Impacts of Climate Change on Surface Water in the Onkaparinga Catchment

Final Report Volume 2: Hydrological Evaluation of the CMIP3 and CMIP5 GCMs and the Non-homogenous Hidden Markov Model (NHMM)

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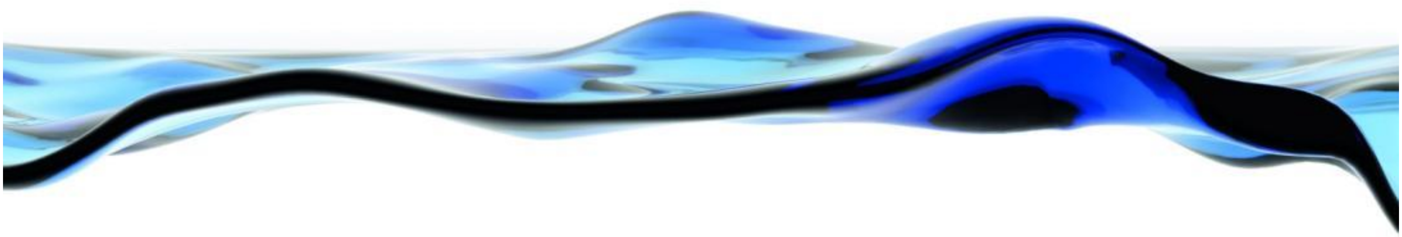

Goyder Institute for Water Research

Technical Report Series No. 14/23

GOYDER INSTITUTE FOR WATER RESEARCH

www.goyderinstitute.org

Goyder Institute for Water Research Technical Report Series ISSN: 1839-2725

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Citation

Westra, S., Thyer, M., Leonard, M. & Lambert, M., 2014, *Impacts of Climate Change on Surface Water in the Onkaparinga Catchment – Volume 2: Hydrological Evaluation of the CMIP3 and CMIP5 GCMs and the Non-homogenous Hidden Markov Model (NHMM),* Goyder Institute for Water Research Technical Report Series No. 14/23, Adelaide, South Australia.

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Executive Summary

This is the second volume of three final reports for the University of Adelaide component of *Task 4: Application Test Bed.* This report provides a hydrological evaluation of the downscaled simulations from Task 3, "Downscaling and climate change projections for South Australia", which uses the non-homogenous hidden Markov model (NHMM) to provide projections of rainfall and other hydrometeorological variables (namely, temperature, radiation, humidity and pressure). The comparison is made based on reanalysis data and hindcasts of a range of general circulation models that have been downscaled using the NHMM. Three sub-catchments of the Onkaparinga catchment (Scott Creek, Echunga Creek and Houlgrave Weir) are used for the case study because of the availability and quality of observational data and its importance as a water supply catchment for the Adelaide region.

The downscaled hydrometeorological forcing variables are converted into catchment-average rainfall and potential evapotranspiration (PET) and then run through the calibrated hydrological model GR4J. This was done for the reanalysis simulations, five climate models of the World Climate Research Program Coupled Model Intercomparison Project Phase 3 (CMIP3) and 15 CMIP5 climate models. One hundred NHMM simulations from each model were compared to simulated flows using observed rainfall and PET (the 'observed-climate flows'). The results were assessed using a range of metrics, including: (a) annual average flows; (b) the 10th, 50th, 95th and 99th percentiles of the daily flow duration curve (FDC); and (c) the annual coefficient of variation.

Reanalysis data

The reanalysis runs are based on the NCEP/NCAR reanalysis product, which is a global gridded dataset of a range of atmospheric variables that are designed to approximate historical conditions. The "reanalysis-climate" flows are estimated using the NHMM simulations of rainfall and PET based on the atmospheric variables from the NCEP/NCAR reanalysis product, and then running them the hydrological model (GR4J). These are compared against the "observed-climate" flows which are based on using the observed rainfall and PET run through the hydrological model. This provides the most suitable data to assess the performance of the NHMM to provide reliable streamflow predictions using historical rainfall and PET conditions. The outcomes of the analysis are as follows:

- Median annual average reanalysis-climate flows underestimated observed-climate flows (8-25%), although observed-climate flows were within the uncertainty bounds of reanalysis-climate flows;
- Median annual coefficient of variation from the reanalysis-climate flows underestimated the observed-climate coefficient of variation (8-12%), although observed-climate flows were within the uncertainty bounds of the reanalysis-climate coefficient of variation;
- Median 10th percentile of the reanalysis-climate FDC overestimated observed-climate flows by 12% at Scott Creek and by 3% at Houlgrave Weir, and underestimated flows by 2% at Echunga Creek;
- Median 50th percentile of the reanalysis-climate FDC flows was well simulated at Scott Creek and Echunga Creek, and slightly overestimated (but well within the uncertainty bounds) at Houlgrave Weir; and
- Median 99th percentile of the reanalysis-climate FDC was underestimated for all catchments (19-30%), and observed-climate flows were outside the uncertainty bounds for all cases except Echunga Creek.

The results indicate that the NHMM produces biased estimates of rainfall and/or PET, leading to an underestimate in average and high flows relative to simulated flows obtained using observed rainfall/PET.

GCM results

The NHMM was conditioned on GCM predictions of atmospheric variables and then run through the hydrological models. These "GCM-climate" flows enable the assessment of whether the GCM+NHMM combination can provide reliable historical-climate streamflow estimates. Results from the CMIP3 and CMIP5 GCM runs were largely consistent with the reanalysis-based results, although the biases were on average slightly lower. Specific conclusions are as follows:

- The median annual average GCM-climate flows underestimated observed-climate flows for most GCMs in Scott Creek (five out of 19 models) and Houlgrave Weir (all models), and was similar to observed-climate flows at Echunga Creek (a similar number of over- and under-estimations).
- The median annual GCM-climate coefficient of variation ranged widely (-15 to + 18% of the observed-climate coefficient of variations), and the observed-climate coefficient of variation was in all cases within the simulated uncertainty bounds.
- The median 10th percentile of the GCM-climate FDC overestimated observed-climate flows for all catchments and models.
- The median 50th percentile of the GCM-climate FDC flows was on average well simulated by most models, with a similar number of over- and under-estimations. The exception is for Echunga Creek, where GCM-climate FDC flows overestimated observed-climate flows for all GCMs.
- The median 99th percentile of the GCM-climate FDC underestimated observed-climate flows in all cases, except for Echunga Creek where six out of 19 models overestimated observed-climate flows.

