



Stochastic Data: Method Statement



Contents

Executive Summary	5
1. Introduction	7
2. Stochastic weather generation	8
2.1 Background	8
2.1.1 Stochastic weather generator	8
2.2 Data	9
2.2.1 Weather datasets	9
2.2.2 Teleconnections	11
2.3 Model selection	13
2.3.1 Daily stochastic rainfall and temperature	15
3. Application of stochastic datasets	15
3.1 Deployable output assessment	16
3.2 Assessment of impact of climate change	16
3.3 Assessment of supply-side option benefits	16
Appendices	17
Appendix A. Stochastic weather generator curve fitting	18
Appendix B. Teleconnection correlations	20
B.1 North Atlantic Oscillation (NAO)	20
B.2 Sea Surface Temperature (SST)	20
B.3 East Atlantic (EA)	21
B.4 Atlantic Multidecadal Oscillation (AMO)	21
B.5 East Atlantic West Russian (EAWR)	22
Appendix C. Curve-fitting applied to stochastic data	23
Appendix D. Stochastic plots	25
D.1 Persistent droughts (2+ years)	25
D.2 12 – 18-month droughts	26
D.3 Seasonal droughts	28
Appendix E. Temperature detrending	32

Tables

Table 2-1 - Summary of available weather datasets	10
Table 2-2 - Summary of available teleconnection series	11
Table 2-3 - Comparison of the two fitted model formats	14

Figures

Figure E-1 - Percentile plots showing the stochastic outputs against the historical record for varying rainfall duration totals (light blue point are simulated; green points are observed during 1900-97).....	5
Figure E-2 - Flow chart illustrating the use of the stochastic datasets	6
Figure 1-1 - Flow chart illustrating the use of the stochastic datasets.	7
Figure 2-1 - Step-by-step process for generating stochastic weather.....	9
Figure 2-2 - Comparison of observed rainfall records at Jersey Airport (JA), Maison St Louis (MSL) and Jersey Water's record	11
Figure 2-3 – Winter rainfall totals at Maison St Louis, showing the overall mean and the mean across each half of the 20 th Century. Despite an apparent difference both the ADF and KPSS stationarity tests suggest no significant trend in the data.....	14
Figure 2-4 - Percentile plots showing the stochastic outputs against the historical record for varying rainfall duration totals (light blue points are simulated; green points are observed during 1900-97).....	15
Figure A-1 - Example of probabilistic curve fitting approach.....	19
Figure B-1 - Seasonal correlation between the North Atlantic Oscillation and rainfall (1900 – 1997).....	20
Figure B-2 - Seasonal correlation between the Sea Surface Temperature and rainfall (1900 – 1997).....	20
Figure B-3 - Seasonal correlation between the East Atlantic and rainfall (1950 – 1997)	21
Figure B-4 - Seasonal correlation between the East Atlantic Index and rainfall (1900 – 1997)	21
Figure B-5 - Seasonal correlation between the Atlantic Multidecadal Oscillation and rainfall (1900 – 1997)	21
Figure B-6 - Seasonal correlation between the East Atlantic West Russian and rainfall (1950 – 1997).....	22
Figure D-1 - Percentile plots for 24 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	25
Figure D-2 - Percentile plots for 36 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	25
Figure D-3 - Q-Q plots for 36 months ending September for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right).....	26
Figure D-4 - Percentile plots for 12 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	26
Figure D-5 - Percentile plots for 18 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	27
Figure D-6 - Q-Q plots for 18 months ending September for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right).....	27

Figure D-7 - Percentile plots for 8 months ending August for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	28
Figure D-8 - Q-Q plots for 8 months ending August for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)	28
Figure D-9 - Percentile plots for spring to summer period 5 months ending August for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	29
Figure D-10 - Q-Q plots for 5 months ending August for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)	29
Figure D-11 - Percentile plots for summer to autumn period 3 months ending October for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	30
Figure D-12 - Q-Q plots 3 months ending October for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)	30
Figure D-13 - Percentile plots for winter period 4 months ending February for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)	31
Figure D-14 - Q-Q plots 4 months ending February for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)	31
Figure E-1 – Detrended temperature data at Maison St Louis. A trend is fitted to annual average temperatures (red dotted line). The trend is used to detrend against the baseline period (blue dashed line). The black line shows the resultant detrended data.	32

Executive Summary

Jersey Water (JW) are updating their Water Resources and Drought Management Plan (WRDMP) to ensure a resilient, secure water supply up to 2065. As part of this work, JW would like to be able to consider droughts beyond those in the historical record including droughts with return periods up to 1 in 500 years, in alignment with the latest Water Resources and Planning Guidelines (WRPG).

This method statement provides a summary of the stochastic datasets that have been generated for Jersey Water using the AtkinsRéalis weather generator and how they will be applied in the WRDMP.

During the weather generation process, two model formats were tested to explore the trade-off between incorporating a larger number of driving teleconnection variables with a shorter historical record and using a smaller number of teleconnection drivers with a longer historical record. The final dataset selected uses the longer historical record from 1900 – 1997 as this was shown to perform better against the historical record particularly when considering long-term rainfall trends (2+ years). This model shows a good fit to the observed data across a range of rainfall duration metrics as illustrated in Figure E-1 and Appendix D.

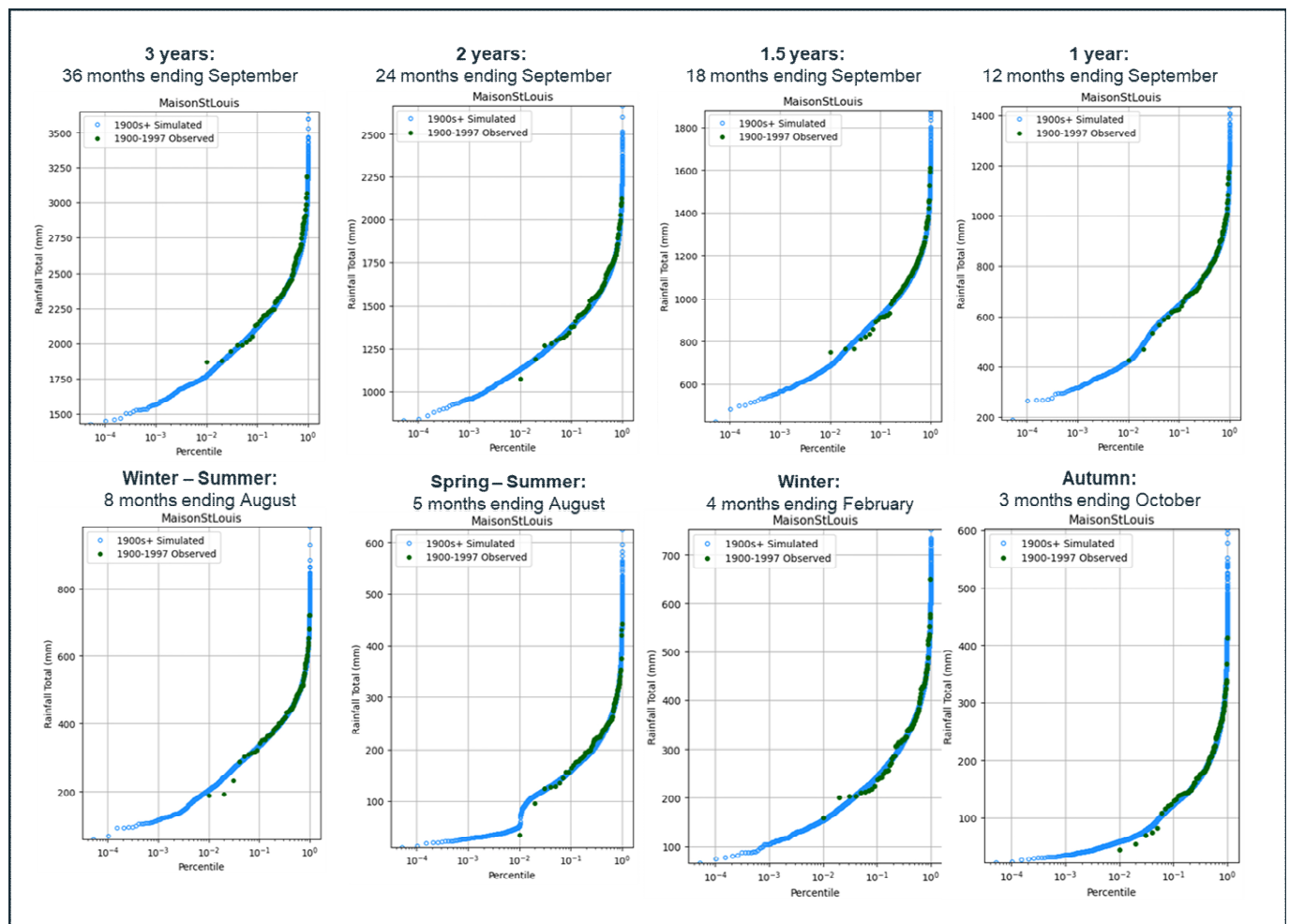


Figure E-1 - Percentile plots showing the stochastic outputs against the historical record for varying rainfall duration totals (light blue point are simulated; green points are observed during 1900-97)

Figure E-2 illustrates the use of the stochastic datasets in ongoing analysis. These are used for:

- Deployable output assessment
- Assessment of the impact of climate change
- Assessment of supply-side option benefits

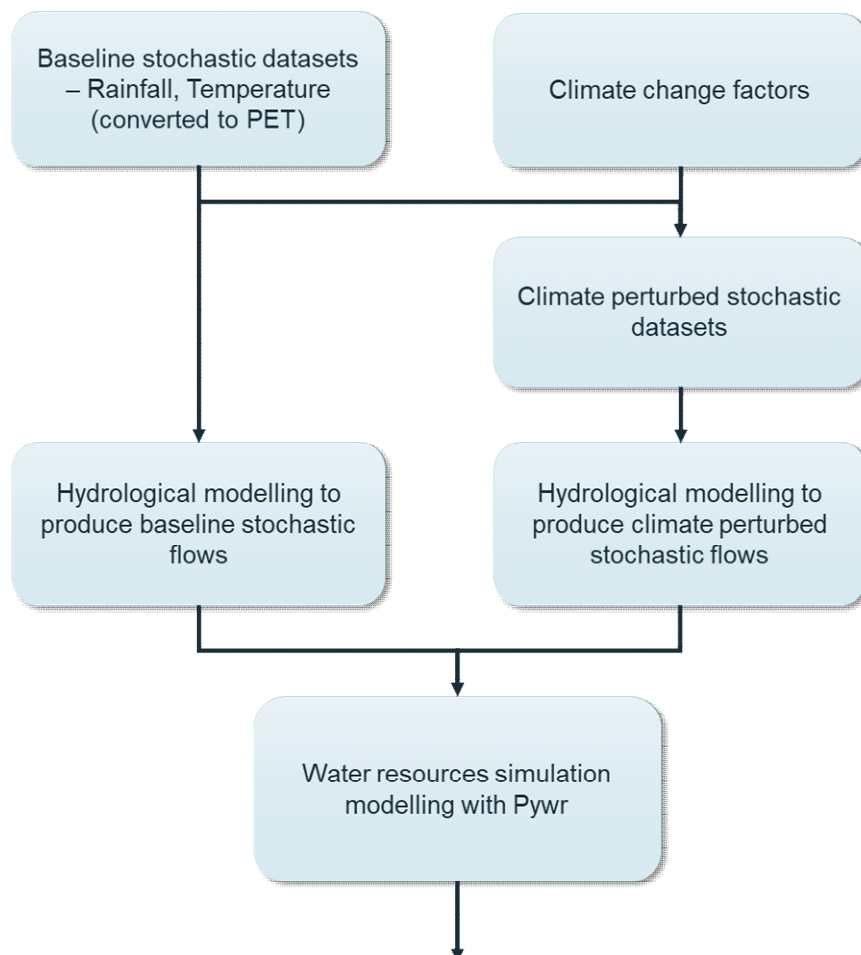


Figure E-2 - Flow chart illustrating the use of the stochastic datasets

1. Introduction

Jersey Water (JW) are updating their Water Resources and Drought Management Plan (WRDMP) to ensure a resilient, secure water supply up to 2065. As part of this work, JW would like to be able to consider droughts beyond those in the historical record including droughts with return periods up to 1 in 500 years, in alignment with the latest Water Resources and Planning Guidelines (WRPG).

