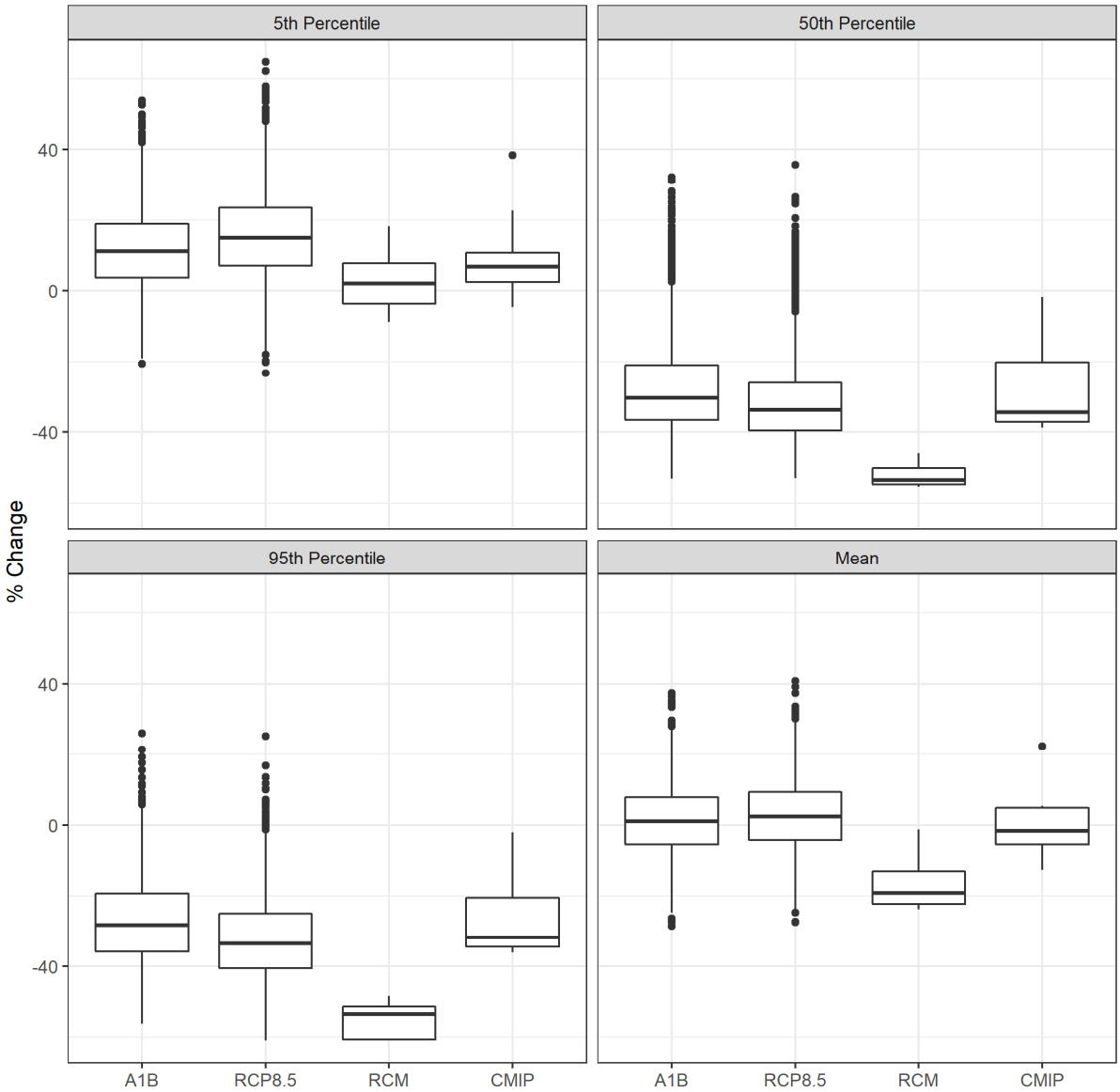


Figure X shows that for all climate models, low flows (where the exceedance probability <50%) at Wimbleball are projected to decrease, relative to the HadUK 1981-2000 baseline period. As shown in Figure X, the Probabilistic RCP8.5 and A1B results show the broadest range of percentage change to flows, ranging between approximately -50% and +30% with a median of approximately +35%. For Q5 the median projected changes are greater under RCP8.5 than A1B whereas for Q95 the median flows are lower for RCP8.5 than A1B.

Given the smaller number of change factors, the variability in flow changes for both the 12 RCMs and 13 GCM CMIP change factors are much narrower than those projected by the probabilistic models, particularly for the 95th percentile flows where the full range of flows sits below the median of the probabilistic projected flows. Again, this highlights that to understand the full range of potential future flow levels the RCMs should be contextualised within the full range of probabilistic projections.


RCM
CMIP
A1B
RCP8.5
Flow
0.00
0.25
0.50
0.75
1.00
Exceedance Probability
HadUK
Stochastic Series



D.5. WReN – Langsett

This case study focuses on the Langsett catchment, which is defined as the Little Don catchment draining to Underbank Reservoir.. The catchment is located in the north-east limit of the Peak District National Park, and has three Yorkshire Water reservoirs: Langsett, Midhope and Underbank reservoirs. Langsett and Midhope reservoirs are used for water storage, and the downstream Underbank reservoir releases compensation flow to the Little Don River [3]. Therefore, Langsett and Midhope reservoirs moderate the magnitude of flow downstream, causing a lower than expected baseflow, with the timing and magnitude of autumn/winter high flows dependent on reservoir levels rather than directly following heavy rainfall events. The Little Don reservoirs are important for Yorkshire Water to provide water to the city of Sheffield and the town of Barnsley.

The catchment is steep, and thus has a flashy response to rainfall events. Runoff in the catchment is influenced by the three reservoirs, public water supply abstraction and regulation from surface and groundwater. Flow was measured at the catchment outlet downstream of Underbank Reservoir between 1956 and 1980 (National River Flow Archive, 2020).

(to be completed)

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