Investigation of observed high flow biases

The underestimation of high flows and annual flow volumes and overestimation of low flows from the reanalysis-climate simulations suggests that the NHMM may be producing systematic biases in the rainfall statistics. Quantile correction of the rainfall (as well as the PET) series was therefore performed to further investigate these biases. Interestingly, some biases remained after quantile correction, indicating that the marginal distributions of rainfall and PET were not fully responsible for the flow bias. Seasonality in rainfall was also well-preserved after quantile correction. However, the reanalysis-climate multi-day extreme wet days were systematically underestimated due to the difficulty in preserving Markovian dependence in extremes. It is therefore likely that biases in flow quantiles are due to the following two factors:

(1) The multi-day consecutive wet spell intensity is underestimated by the NHMM algorithm, so that biases remain even after quantile-correcting the marginal precipitation and PET distributions. This can lead to an underestimation in extreme rainfall periods, which are a major contributor to the total annual flows; and
(2) The runoff coefficient in the Onkaparinga is low (e.g. 0.14 at Houlgrave Weir), and the flows are highly 'elastic', with small changes in rainfall leading to large changes in runoff. This implies that small rainfall errors are likely to be amplified in predicted flows.

Neither of these factors are addressed easily – the issues with day-to-day dependence are inherent issues associated with the NHMM architecture, whereas the high sensitivity of the Onkaparinga catchment to potentially small errors in rainfall are due to the semi-arid catchment hydrology.

Implications

The biases in the streamflow produced by the downscaling NHMM algorithm are sufficiently large that they cannot be treated as negligible. However, developing approaches to address this issue is not straightforward. Future research is needed to improve downscaling techniques so that they can reproduce the simulation of multi-day rainfall amounts and that these approaches are tested using a split-sample procedure. Until this is undertaken, it is recommended that a pragmatic "relative change" approach be adopted to assess the impact of climate change on streamflow in the Onkaparinga catchment, and that users be aware of the assumption that the biases in the historical period are the same as future climate period. This "relative change" approach is adopted in the third volume of this report.

1 Introduction

This is the second of three final reports for the University of Adelaide component of *Task 4: Application Test Bed* for the Goyder Climate Change project. The overall Goyder Climate Change project aims to develop a benchmark suite of downscaled climate projections and climate variable time series for South Australia. The contribution of Task 4 is to apply the downscaled data in a series of hydrology test cases to provide iterative feedback on the overall downscaling activity throughout the project lifecycle.

The Onkaparinga catchment has been identified as the case study location for this project. The catchment was selected because of the availability and quality of observational data and its importance as a water supply catchment for the Adelaide region. The University of Adelaide component of Task 4 involves applying the rainfall-runoff model 'GR4J' [*Perrin et al.*, 2003] to three sub-catchments in the Onkaparinga: Houlgrave Weir, Echunga Creek and Scott Creek. Each of these sub-catchments has long records of historical daily flows, and collectively they represent the majority of the flow volume in the Onkaparinga upstream of the Happy Valley diversion. This enables the downscaled hydrometeorological forcing variables (rainfall, temperature, radiation, humidity and pressure) to be tested by comparing simulated flows obtained from historically-forced GCMs with flows obtained from instrumental records of rainfall and potential evapotranspiration (PET). The implications of future climate change on flows in the three sub-catchments can then be evaluated.

The work has been divided into the following three reports:

> **Report 1:** *Hydrological Model Development and Sources of Uncertainty*. This report focuses on assessing the relative contribution of the principal sources of hydrological model uncertainty: input errors, output errors and model structural errors. The Bayesian Total Error Analysis methodology is used as the basis of the analysis. Findings are used to improve the model structure, and develop a set of models that can be used to produce the climate projections.
>
> The outcome was the development of a set of non-stationary hydrological model structures that led to improvements in the prediction of flows during a drier confirmatory period.
>
> **Report 2 (this report):** *Hydrological* e*valuation of Non-homogenous Hidden Markov Model (NHMM) projections*. This report describes the comparison of historical flows in three sub-catchments of the Onkaparinga. Estimated flows are obtained by passing the NHMM projections of rainfall and other meteorological variables through a calibrated hydrological model. A total of five General Circulation Models (GCMs) from the Coupled Model Intercomparison Project Phase 3 (CMIP3) archive, 15 GCMs from the CMIP5 archive and a reanalysis model run are evaluated.
>
> **Report 3:** *Impact of climate change on flows in the Onkaparinga catchment.* This report outlines projections for future flows in the Onkaparinga catchment, for 30-year future time slices centred on 2030, 2050, 2070 and 2085. Attributes of future flows include aggregate annual and seasonal flow patterns, low flows and peak high flows.

2 Overview of this Report

This report describes the hydrological evaluation of the non-homogenous hidden Markov model (NHMM). This model has been developed over a period of more than a decade [*Bates et al.*, 1998; *Charles et al.*, 1999a; *Charles et al.*, 1999b; *Hughes et al.*, 1999], and was found to perform reasonably in benchmark studies based on a range of average and extreme rainfall statistics [*Frost et al.*, 2011]. The NHMM simulations were developed by the CSIRO as part of Task 3 of the Goyder Climate Change project, with an important contribution of Task 4 being assess the hydrological performance of the downscaled datasets generated in Task 3.

This report draws largely from the third milestone report [*Westra et al.*, 2013], which focused on evaluating the NHMM simulations based on the NCEP reanalysis as well as historical runs from five GCMs in the CMIP3 archive. Since that report, several versions of simulations from 15 climate models in the CMIP5 archive have also been made available, and the historical simulations from these models were assessed. This report describes the results from one of the most recent sets (set 9) of the CMIP5 NHMM simulations.