The method that has been applied in the water industry in the UK is the generation of stochastic datasets consisting of timeseries of rainfall and potential evapotranspiration. AtkinsRéalis developed a stochastic weather generator that has most recently produced long records of spatially coherent weather data for all the regional water resources groups in England and Wales for the WRMP24 submission¹. These weather datasets have been used as the basis for the supply forecasts of all companies in England and Wales and therefore underpin these assessments across the whole industry.

This method statement provides a summary of the stochastic datasets that have been generated for Jersey Water using the AtkinsRéalis weather generator and how they will be applied in the WRDMP. Figure 1-1 summarises the use of the stochastic datasets. in this work.

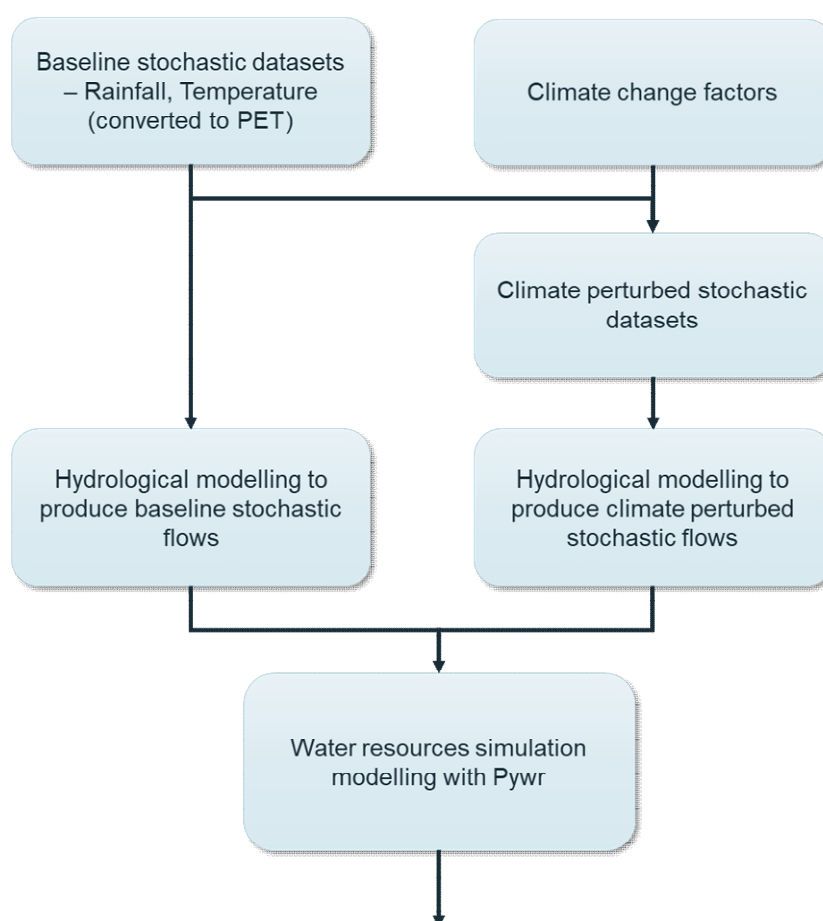


Figure 1-1 - Flow chart illustrating the use of the stochastic datasets.

¹ Regional Climate Data Tools project, Atkins 2020

This document is structured as follows:

- Section 2: Generation of the stochastic datasets, including overview of the generation process and model selection;
- Section 3: Application of the stochastic datasets.

2. Stochastic weather generation

2.1 Background

Understanding the risk of droughts can be particularly challenging given the numerous methods for quantifying drought (e.g. rainfall, effective rainfall, flow, water system response, etc.) as well as the variable spatial extent and duration over which droughts occur. Additionally, observed records provide just one possible timeseries out of the thousands of alternatives that could have plausibly occurred under the same long-term average climate conditions.

The need for water companies to consider drought beyond those in the historical record has increased in recent years due to the introduction of requirements and guidelines that call for water companies to show how they will make their systems resilient to droughts of 1 in 200 (for the plans produced in 2018-19) and now 1 in 500-year in the latest round of planning.

The use of stochastic approaches to model rainfall patterns has begun to be applied operationally over the last 10-15 years as it represents a computationally efficient tool for generating a wider range of possible drought events than was actually seen in the historic record.

2.1.1 Stochastic weather generator

The AtkinsRéalis weather generator is a multi-site rainfall generator based on the model originally developed by Serinaldi and Kilsby². The model analyses the observed relationships between monthly rainfall and climatic drivers (or teleconnections) along with 'random chance'. The basic concept behind this approach is that the observed record provides only one set of actual weather data (i.e. the one that did occur), out of the possible range of conditions that might have plausibly occurred.

The implicit assumption in this approach is that the observed record is reasonably 'typical' in terms of its overall probabilistic behaviour. Where deviations occur between the observed record and modelled data a judgement needs to be taken as to whether the historical drought event was statistically less likely (i.e. a greater than 1 in 100 event) or whether the modelled deviation represents other climatic influences not represented in the model that should be corrected for. To approach this issue, we developed a framework and automated curve fitting module for applying any corrections. This module:

- Minimises the amount of adjustment carried out;
- Applies a structured probabilistic statement to define any adjustments;
- Provides a framework for defining the metrics against which to adjust.

Appendix A provides more detail on the curve fitting framework and application. Figure 2-1 illustrates the step-by-step weather generation process applied for Jersey Water.

² Serinaldi & Kilsby (2012), A modular class of multisite monthly rainfall generators for water resource management and impact studies, Journal of Hydrology 465-465 (2012) 528-540

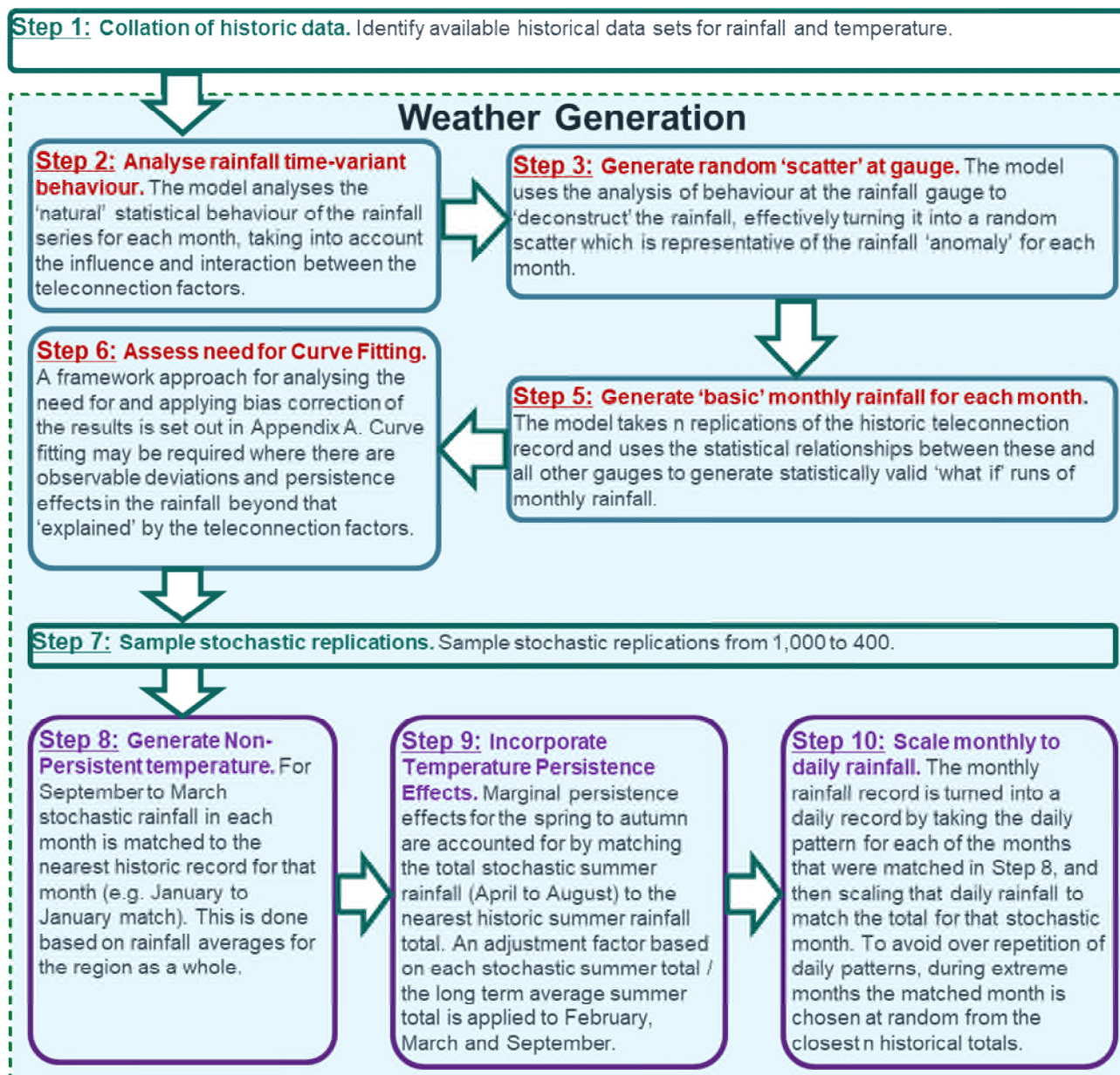


Figure 2-1 - Step-by-step process for generating stochastic weather

2.2 Data

2.2.1 Weather datasets

Table 2-1 details the available historical weather datasets available for this project. The stochastic weather generation model requires a long record of monthly rainfall totals. Daily records of rainfall and PET or temperature are also required to generate the final daily stochastic sequences. The daily historical records can be sourced from a shorter historical period than the monthly rainfall (i.e. 30+ years) however to avoid including the influence of climate change in the output this must be prior to 2000.

There are no pre-estimated PET datasets for Jersey, therefore temperature is used and PET calculated for hydrological modelling using the Oudin formula³. The daily maximum and minimum temperature records for Maison St Louis were used to infer daily average temperatures.

Table 2-1 - Summary of available weather datasets

Source	Variable	Site	Temporal resolution	Time Period
Jersey MET	Rainfall (MSL)	Maison St Louis	Monthly	Jan 1894 – Jul 2023
Jersey MET	Rainfall	Maison St Louis	Daily	Jan 1894 – Jul 2023
Jersey MET	Rainfall (JA)	Jersey Airport	Monthly	Feb 1951 – Jul 2023
Jersey MET	Rainfall	Jersey Airport	Hourly	Jan 1931 – Dec 2021
Jersey Water	Rainfall (JW)	n/a	Monthly	Jan 1865 – Nov 2023
Jersey MET	Temperature Max	Maison St Louis	Daily	Jan 1894 – Aug 2020
Jersey MET	Temperature Min	Maison St Louis	Daily	Jan 1894 – Jun 2019
Jersey Water	Temperature Min/Max	Handois	Daily	Apr 1994 – Oct 2023
Jersey Water	Temperature Min/Max	Millbrook	Daily	Apr 1994 – Oct 2023

During the scoping phase it was agreed that one stochastic series for the island is sufficient. This is due to several factors:

- Analysis of the three observed rainfall datasets (at a monthly and annual level) shows high correlation in the distribution and quantity of total rainfall between the sites (see Figure 2-2).
- From discussion with Jersey Water specialists, it is our understanding that the rainfall record received from Jersey Water is likely an amalgamation of rainfall records from multiple sites across the island⁴, it would therefore be difficult to assign this to a specific location across the island.
- There is only one hydrological model for the island with all other inflows generated from this; therefore there would be little value from multiple stochastic series.