The remainder of this report is structured as follows. In Section 3, the metrics used to evaluate climate model performance in simulating flows in the Onkaparinga are provided. This is followed by a summary of the evaluation of the reanalysis and CMIP3 models (Section 4), and of the more recent CMIP5 models (Section 5). A detailed analysis of possible biases in high flows is then given in Section 6, including an analysis of the implication of quantile-correcting rainfall and potential evapotranspiration prior to use in simulations. Finally, discussion and conclusions are provided in Section 7.

3 Hydrological Performance Metrics

A number of performance metrics were selected to compare flows estimated using historical rainfall and potential evapotranspiration (henceforth referred to as the 'observed-climate flows') with flows estimated using the NHMM simulations obtained using the reanalysis and GCM hindcast data (the 'reanalysis-climate' or 'GCM-climate' flows). Flows were derived using the calibrated version of the standard version of GR4J described in volume one of this report series. Metrics include:

- **Annual flow statistics**, including estimates of annual average flows, the coefficient of variation, low flow years, and time series of annual flows (for the reanalysis data only). These metrics are important for water security and drought risk assessments.
- **Seasonal flow statistics**, which evaluate whether the seasonal cycle and thus the timing of flows throughout the year is adequately preserved. This is critical in highly seasonal catchments such as those in the Onkaparinga, and provides important information for water security assessments and the setting of environmental flows.
- **Flow duration curves**, which provide an overview of how well the simulated flows represent the full distribution of observed-climate flows. We calculate flow duration curves (FDCs) over (i) all flow days; (ii) the highest two percent of flow days; (iii) individual seasons; and (iv) rising and falling limbs of the hydrograph. The curve for the top two percent of flow days is useful given the importance of high flows to the total water balance; for example in Scott Creek, the top two percent of flow days, comprising about seven days per year, accounts for 35% of the total flow volume (see Section 6.4 in volume one of this series). Furthermore, given that flows in summer in the Onkaparinga are significantly lower than in winter, it is helpful to analyse flow duration curves separately by season. Finally, examining different portions of the hydrograph assists in diagnosing possible sources of biases associated with hydrograph peaks or hydrograph recessions. FDCs are useful for water allocation modelling, setting environmental flows and (for the highest portion of the FDC) providing an indication of flood risk.
- **Summary statistics**, including annual average flows and various flow percentiles, are useful to enable comparison between a large number of models and between simulations. The percentiles selected for analysis are the (i) 10 percentile flows, which are useful for allocation of environmental flows; (ii) median flows; and (iii) high flows, including the 95 and 99 percentiles. Note that the NHMM algorithm is not designed to capture extreme precipitation events; therefore caution is required when interpreting the 99 percentile flow as a surrogate for extreme flows such as those that cause floods. Each of the above statistics are calculated for each of the 100 NHMM simulations, and the 5, 25, 50, 75 and 95 percentiles from these runs are presented to provide an indication of model spread.

To illustrate the application of each metric, several example plots for each metric are given below using Scott Creek data. Similar figures describing these performance metrics for the reanalysis and GCM hindcasts and for the three sub-catchments were given in Westra *et al*. [2013] for the CMIP3 simulations, and the results are summarised in Section 4. The CMIP5 simulations produced results that are consistent with the CMIP3 simulations, and thus only some summary plots are presented for these models (Section 5).

3.1 Annual flow statistics

The time series of annual flows at Scott Creek catchment is given in Figure 1. In the case of the reanalysis data, the annual flows simulated from observed rainfall and APET can be expected to match the downscaled estimates, because the large-scale hydroclimatic forcings should be equivalent. This can be seen in the figure, with years that have high observed-climate flows typically also being high when using reanalysis data, and vice versa. There is some evidence that the observed data has a greater level of variability compared to the modelled data, with 11 out of 16 years of observed data being outside the 50% reanalysis-based intervals in this plot. This is particularly evident for the high flow years, which can also be seen when comparing the 90th percentile of the annual flows between observed-climate flows and simulated-climate flows (Table 1).

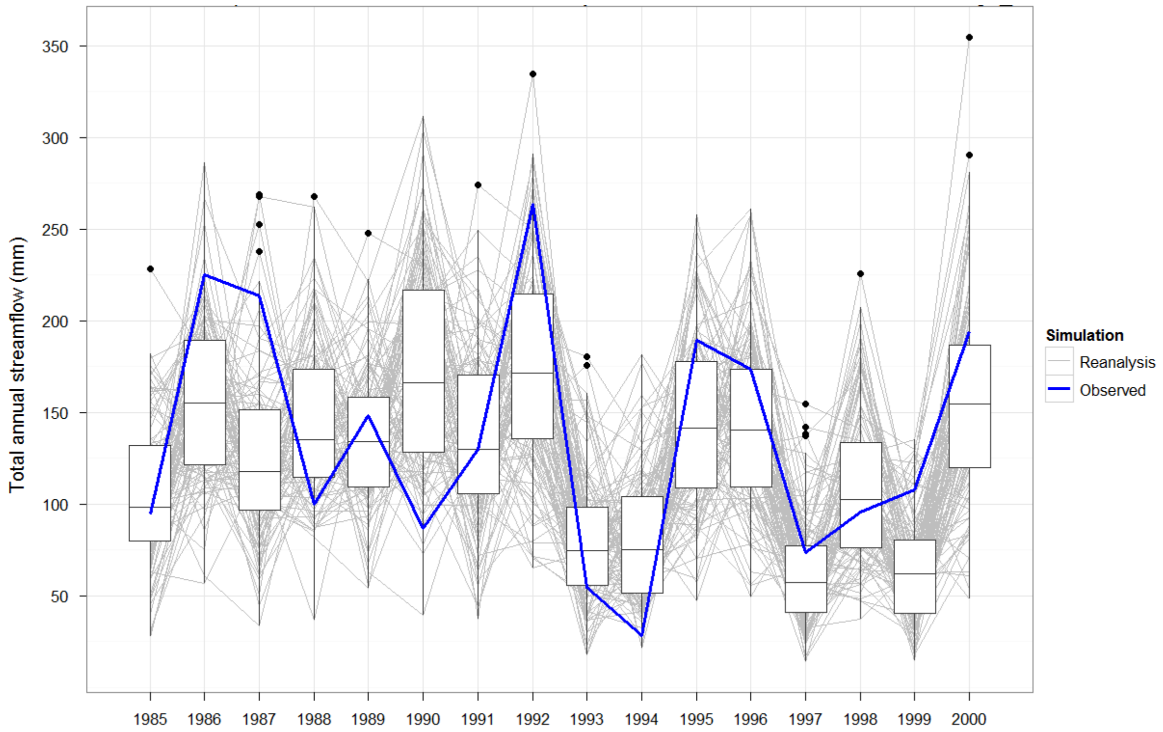

Figure 1: Annual total flows from 1985 to 2000 at Scott Creek. Upper and lower 'hinges' represent the 25th and 75th percentiles of the reanalysis data, respectively, while the whiskers extend to 1.5 times the interquartile range. Dots represent points beyond the whiskers.

The finding of a slight underestimation in variance can also be seen from the annual coefficient of variation statistics presented in Table 1. The observed-climate coefficient of variation is within the 90 percent uncertainty interval from the reanalysis-climate simulations, so it is unclear whether this is random variation or a systematic bias.

3.2 Seasonal flow statistics

The monthly average flow rate in the catchment is given in Figure 2, and again shows that the flows generated using observed rainfall and potential evapotranspiration were within the bounds of the flows obtained using downscaled rainfall and potential evapotranspiration driven by reanalysis data. The distinct seasonality of flows in Scott Creek is clearly evident, with the majority of flows occurring in the months from June to October. Generally the flows from observed rainfall and APET are above the median flows from the reanalysis data, although they are well within range of reanalysis results.

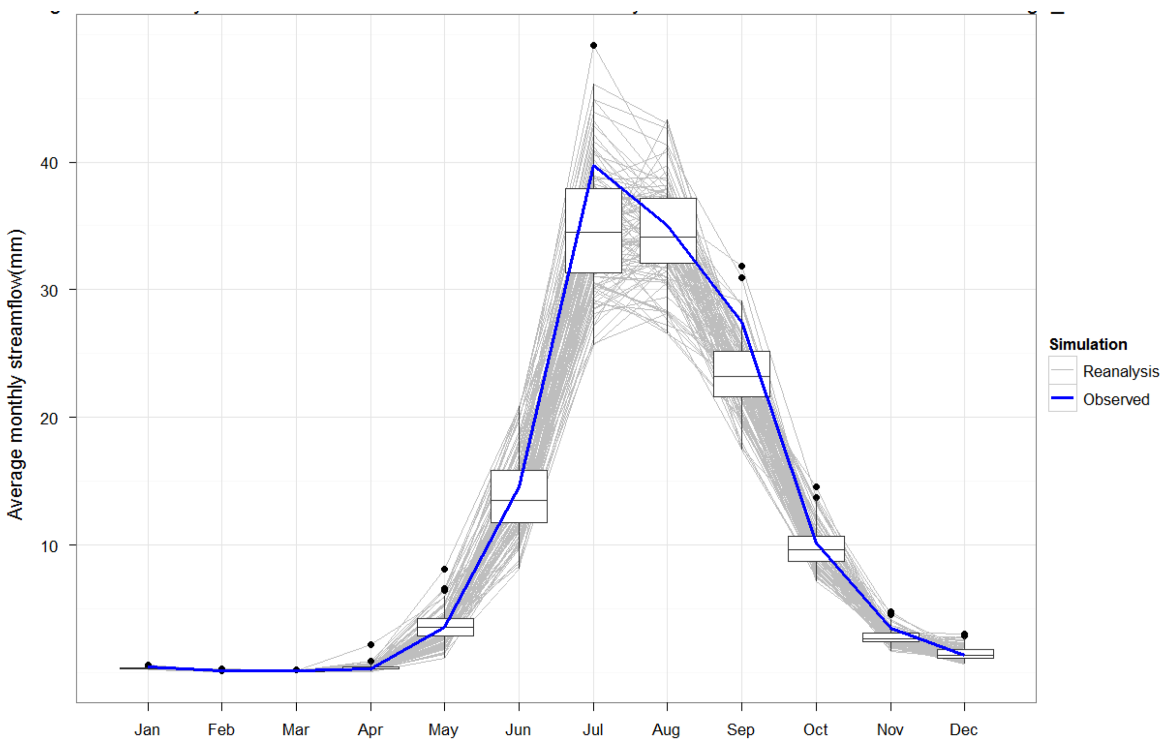

Figure 2: Monthly average flow.

3.3 Flow duration curves

The flow duration curve describes the percentage of time that a flow rate in a stream is equal to or greater than a given value. The flow duration curve obtained from the standard version of GR4J using the observed rainfall and APET data (blue line), as well as the reanalysis data (grey lines), is given in Figure 3. Generally, the observed curve falls within the bounds of the curves generated from reanalysis data. For high-flows, the reanalysis data seems to underestimate flows slightly (Figure 4), whereas for low flows, the reanalysis data overestimates flows slightly. In all cases, observed-climate flows are within the range of the reanalysis-climate flows.