³ Implementation of this is available as part of the hydrological GR6J model

⁴ Discussion during project progress meeting, 13/12/2023

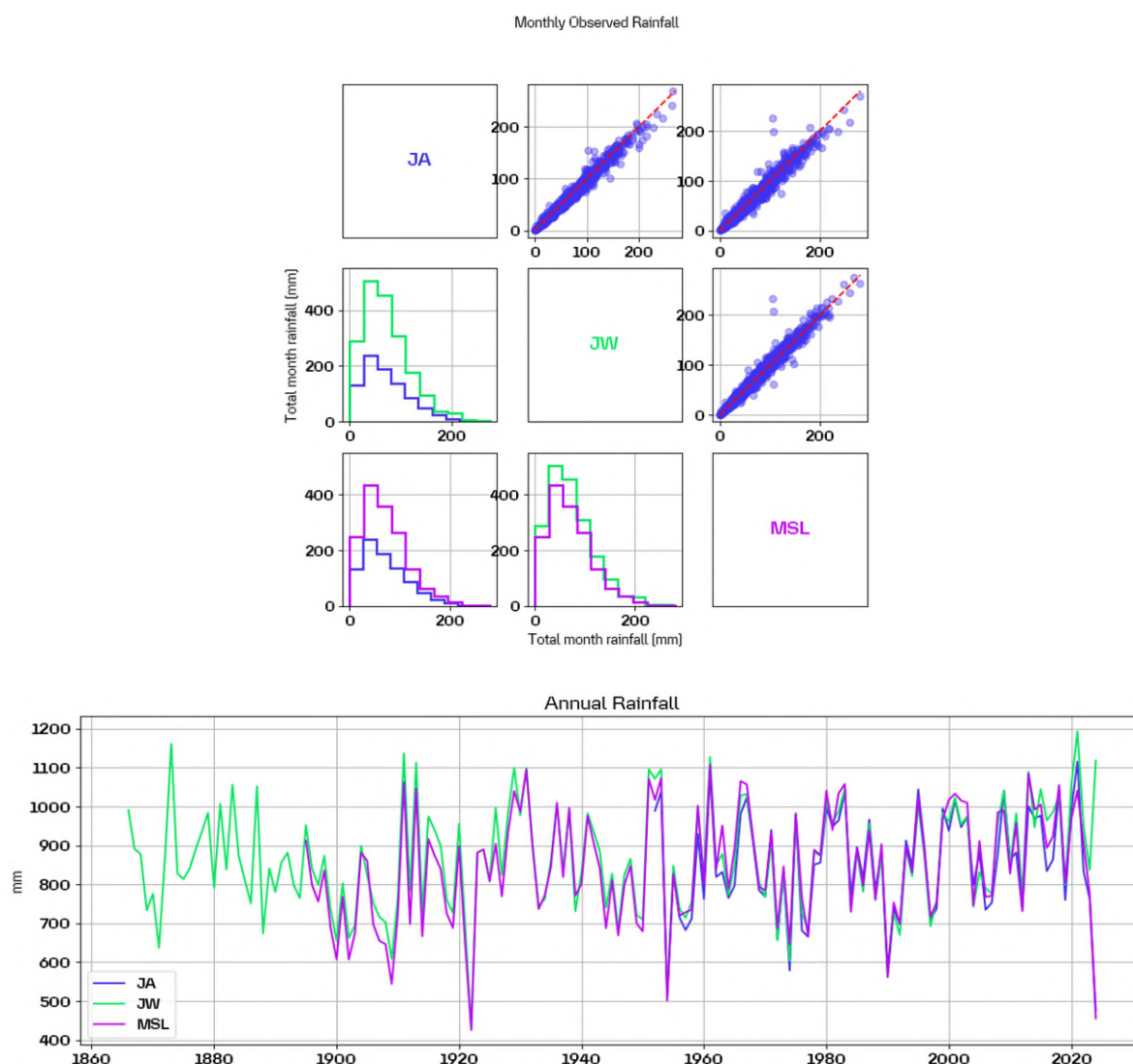


Figure 2-2 - Comparison of observed rainfall records at Jersey Airport (JA), Maison St Louis (MSL) and Jersey Water's record

2.2.2 Teleconnections

The stochastic weather generator uses historical teleconnection series, or climatic drivers, to fit the models and generate the stochastic datasets. Table 2-2 details teleconnections that are readily available and relevant for these purposes.

Table 2-2 - Summary of available teleconnection series

Dataset	Period Covered	Main driving behaviour	Source
North Atlantic Oscillation (NAO)	1821 – 2019	One of the major modes of variability of the Northern Hemisphere atmosphere. Particularly important in winter.	Jones, P.D., Jónsson, T. and Wheeler, D., 1997: Extension to the North Atlantic Oscillation using early instrumental pressure observations from Gibraltar and South-West Iceland. <i>Int. J. Climatol.</i> 17, 1433-1450. doi: 10.1002/(SICI)1097-

Dataset	Period Covered	Main driving behaviour	Source
			0088(19971115)17:13<1433::AID-JOC203>3.0.CO;2-P
Sea Surface Temperature (SST)	1856 – 2019	Increases in Sea Surface Temperature can impact climate patterns including temperature and precipitation. Changes in sea surface temperature can shift storm tracks, potentially contributing to droughts in some areas.	Kaplan SST V2 data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA
East Atlantic (EA)	1950 – 2019	The EA pattern is the second prominent mode of low frequency variability over the North Atlantic and appears as a leading mode in all months. The positive phase of the EA is associated with above average surface temperatures in Europe in all months and above average precipitation over northern Europe.	National Weather Service Climate Prediction Center, NOAA, https://www.cpc.ncep.noaa.gov/data/teledoc/ea.shtml
East Atlantic Index (EA _{Index})	1850 – 2016	A derived index representing the East Atlantic pattern outlined above.	Series originally calculated by Met Office to extend back past 1950 dataset.
East Atlantic / Western Russia (EAWR)	1950 – 2019	The is one of the three prominent teleconnection patterns that affect Eurasia through the year. It consists of four main anomaly centres. The positive phase is associated with below average precipitation across central Europe.	National Weather Service Climate Prediction Center, NOAA, https://www.cpc.ncep.noaa.gov/data/teledoc/eawruss.shtml
Atlantic Multidecadal Oscillation Index (AMO)	1950 – 2019	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 each last for 20-40 years. The AMO effects air temperatures and rainfall over the Northern Hemisphere. It is associated with changes in the frequency of North American droughts and is reflected in the frequency of severe Atlantic hurricanes.	Enfield, D.B., A.M. Mestas-Nunez, and P.J. Trimble, 2001: The Atlantic Multidecadal Oscillation and its relationship to rainfall and river flows in the continental U.S., <i>Geophys. Res. Lett.</i> , 28: 2077-2080
Scandinavia n (SCA)	1950 – 2019	The positive phase of the Scandinavia pattern is associated with below average temperatures across western Europe. It is also associated with above average precipitation across central and southern Europe and below average precipitation across Scandinavia.	National Weather Service Climate Prediction Center, NOAA, https://www.cpc.ncep.noaa.gov/data/teledoc/scand.shtml

Appendix B summarises the seasonal correlation between the historical rainfall at Maison St Louis and each of these teleconnection series. This analysis suggests:

- The NAO is a less significant driver for precipitation in Jersey compared to other parts of the United Kingdom (particularly during winter months where it exerts the most influence across the north west of England).
- SST indicates a slight negative correlation across all seasons apart from winter. This is comparable to that seen across England and Wales.
- The EA series suggests a small positive correlation across all seasons and shows more of a relationship to rainfall than the calculated index.

- AMO shows little correlation in spring and summer and a slight positive correlation in winter.
- The EAWR shows a reasonable negative correlation across autumn and winter months.

These results indicate a reasonable level of explanatory power in the teleconnection datasets to allow the stochastic weather generator to be applied.

2.3 Model selection

The latest round of stochastic datasets used by water companies in England and Wales for the most recent round of planning (known as WRMP24) used observed data from 1950-1997. By starting the observed record in 1950 rather than earlier a greater number of teleconnections were able to be utilised to drive the model. However, this comes with a trade-off against being able to incorporate a wider range of variability across each teleconnection series. For the WRMP24 stochastic generation, the datasets were validated against the longer historical period and shown to still include a sufficient level of extreme droughts of similar and varied magnitude to those seen prior to 1950, such as those in the 1920's.

For this project two model formats were initially tested and reviewed:

- A set-up equivalent to the latest WRMP24 stochastic datasets, starting in 1950 and with a full suite of available teleconnections.
- An alternative set-up utilising observed datasets from 1900-1997 but with a reduced set of teleconnections to drive the model.

In each case the models were fitted by reviewing the significance of each of the teleconnection explanatory factors and updating accordingly. For the 1950's+ model the EAWR showed the largest significance alongside summer SST. For the 1900's+ model the SST and the EA Index showed the largest influence.

The need for and application of any bias corrections was reviewed and applied independently for each model with the same metrics being selected for each. The autumn bias correction was selected due to a distinct trend observed in the data across this period. This trend could be observed in several data points in the historical record and potentially indicates the influence of climatic behaviour not represented in the model such as heatwaves from France causing continued dry weather in Jersey.

Appendix D includes comparative plots of the stochastic outputs against the historical data for numerous drought metrics. Both models perform reasonably well at periods of 12 – 18 months. For seasonal metrics, the 1950's+ dataset achieves a greater number of more extreme winter to summer and summer only droughts.

However, the plots also show that the stochastic data produced using historical data from 1900 onwards performs better when considering winter rainfall and persistent rainfall patterns across 2 or more years. Analysis of the observed record shows a higher proportion of winter droughts and long-term droughts in Jersey in the first half of the 20th Century (for example droughts around 1921, 1907, 1949 and 1944). We carried out an additional check of the observed winter rainfall record to assess whether this may represent a statistical trend in winter rainfall that occurred during the 20th Century which could indicate that the 1950's+ driven model is more appropriate to current baseline conditions.

Figure 2-3 shows the observed record of winter rainfall totals (October – March) in Jersey. Two statistical tests for stationarity⁵ were applied to this dataset to determine the presence of a statistically significant trend or not (the ADF and KPSS tests). Both found no statistical evidence of non-stationarity across the data, thus supporting the underlying assumptions of the stochastic model and the use of the larger historical dataset.

⁵ Stationarity refers to the statistical properties of a time series (mean, variance and covariance) and checks that these do not change over time. The weather generator takes a 'baseline' dataset and assumes this is stationary.

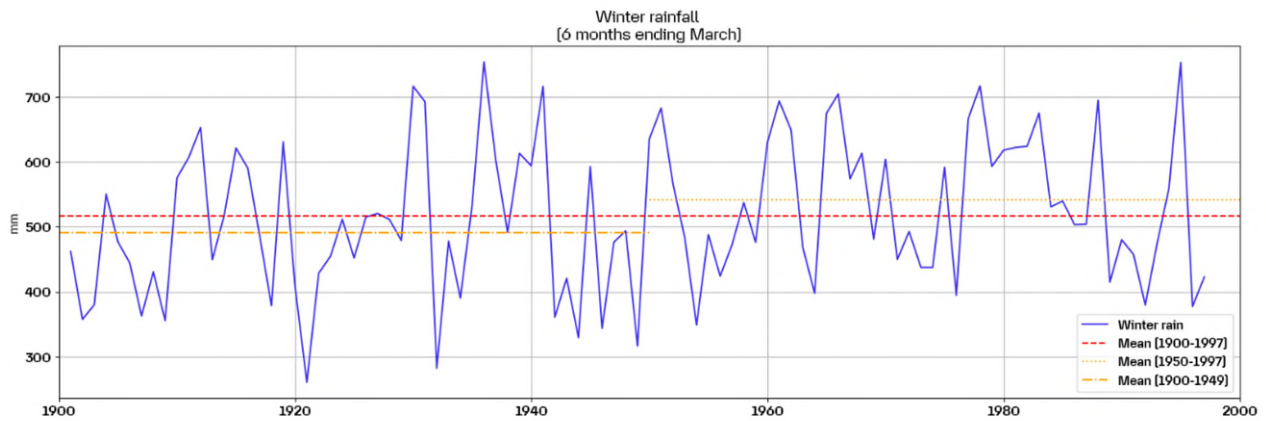


Figure 2-3 – Winter rainfall totals at Maison St Louis, showing the overall mean and the mean across each half of the 20th Century. Despite an apparent difference both the ADF and KPSS stationarity tests suggest no significant trend in the data.