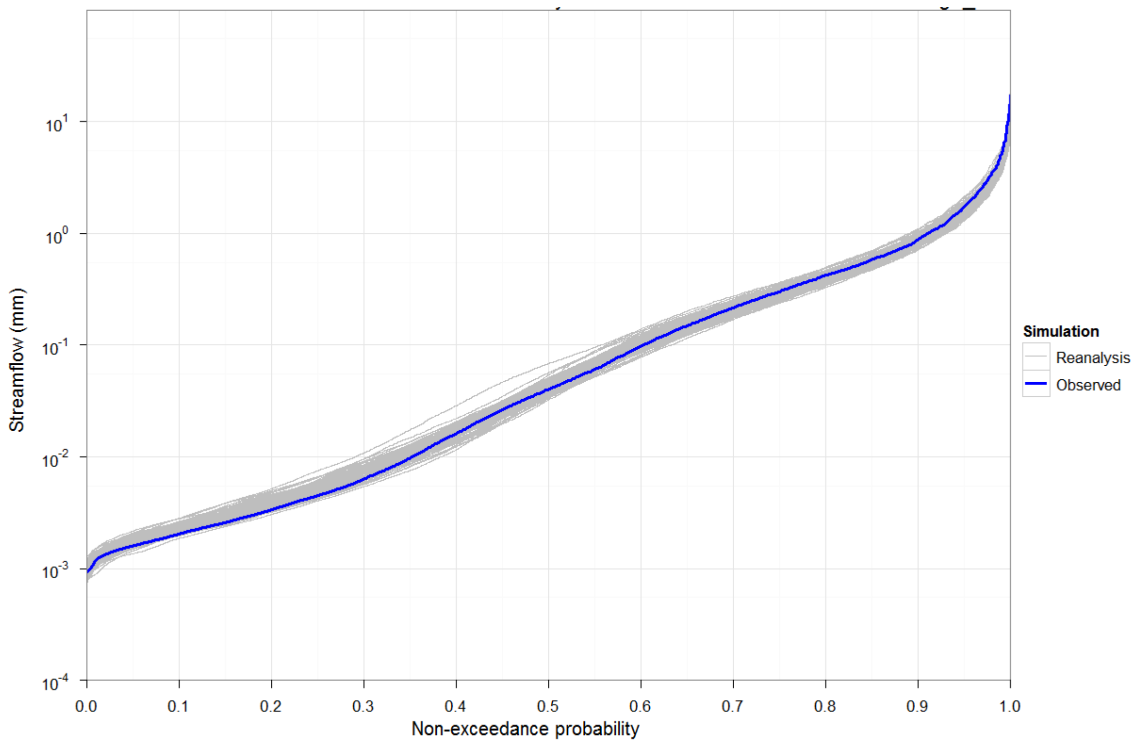

Figure 3: Flow duration curve for Scott Creek based on reanalysis climate data.

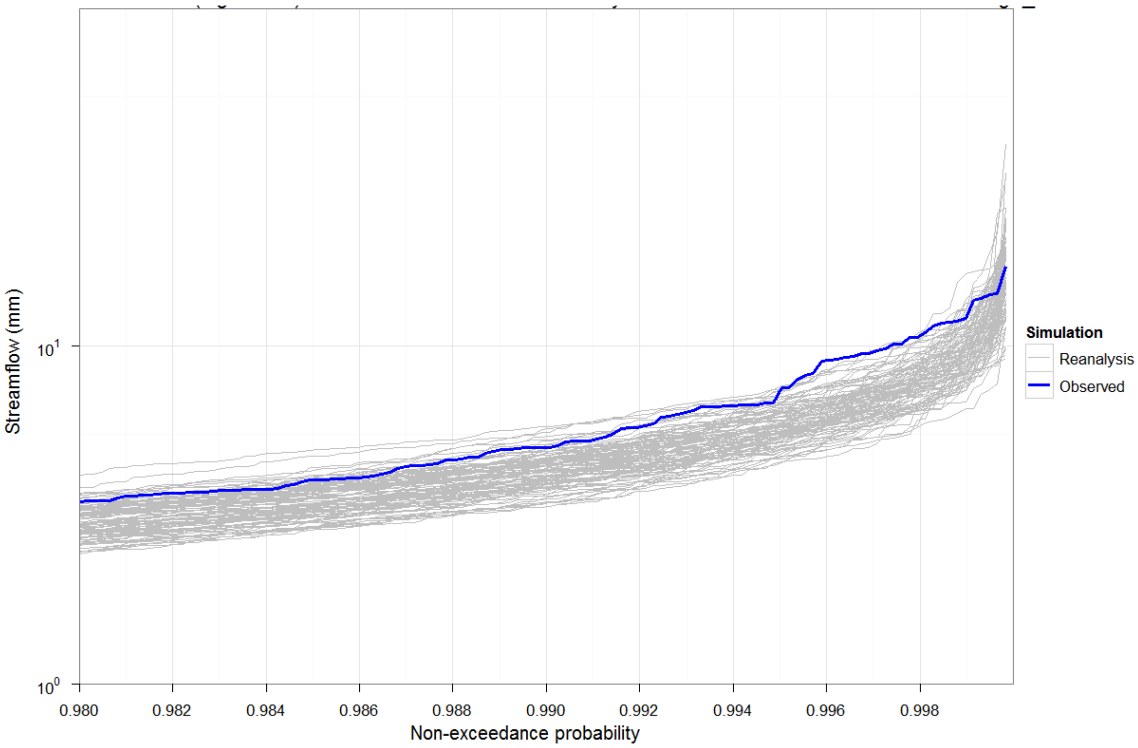

Figure 4: Flow duration curve for Scott Creek based on reanalysis climate data – top 2% of flows.

Finally, summary statistics are given in Table 1, again based on the reanalysis data. The observed-climate data is slightly above the 75 percentile of the simulated runs in terms of the annual mean and 99 percentile flows, and below the 25 percentile of the simulated runs for the 5 percentile flow. Nevertheless for all these statistics the observed flow is well within the range of simulated values.

Table 1: Summary statistics from the reanalysis data at Scott Creek. The observed-climate flows represents flows from the calibrated GR4J using observed rainfall and PET inputs, while the simulated runs are based on the NCEP reanalysis. Units of mm.

		Percentile from the simulated runs				
Metrics	**Observed-climate flows**	**5**	**25**	**50**	**75**	**95**
Annual mean	142	108	116	125	132	143
Annual standard deviation	69.6	42.2	50.0	55.6	62.4	72.3
Annual coefficient of variation	0.491	0.348	0.419	0.451	0.487	0.552
10^{th} percentile of annual flows	64.8	41.4	52.3	58.9	64.8	78.8
90^{th} percentile of annual flows	224	159	175	193	208	236
10^{th} percentile of daily flows	0.00203	0.00200	0.00212	0.00228	0.00242	0.00261
50^{th} percentile of daily flows	0.0407	0.0345	0.0392	0.0423	0.0466	0.0498
95^{th} percentile of daily flows	1.80	1.35	1.48	1.62	1.75	1.90
99^{th} percentile of daily flows	5.32	3.52	3.92	4.26	4.57	5.16

4 Assessment of Simulations from the Reanalysis and CMIP 3 Archive

In this section, the results from the reanalysis data and the hindcasts from five GCMs listed in Table 2 are presented as a set of summary statistics. The statistics are provided for Scott Creek (Figure 5), Echunga Creek (Figure 6) and Houlgrave Weir (Figure 7) catchments. For the reanalysis data and each GCM, 100 daily resolution NHMM simulations were provided by CSIRO at each catchment, and the box-and-whisker plots produced in the figures depict the minimum value, the 25, 50 and 75 percentile values and the maximum value of each statistic across all the 100 simulations.

Table 2: List of CMIP3 climate models used for the analysis

Climate model ID	Climate Modelling Group	Country
GFDL CM2.0	U.S. Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA
GFDL CM2.1	U.S. Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA
MIROC3.2 (medres)	Centre for climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Centre for Global Change	Japan
CSIRO-Mk3.5	Commonwealth Scientific and Industrial Research Organisation, Atmospheric Research	Australia
ECHAM5/MPI	Max Planck Institute for Meteorology	Germany

The median of the NHMM results are summarised in Table 3, showing areas of consistent over- and under-estimation of the reanalysis-climate and GCM-climate relative to the observed-climate flows. The conclusions are summarised in Sections 4.1-4.5 below.

Table 3: Percentage difference between the median reanalysis/GCM-climate flow and the observed-climate flows. GCM results are presented as a range for the five CMIP3 GCMs. Negative sign means the reanalysis/ GCM-climate flows underestimates observed flows, whereas positive sign means the reanalysis/ GCM-climate flows overestimate observed flows.

Simulation/Statistic	**Catchment**		
	Scott Creek	**Echunga Creek**	**Houlgrave Weir**
Reanalysis			
Average annual flows	-12%	-25%	-8%
CV of annual flows	-8%	-8%	-12%
Low (10^{th} percentile) daily flows	+12%	-2%	+3%
Median (50^{th} percentile) daily flows	+4%	0%	+8%
High (99^{th} percentile) daily flows	-20%[*]	-30%	-19%[*]
GCM			
Average annual flows	-11% to +1%	-8% to +15%	-14%[*] to -2%
CV of annual flows	-2% to 17%	-9% to 18%	-15% to -4%
Low (10^{th} percentile) daily flows	+11% to +25%	+2% to +60%[*]	+1% to +14%
Median (50^{th} percentile) daily flows	-14% to +6%	+1% to +47%[*]	-11% to +13%
High (99^{th} percentile) daily flows	-18%[*] to -9%	-15% to 0%	-22%[*] to -15%[*]

[*] at least one of the observed-climate flows are outside the 90% uncertainty interval of the NHMM flows

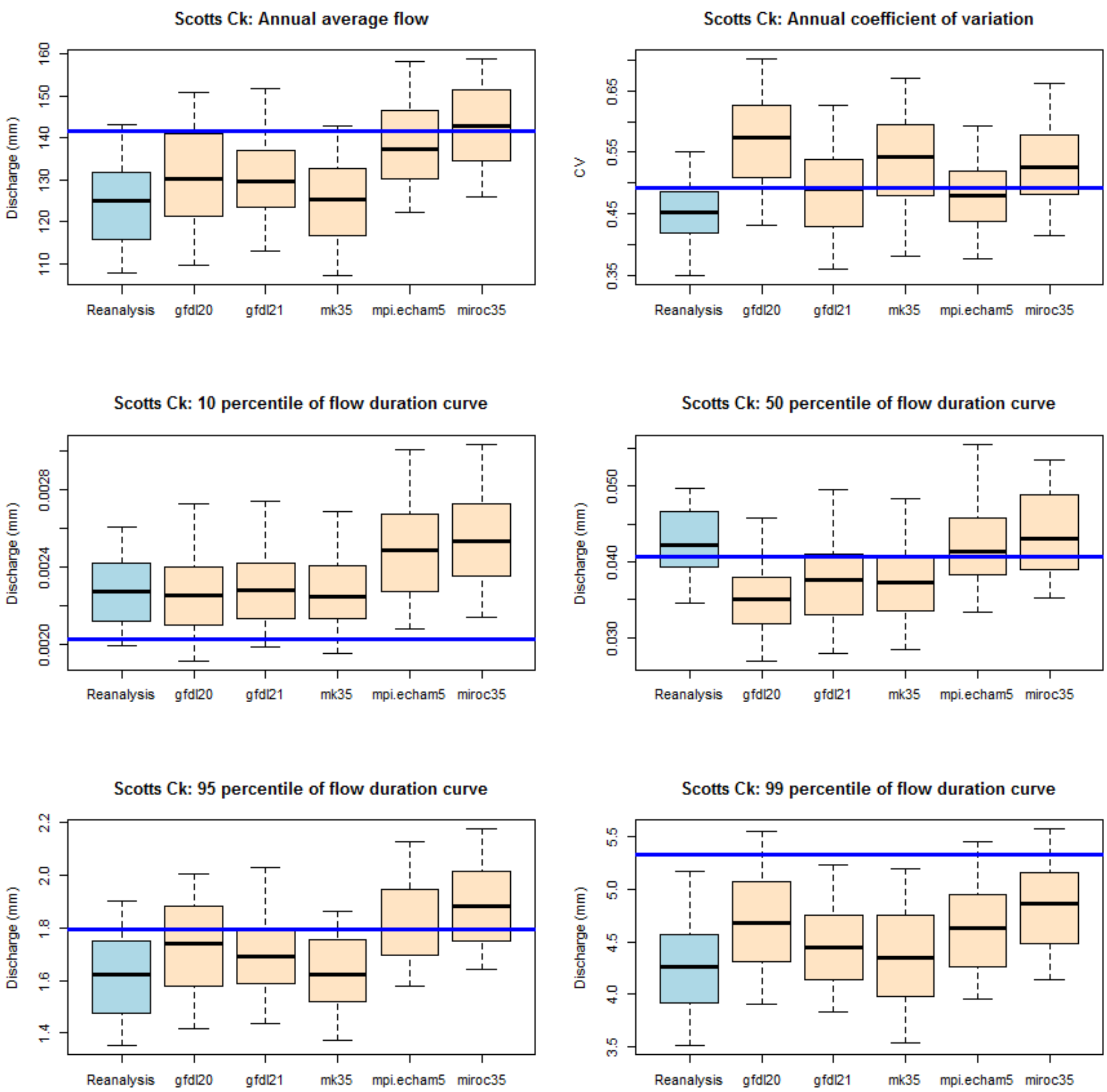

Figure 5: Box and whisker plots of average annual flow, and the 10, 50 and 99 percentiles of the flow duration curve based on models from the CMIP3 archive, for Scott Creek catchment. The observed-climate value is given by the blue horizontal line. The box describes the 25, 50 and 75 percentile values obtained from the 100 NHMM simulations, whereas the whiskers indicate the 5 and 95 percentile values.