Table 2-3 compares the key differences between the two model setups. Based on these outputs the 1900 – 1997 stochastic dataset has been selected for use in Jersey Water’s WRDMP. This dataset performs well across a range of rainfall duration metrics (as presented in Figure 2-4) and the ability to include a wider range of variability within the teleconnection record, many of which follow multi-decadal patterns, has been assessed to be more appropriate in this case than the inclusion of more teleconnection series.

Table 2-3 - Comparison of the two fitted model formats

	1950 – 1997 model	1900 – 1997 model
Initially available teleconnections	NAO, SST, EA, AMO, SCA, EAWR	NAO, SST, EA_Index, AMO
Final selected formula	$\mu = month + NAO + SST + AMO + EA + EAWR$ $+ SCA + month: NAO$ $+ month: SST + month: EA$ $+ month: EAWR + AMO: EAWR$ $+ EA: EAWR$ $\sigma = month + NAO + SST + EA$	$\mu = month + NAO + SST + EA_{Index}$ $+ month: NAO + month: SST$ $+ SST: AMO$ $\sigma = month + SST + EA_{Index}$
Explanatory factor significance	High significance across EAWR as well as summer SST.	High significance across SST as well as the EA_Index.
Bias corrections (curve-fitting) applied (see Appendix C)	- Annual: 12 months ending September - Winter-Summer: 9 months ending August - Summer: 5 months ending August - Autumn: 3 months ending October	- Annual: 12 months ending September - Winter-Summer: 9 months ending August - Summer: 5 months ending August - Autumn: 3 months ending October
Number of final stochastic replicates / Number of stochastic years*	400 replicates 19,200 years	200 replicates 19,600 years

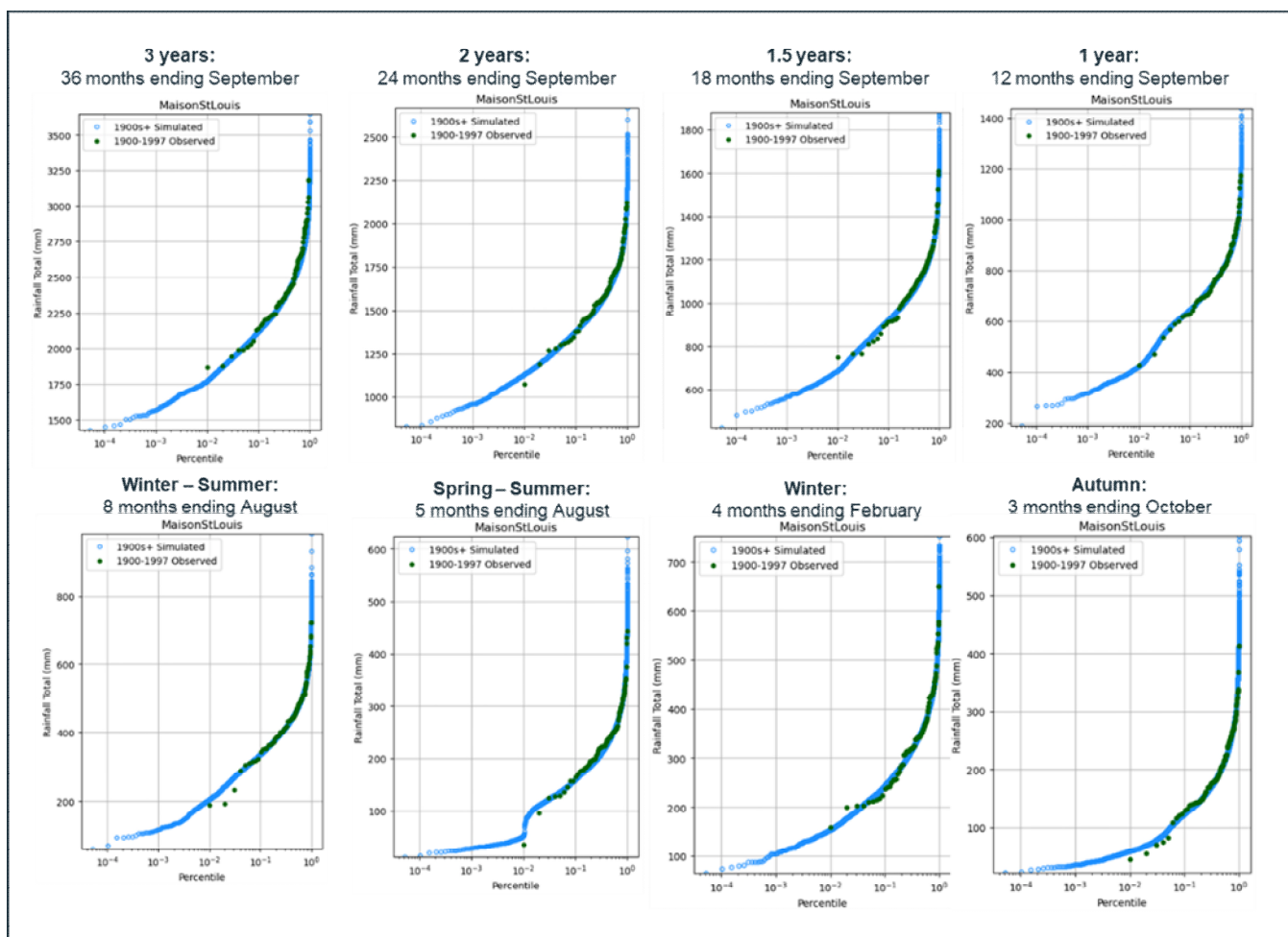


Figure 2-4 - Percentile plots showing the stochastic outputs against the historical record for varying rainfall duration totals (light blue points are simulated; green points are observed during 1900-97)

2.3.1 Daily stochastic rainfall and temperature

As outlined previously in Figure 2-1, the daily stochastic data is generated through resampling against the historical record. To provide the largest possible set of rainfall patterns and behaviour to sample from this has been carried out against the full historical record (1900 – 1997)⁶ and the historical temperature record detrended to the 1981-2000 baseline period to provide a baseline dataset and align with the climate change baseline period (see Appendix E).

3. Application of stochastic datasets

The stochastic datasets produced are used to underpin Jersey Water's assessment of their reliable supply including:

- Deployable output assessment
- Assessment of the impact of climate change
- Assessment of supply-side option benefits

⁶ The period between 1921 and 1924 inclusive is missing.

3.1 Deployable output assessment

The stochastic datasets are used in the assessment of the baseline deployable output (at varying levels of drought return period). As illustrated in Figure 1-1 this process involves running the stochastic data through the hydrological model to generate the necessary stochastic flows before inputting these into the water resources model. The methodology for this is outlined in the Water Resources Modelling Method Statement.

3.2 Assessment of impact of climate change

The stochastic datasets are used in the assessment of climate change impacts on deployable output. This is undertaken by applying monthly rainfall and temperature change factors to the baseline stochastic datasets for each of the climate scenarios before generating climate perturbed stochastic flows and then assessing the change in deployable output in the water resources model. The approach to selecting and calculating the climate change scenarios is outlined in the Climate Change and Scenarios Method Statement.

3.3 Assessment of supply-side option benefits

In addition to the deployable output, the stochastic datasets are used to assess some of the benefits of different options. This primarily includes assessing their DO benefit but may also cover supporting quantitative assessments of some of their other benefits; for instance, improvements that each option may bring to system resilience. The approach to option benefit assessment is detailed in the Decision-Making Method Statement.

Appendices

Appendix A. Stochastic weather generator curve fitting

The stochastic weather generator includes a bias-correction curve fitting module alongside a framework for selecting and applying the curve-fitting.

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' 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-month rainfall total ending September (the hydrological year) and 12-month ending December (calendar year);
- **Winter – Summer periods**, containing 9-month 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, and 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 the rainfall series 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 (if relevant).

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. This is illustrated by Figure A-1.

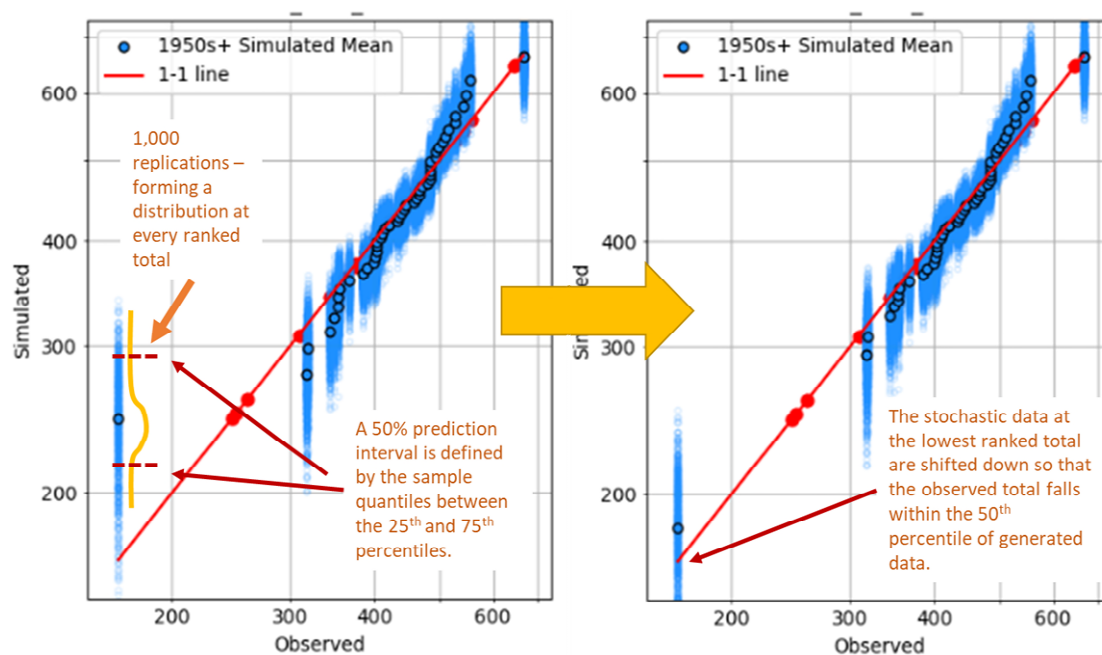


Figure A-1 - Example of probabilistic curve fitting approach

Step 5: Analyse any remaining deviation in the results against the next defined 'period' and metrics
Repeat the process for shorter duration drought periods.

Appendix B. Teleconnection correlations

The following sub-sections show the seasonal correlations between rainfall at Maison St Louis and each of the teleconnections. Where the data is available these are based on historical data from 1900 up to 1997 (NAO, SST, EA_Index, AMO).

B.1 North Atlantic Oscillation (NAO)

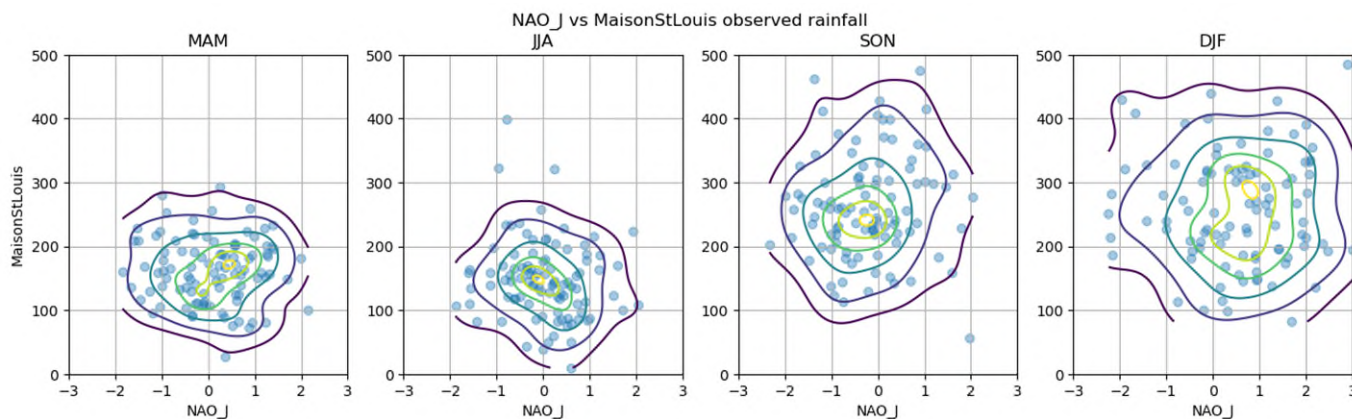


Figure B-1 - Seasonal correlation between the North Atlantic Oscillation and rainfall (1900 – 1997)

B.2 Sea Surface Temperature (SST)

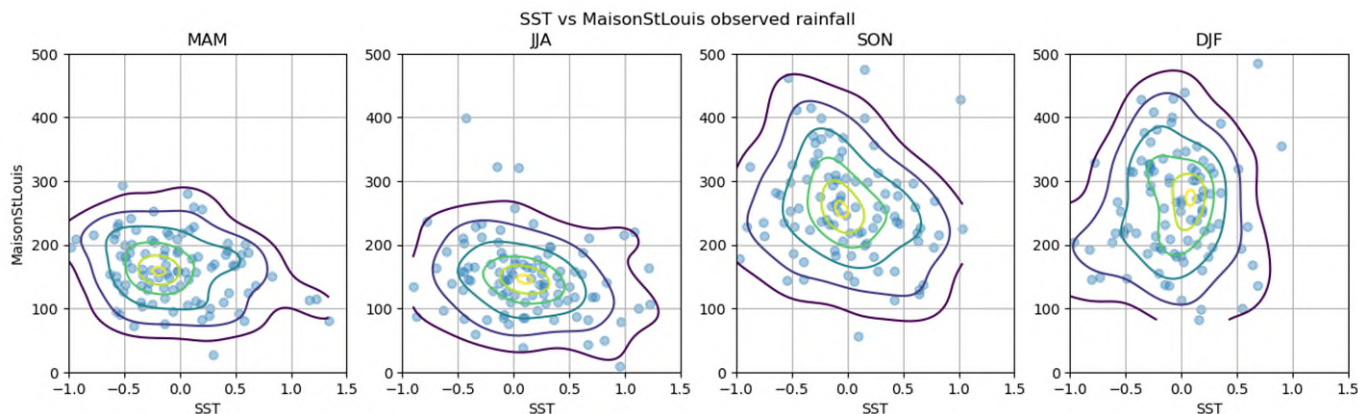


Figure B-2 - Seasonal correlation between the Sea Surface Temperature and rainfall (1900 – 1997)

B.3 East Atlantic (EA)

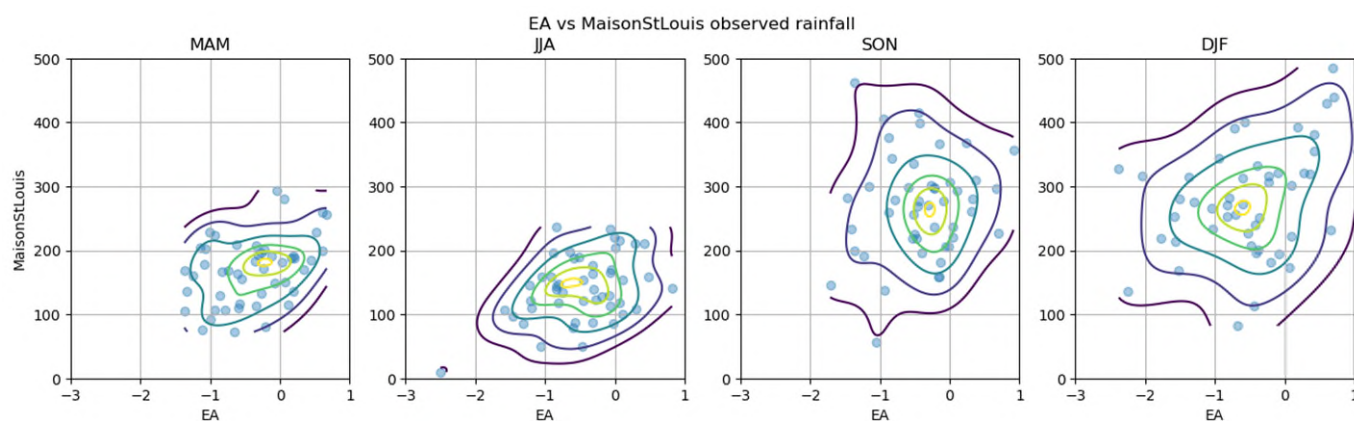


Figure B-3 - Seasonal correlation between the East Atlantic and rainfall (1950 – 1997)

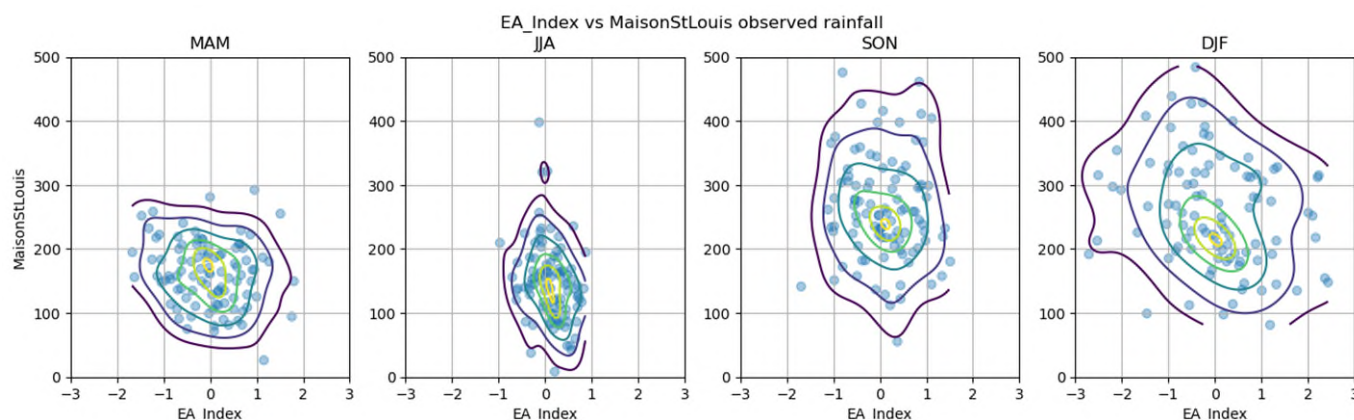


Figure B-4 - Seasonal correlation between the East Atlantic Index and rainfall (1900 – 1997)

B.4 Atlantic Multidecadal Oscillation (AMO)

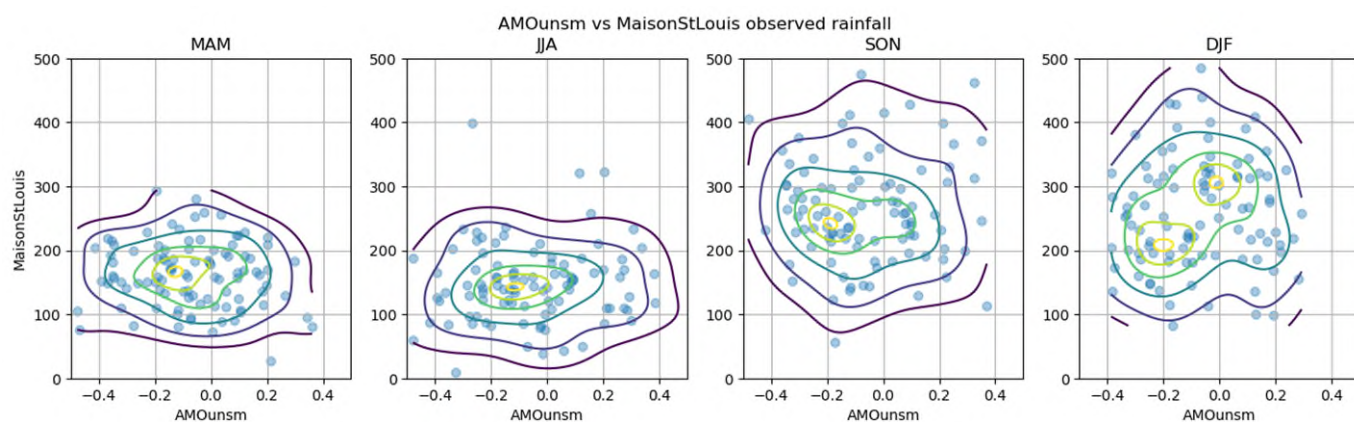


Figure B-5 - Seasonal correlation between the Atlantic Multidecadal Oscillation and rainfall (1900 – 1997)

B.5 East Atlantic West Russian (EAWR)

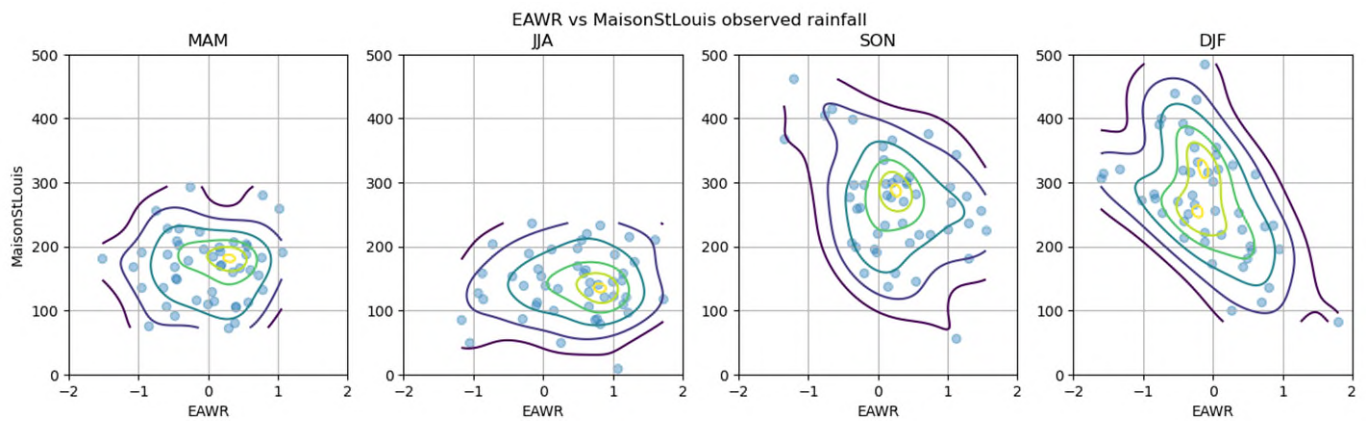


Figure B-6 - Seasonal correlation between the East Atlantic West Russian and rainfall (1950 – 1997)

Appendix C. Curve-fitting applied to stochastic data

This appendix summarises the curve-fitting applied to the stochastic data generated for Jersey Water (i.e. the 1900-1997 dataset). This is presented in terms of the Steps outlined in Appendix A.

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

The 'periods' tested were:

- Longer than annual
- Annual
- Winter-Summer
- Summer
- Autumn

Step 2: Define specific metrics within each period

The following rainfall total metrics were tested within each period:

- **Longer than annual:** 30 months ending September, 24 months ending September and 18 months ending September;
- **Annual:** 12 months ending September and 12 months ending December;
- **Winter – Summer:** 9 months ending August and 8 months ending August;
- **Summer:** 5 months ending August;
- **Autumn:** 3 months ending October, 3 months ending November and 4 months ending November.

Steps 3, 4 & 5: Automated bias correction and probabilistic curve fitting for each period

The output of the automated bias correction is shown below.

Longer than annual

- No stochastic values more than 10% from observed data so no bias-correction carried out.