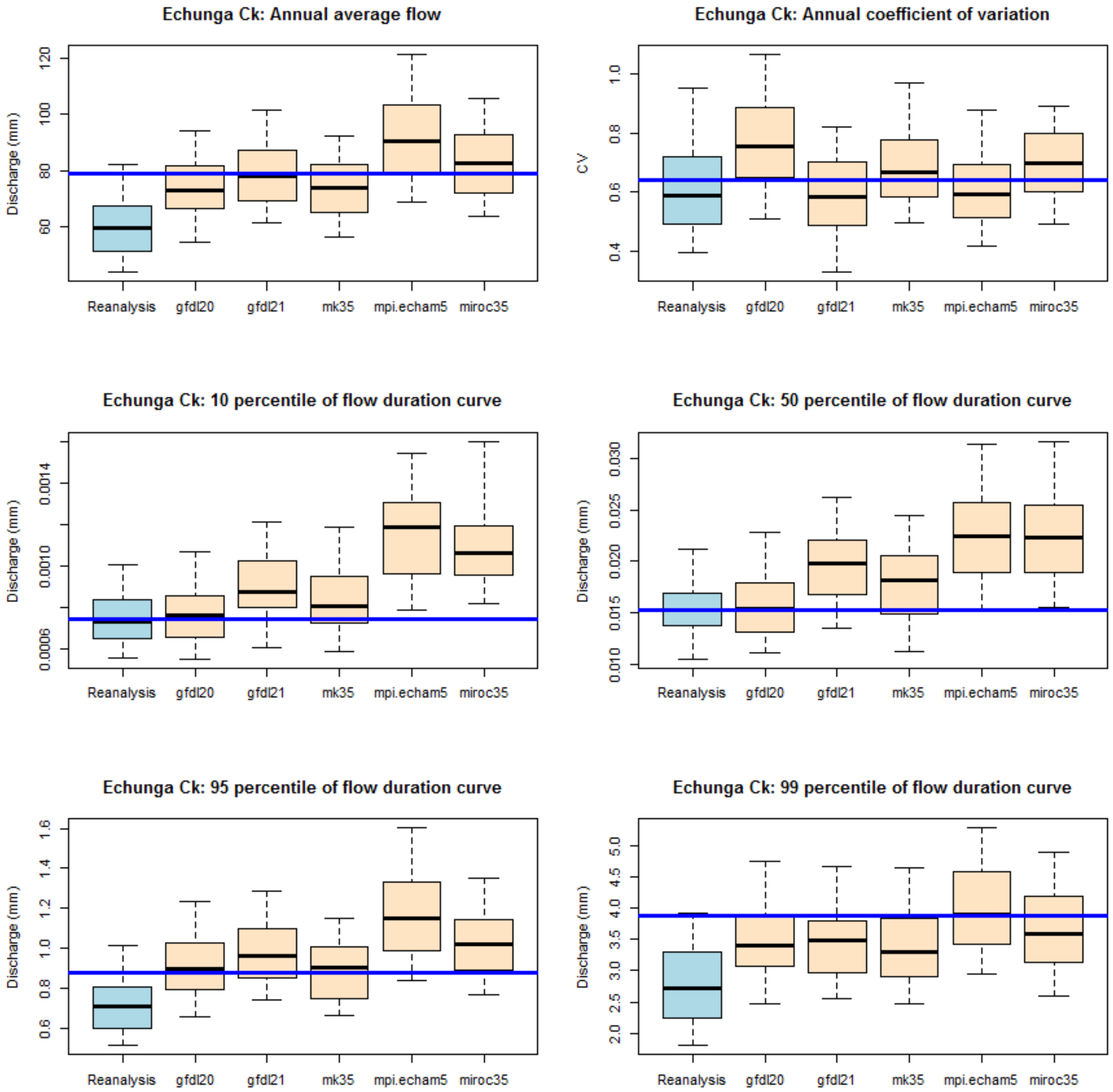

Figure 6: As per Figure 5 but for Echunga Creek.