Annual

- 12 months ending September: 2 observed values more than 10% from the simulated (average difference 18.4%)
- 12 months ending December: 2 observed values more than 10% from the simulated (average difference 15.2%)
- Bias correct 12 months ending September

Calculating bias corrections for Maison St. Louis Rainfall

```
0.00%ile observed values (year 1921): adjust by 0.87 to meet 50.00% prediction interval
1.02%ile observed values (year 1949): adjust by 0.88 to meet 50.00% prediction interval
2.04%ile observed values (year 1976): adjust by 0.95 to meet 50.00% prediction interval
3.06%ile observed values (year 1989): adjust by 0.98 to meet 50.00% prediction interval
4.08%ile observed values (year 1906): adjust by 0.99 to meet 50.00% prediction interval
5.10%ile observed values (year 1909): adjust by 0.99 to meet 50.00% prediction interval
7.14%ile observed values (year 1907): adjust by 0.99 to meet 50.00% prediction interval
8.16%ile observed values (year 1932): adjust by 0.98 to meet 50.00% prediction interval
9.18%ile observed values (year 1944): adjust by 0.98 to meet 50.00% prediction interval
10.20%ile observed values (year 1913): adjust by 0.99 to meet 50.00% prediction interval
11.22%ile observed values (year 1908): adjust by 1.00 to meet 50.00% prediction interval
18.37%ile observed values (year 1991): adjust by 1.00 to meet 50.00% prediction interval
```

Winter – Summer

- 9 months ending August: 3 observed values more than 10% from the simulated (average difference 20.4%)

- 8 months ending August: 3 observed values more than 10% from the simulated (average difference 23.2%)
- Bias correct 9 months ending August

Calculating bias corrections for Maison St. Louis Rainfall

0.00%ile observed values (year 1976): adjust by 0.82 to meet 50.00% prediction interval
 1.02%ile observed values (year 1949): adjust by 0.86 to meet 50.00% prediction interval
 2.04%ile observed values (year 1921): adjust by 0.96 to meet 50.00% prediction interval
 6.12%ile observed values (year 1987): adjust by 0.98 to meet 50.00% prediction interval
 7.14%ile observed values (year 1989): adjust by 0.98 to meet 50.00% prediction interval
 8.16%ile observed values (year 1918): adjust by 0.96 to meet 50.00% prediction interval
 9.18%ile observed values (year 1932): adjust by 0.95 to meet 50.00% prediction interval
 10.20%ile observed values (year 1944): adjust by 0.98 to meet 50.00% prediction interval
 11.22%ile observed values (year 1913): adjust by 0.99 to meet 50.00% prediction interval

Summer

- 5 months ending August: 2 observed values more than 10% from the simulated (average difference 39.9%)

Calculating bias corrections for Maison St. Louis Rainfall

0.00%ile observed values (year 1976): adjust by 0.43 to meet 50.00% prediction interval
 1.02%ile observed values (year 1949): adjust by 0.97 to meet 50.00% prediction interval
 7.14%ile observed values (year 1908): adjust by 1.01 to meet 50.00% prediction interval
 9.18%ile observed values (year 1911): adjust by 1.01 to meet 50.00% prediction interval
 10.20%ile observed values (year 1990): adjust by 1.02 to meet 50.00% prediction interval
 11.22%ile observed values (year 1984): adjust by 1.04 to meet 50.00% prediction interval
 12.24%ile observed values (year 1955): adjust by 1.02 to meet 50.00% prediction interval
 13.27%ile observed values (year 1900): adjust by 1.02 to meet 50.00% prediction interval
 14.29%ile observed values (year 1975): adjust by 1.03 to meet 50.00% prediction interval
 15.31%ile observed values (year 1957): adjust by 1.02 to meet 50.00% prediction interval
 16.33%ile observed values (year 1952): adjust by 1.02 to meet 50.00% prediction interval
 17.35%ile observed values (year 1991): adjust by 1.02 to meet 50.00% prediction interval
 18.37%ile observed values (year 1919): adjust by 1.03 to meet 50.00% prediction interval

Autumn

- 3 months ending October: 5 observed values more than 10% from simulated (average difference 26.5%)
- 3 months ending November: 1 observed value more than 10% from simulated (average difference 42.6%)
- 4 months ending November: 1 observed value more than 10% from simulated (average difference 46%)
- Bias correct 3 months ending October

Calculating bias corrections for Maison St. Louis Rainfall

0.00%ile observed values (year 1978): adjust by 0.85 to meet 50.00% prediction interval
 1.02%ile observed values (year 1969): adjust by 0.79 to meet 50.00% prediction interval
 2.04%ile observed values (year 1989): adjust by 0.88 to meet 50.00% prediction interval
 3.06%ile observed values (year 1921): adjust by 0.87 to meet 50.00% prediction interval
 4.08%ile observed values (year 1972): adjust by 0.90 to meet 50.00% prediction interval
 6.12%ile observed values (year 1947): adjust by 1.00 to meet 50.00% prediction interval
 7.14%ile observed values (year 1926): adjust by 1.01 to meet 50.00% prediction interval
 8.16%ile observed values (year 1940): adjust by 1.01 to meet 50.00% prediction interval
 9.18%ile observed values (year 1936): adjust by 1.03 to meet 50.00% prediction interval
 10.20%ile observed values (year 1920): adjust by 1.02 to meet 50.00% prediction interval
 11.22%ile observed values (year 1908): adjust by 1.05 to meet 50.00% prediction interval
 12.24%ile observed values (year 1971): adjust by 1.03 to meet 50.00% prediction interval
 13.27%ile observed values (year 1913): adjust by 1.02 to meet 50.00% prediction interval
 14.29%ile observed values (year 1911): adjust by 1.01 to meet 50.00% prediction interval
 15.31%ile observed values (year 1977): adjust by 1.00 to meet 50.00% prediction interval

Appendix D. Stochastic plots

D.1 Persistent droughts (2+ years)

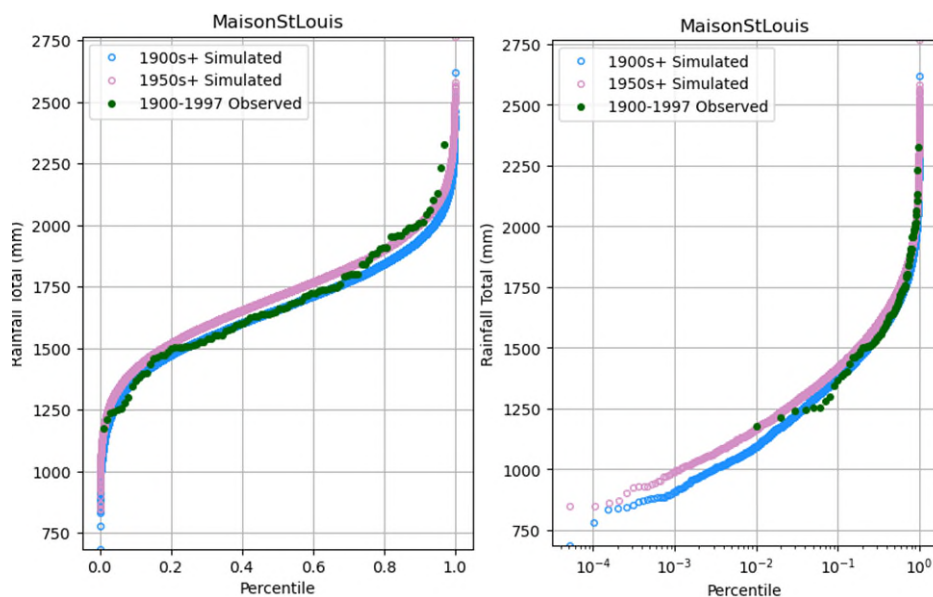


Figure D-1 - Percentile plots for 24 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

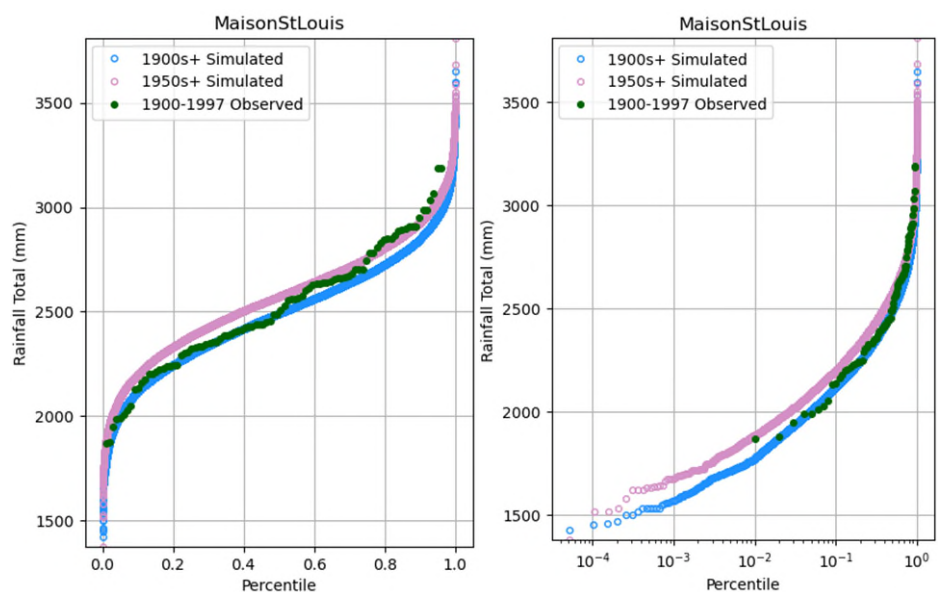


Figure D-2 - Percentile plots for 36 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

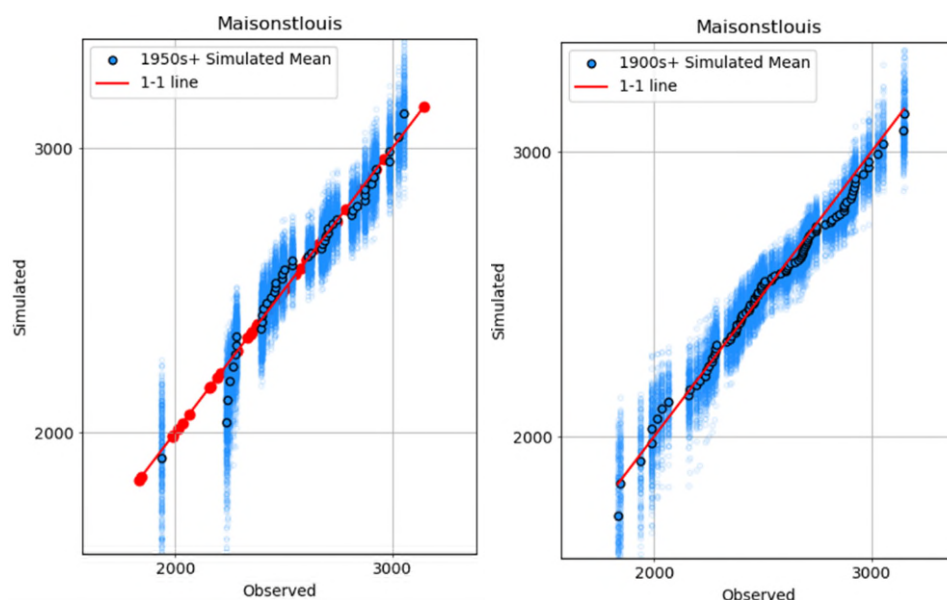


Figure D-3 - Q-Q plots for 36 months ending September for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)

D.2 12 – 18-month droughts

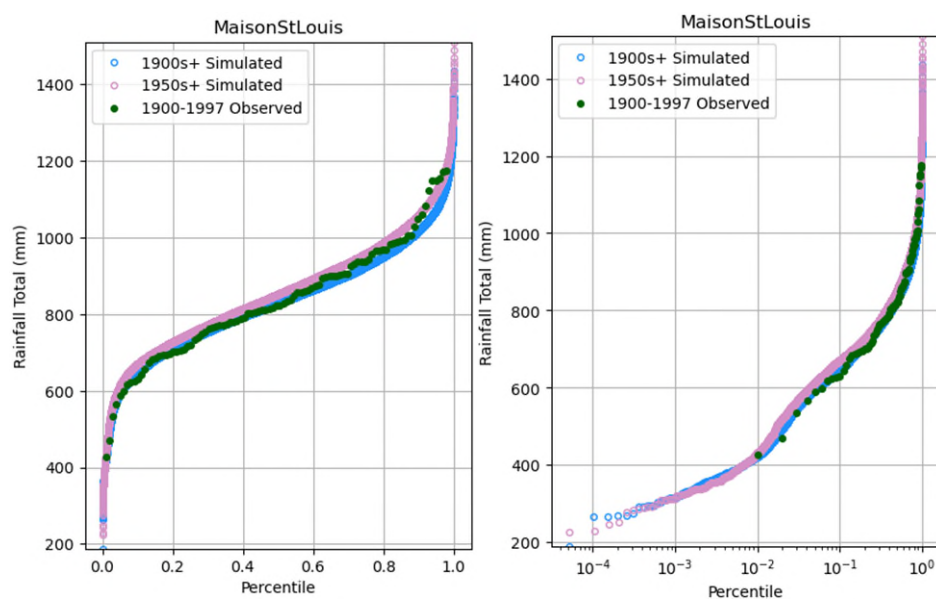


Figure D-4 - Percentile plots for 12 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

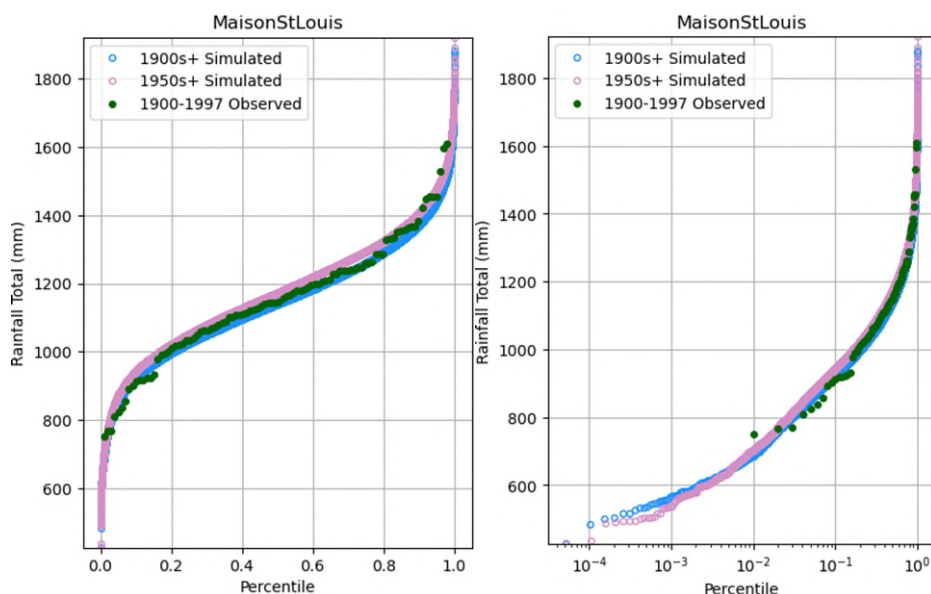


Figure D-5 - Percentile plots for 18 months ending September for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

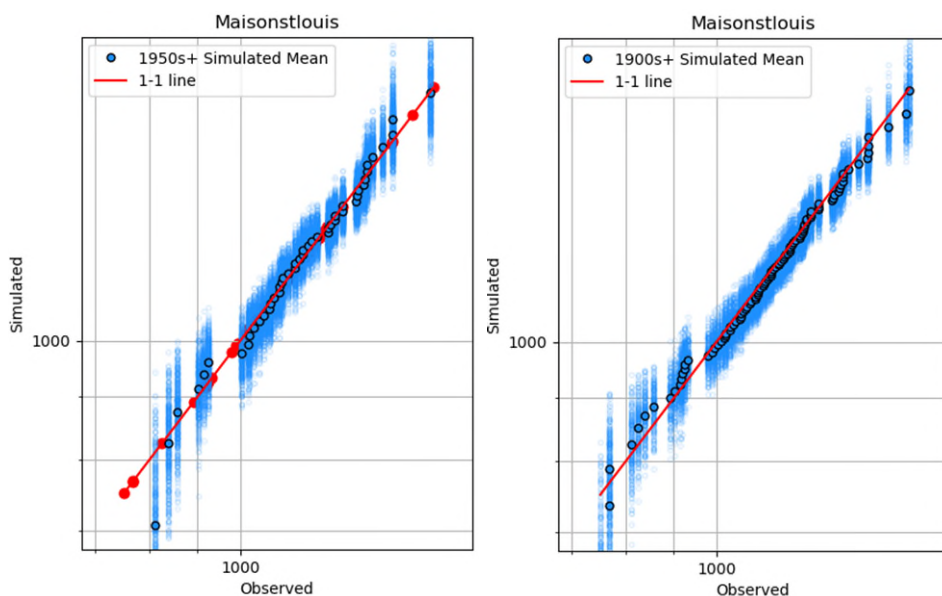


Figure D-6 - Q-Q plots for 18 months ending September for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)

D.3 Seasonal droughts

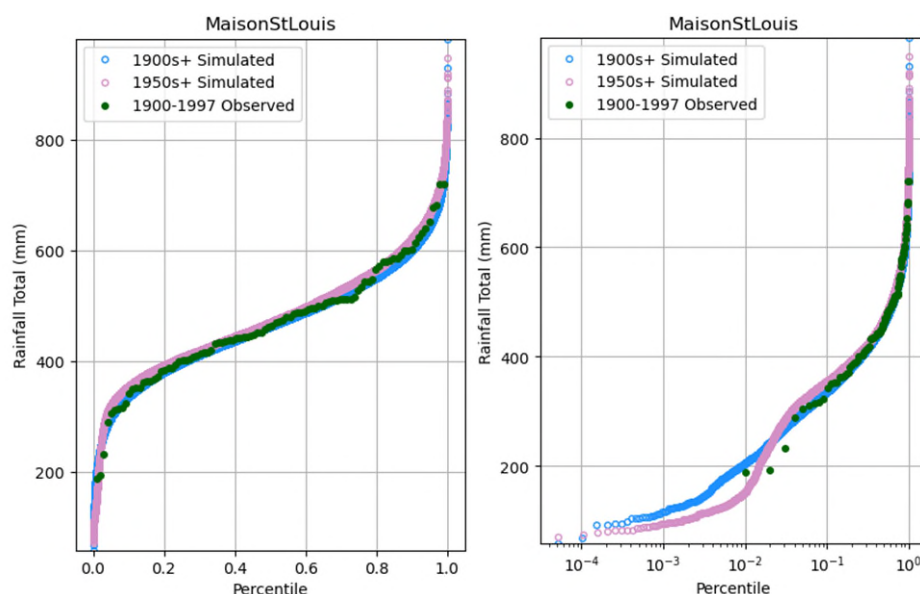


Figure D-7 - Percentile plots for 8 months ending August for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

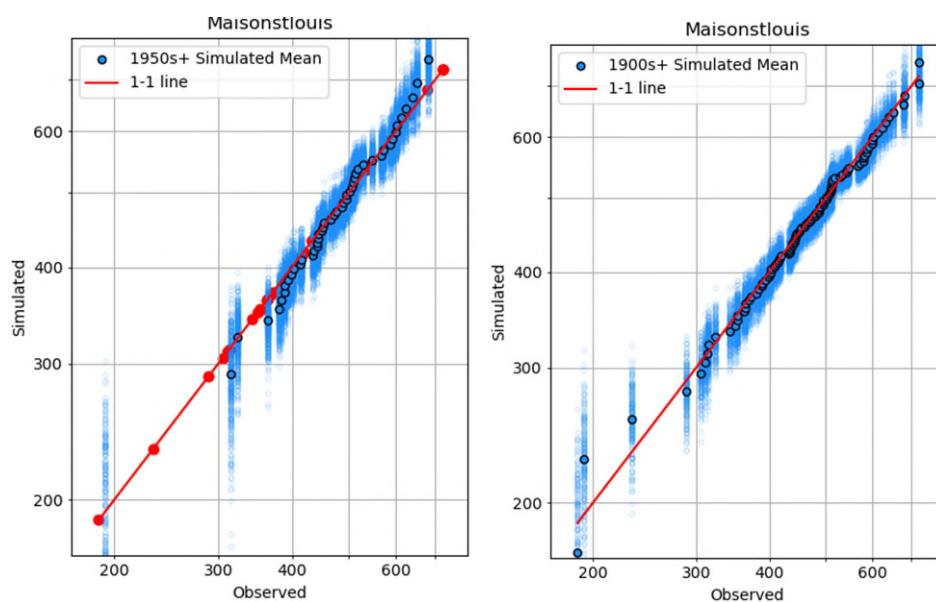


Figure D-8 - Q-Q plots for 8 months ending August for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)

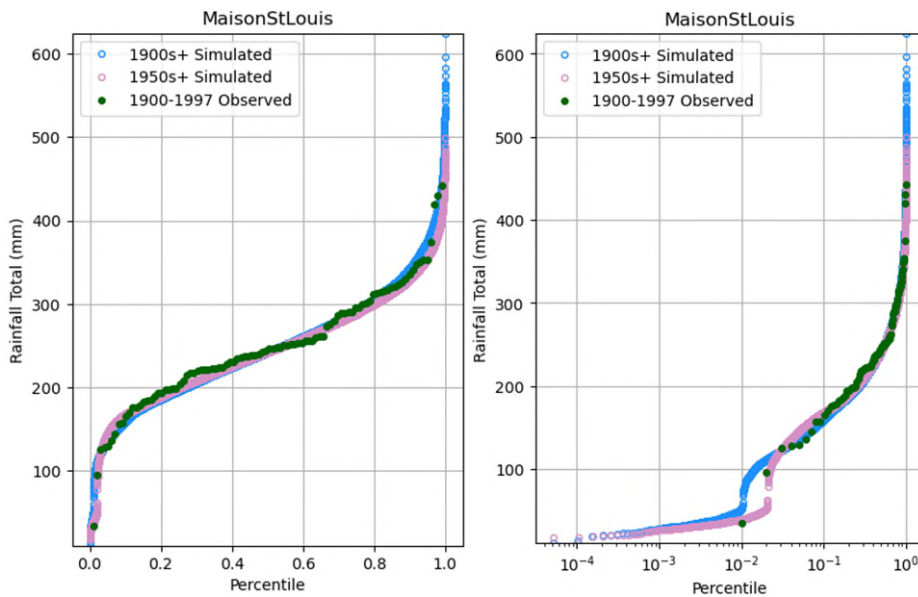


Figure D-9 - Percentile plots for spring to summer period 5 months ending August for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

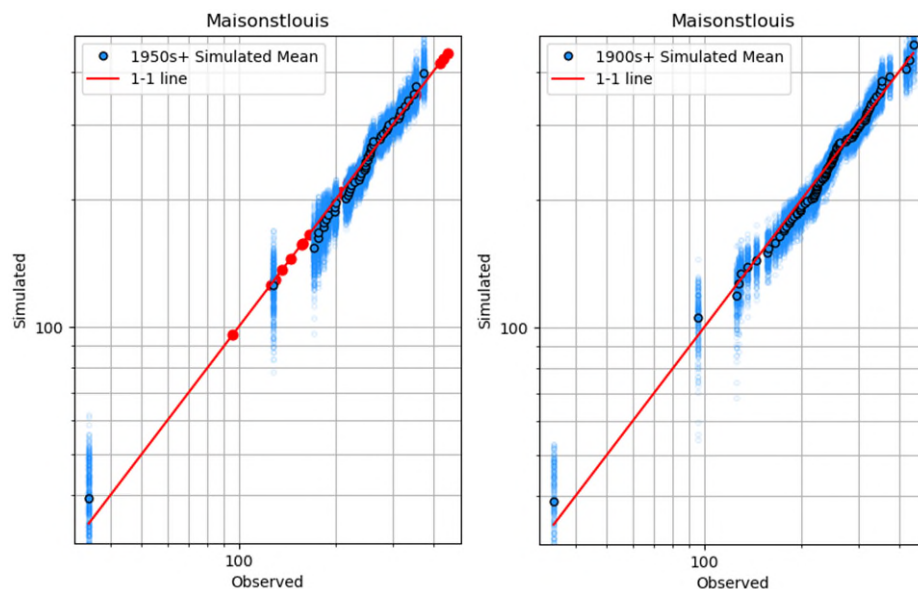


Figure D-10 - Q-Q plots for 5 months ending August for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)

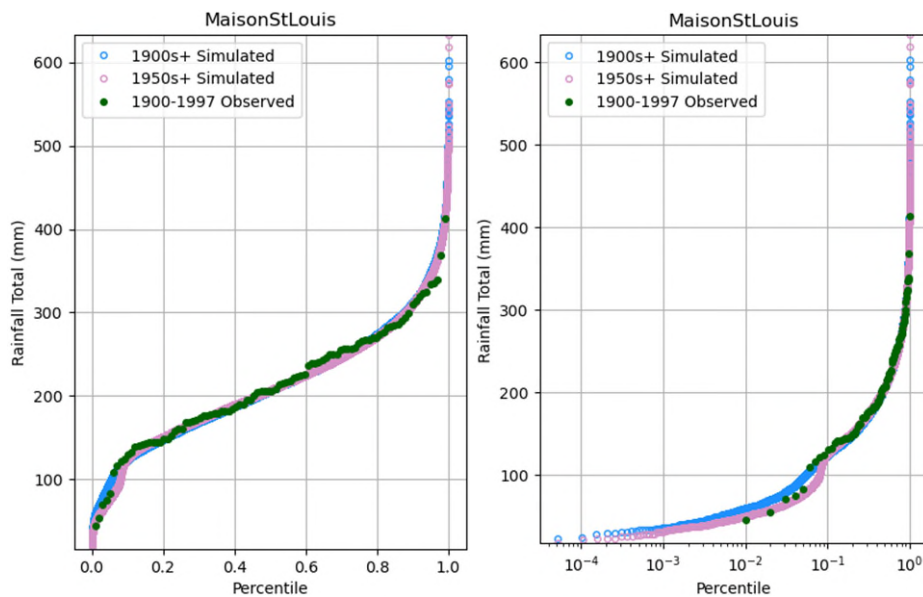


Figure D-11 - Percentile plots for summer to autumn period 3 months ending October for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

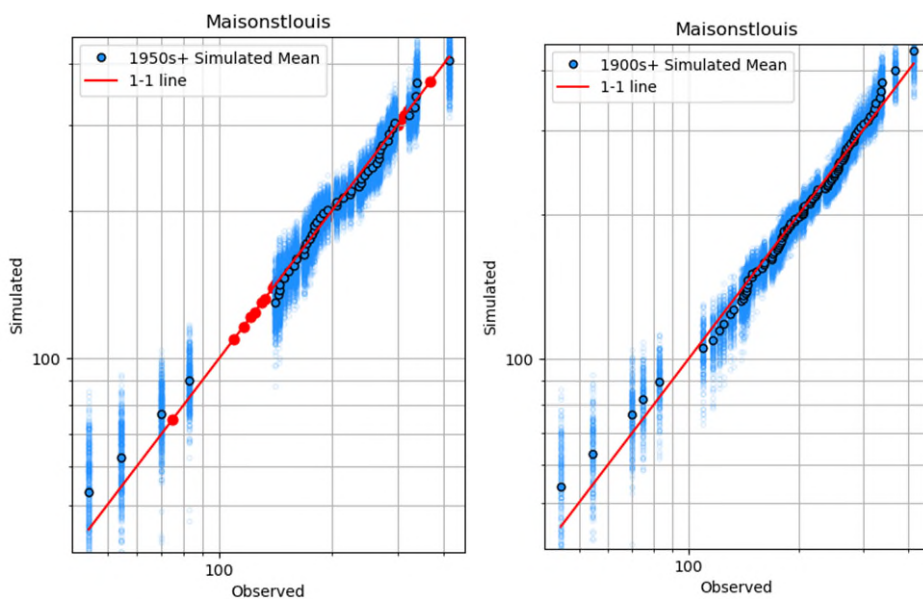


Figure D-12 - Q-Q plots 3 months ending October for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)

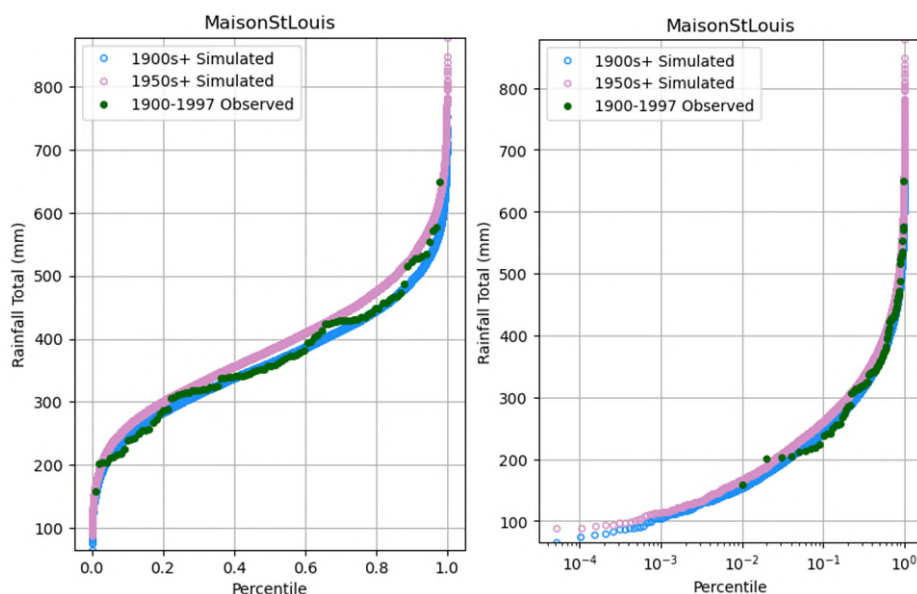


Figure D-13 - Percentile plots for winter period 4 months ending February for stochastics generated with 1900-1997 historical data (blue) and 1950-1997 historical data (pink)

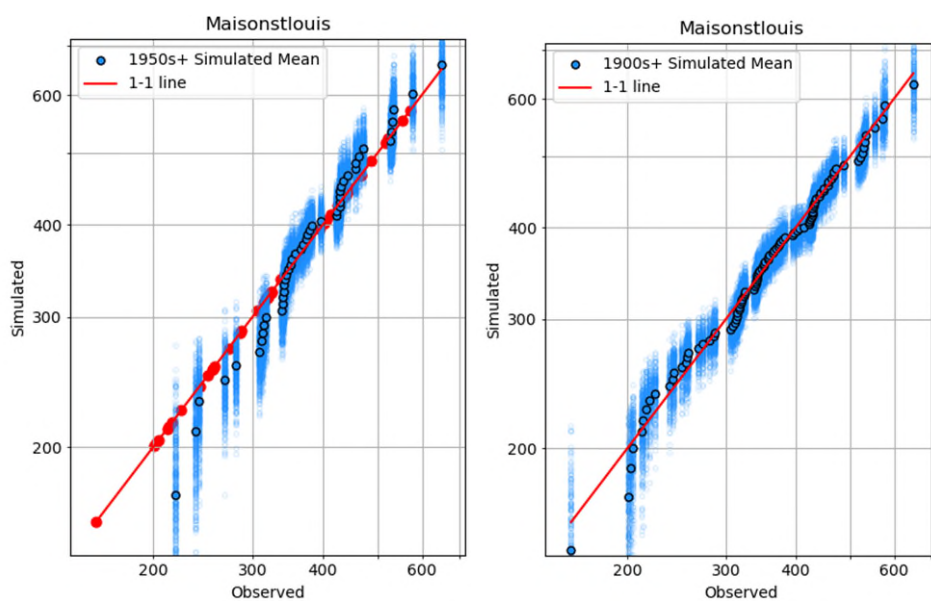


Figure D-14 - Q-Q plots 4 months ending February for stochastic generated with 1950-1997 historical data (left) and 1900-1997 historical data (right)

Appendix E. Temperature detrending

While there is little evident trend in the historical rainfall record, temperature can be seen to increase across the observed record. This is somewhat accounted for by restricting the model generation data to before 1997. However, in order to ensure no climate trends are included in the stochastic datasets that would result in either climate influences being double-counted or overlooked, the historical temperature data has been detrended to the 1981-2000 baseline period prior to resampling.

Figure E-1 shows the observed and detrended data for annual average temperatures at Maison St Louis. The detrended annual average data is used to calculate an annual detrending factor that is applied to the daily sequences.

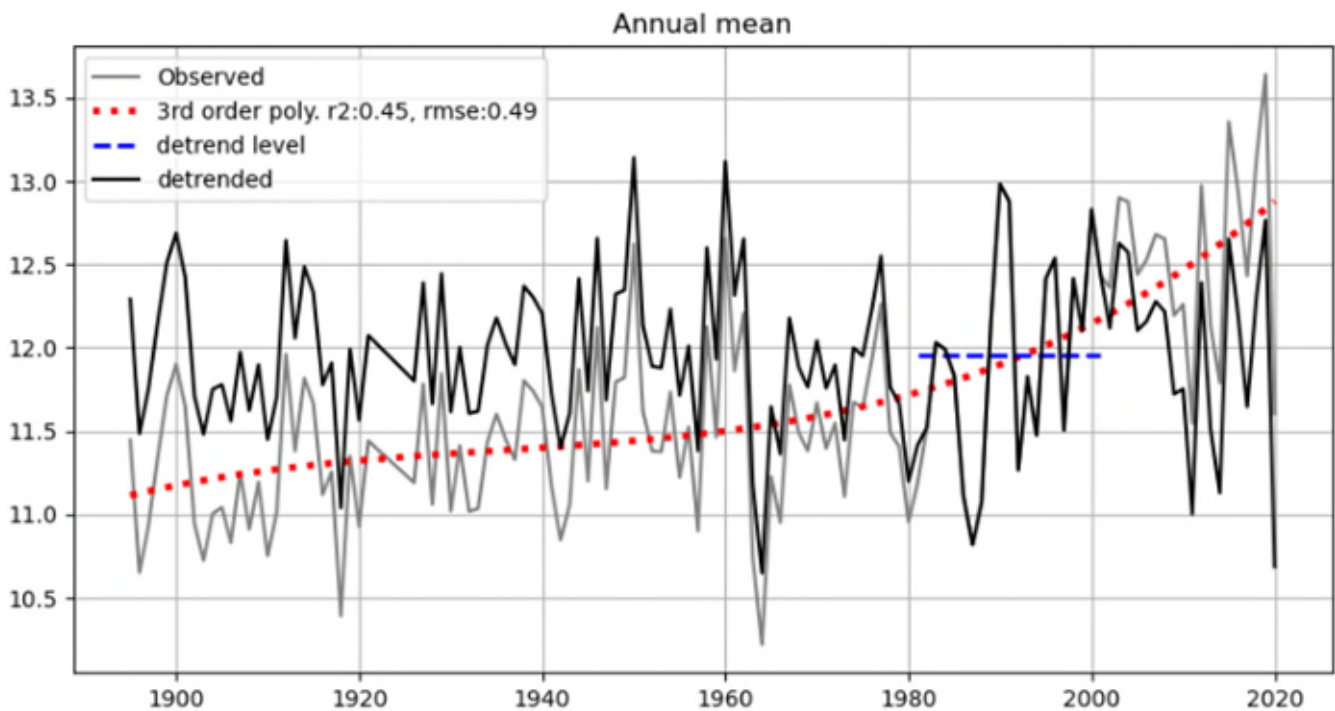


Figure E-1 – Detrended temperature data at Maison St Louis. A trend is fitted to annual average temperatures (red dotted line). The trend is used to detrend against the baseline period (blue dashed line). The black line shows the resultant detrended data.