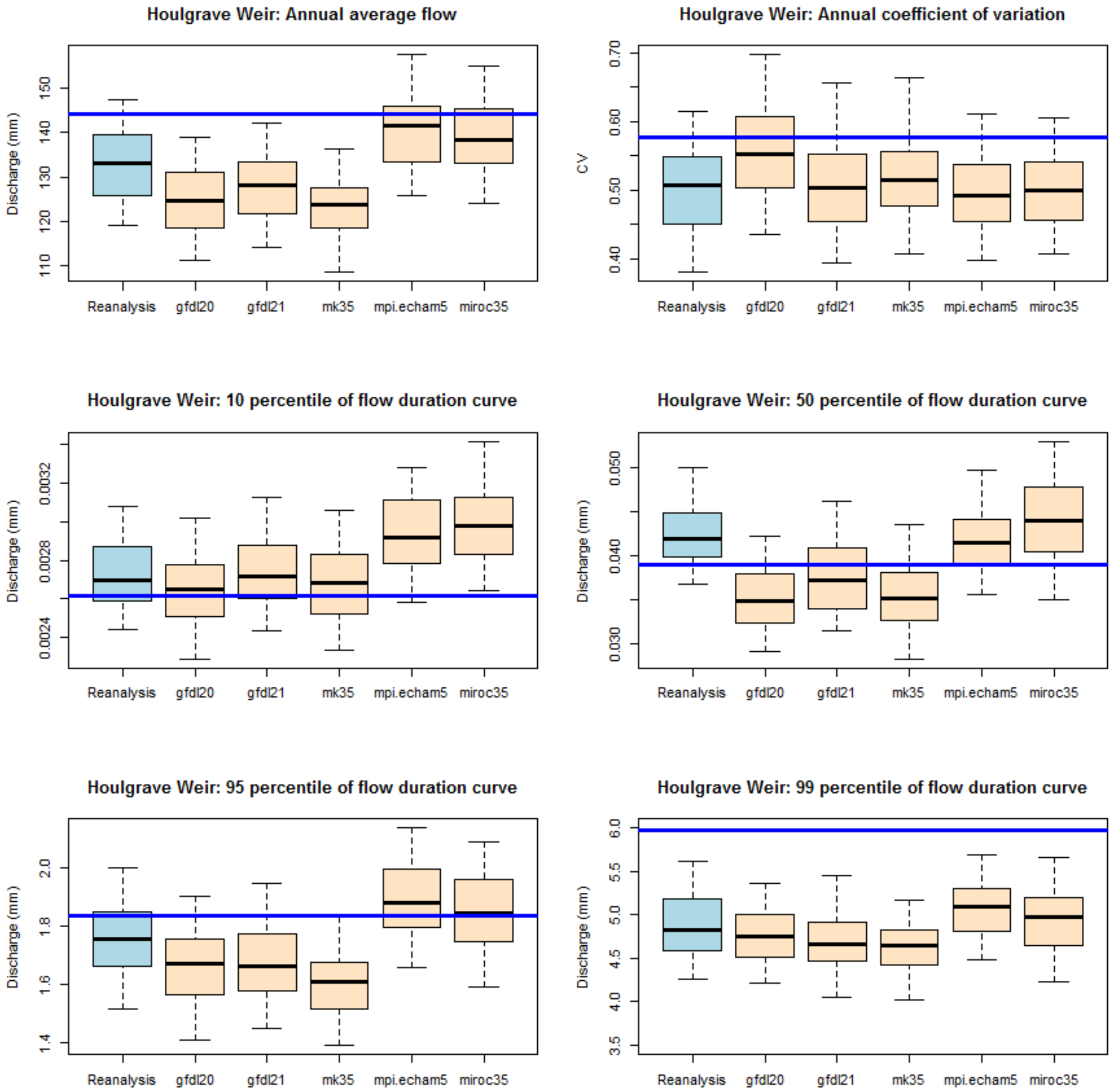

Figure 7: As per Figure 5 but for Houlgrave Weir.

4.1 Annual flow volume

The results for annual flow volumes (top left panel in Figure 5-Figure 7) are summarised as follows:

- Reanalysis results
  - The median annual average reanalysis-climate flows underestimated observed-climate flows (8-25%), although the observed-climate flows were within the uncertainty bounds of reanalysis-climate flows;
  - It is likely that the bias in annual flows is due to the bias in simulation of high flow events (see 99th percentile flow results below), since a small number of high-flow days contribute towards a large proportion of the annual water balance.
- GCM results
  - The median annual average GCM-climate flows underestimated observed-climate flows for most GCMs in Scott Creek (four out of five models) and Houlgrave Weir (all models), and was similar to observed-climate flows at Echunga Creek (a similar number of over- and under-estimations);
  - The observed flows were within the uncertainty bounds for Scott Creek and Echunga Creek, and above the uncertainty bounds for three models (GFDL20, GFDL21 and CSIRO-MK3.5) at Houlgrave Weir.

4.2 Annual coefficient of variation (CV)

The results the annual coefficient of variation (top right panel in Figure 5-Figure 7) are summarised as follows:

- Reanalysis results
  - The reanalysis-climate CV is slightly below the observed-climate CV for all three catchments, but the observed-climate CV is well within the reanalysis-climate uncertainty bounds for all cases.
- GCM results3
  - There is some variation between GCM-climate CV values, with some GCMs overestimating observed-climate CV values, while other GCMs underestimate observed-climate CV values. The exception is for Houlgrave Weir, with all GCMs underestimating observed-climate CV values. In all cases, the observed-climate CV values are within the uncertainty bounds of the GCM-climate CV values.

4.3 Daily low flows (10th percentile flows)

The results the daily low flows (middle left panel in Figure 5-Figure 7) are summarised as follows:

- Reanalysis results
  - Reanalysis-climate low flows overestimated observed-climate flows by 9% (Scott Creek) and 6% (Houlgrave Weir), and underestimated observed-climate flows by 9% (Echunga Creek). In all cases, the results were within the uncertainty bounds from the NHMM simulations.
- GCM results
  - GCM-climate low flows overestimated observed-climate low flows for all catchments and GCMs (except for GFDL20, GFDL21 and CSIRO MK3.5 at Echunga Creek), although the observed data were mostly within the uncertainty bounds. The exception is for

MIROC3.2 (medres) and ECHAM/MPI, for which the observed-climate flows were outside of the uncertainty bounds of the GCM-climate flows at all catchments.

4.4 Daily median flows (50^{th} percentile flows)

The results the daily median flows (middle right panel in Figure 5-Figure 7) are summarised as follows:

- Reanalysis results
  - Reanalysis-climate flows are well simulated at Scott Creek and Echunga Creek, and were slightly above observed-climate flows (but well within the uncertainty bounds) at Houlgrave Weir.
- GCM results
  - For Scott Creek and Houlgrave Weir, some GCMs overestimated and other GCMs underestimated median flows, with no obvious pattern. Observed-climate flows were well within the GCM-climate uncertainty bounds for all GCMs.
  - For Echunga, GFDL20, GFDL21 and CSIRO-MK3.5 performed well, but MIROC3.2 (medres) and ECHAM/MPI overestimated observed-climate flows by close to 50%. Note that the median daily flow rate is about an order of magnitude lower than the mean daily flow rate (0.0152mm/day vs 0.22mm/day), and therefore the flow bias for the 50^{th} percentile flows will not significantly impact on total annual flow volume.

4.5 Daily high flows (95^{th} and 99^{th} percentile flows)

The results the daily high flows (bottom panels in Figure 5-Figure 7) are summarised as follows:

- Reanalysis results
  - Reanalysis-climate high flows underestimated observed-climate high flows in all cases, with a greater degree of underestimation for the 99^{th} percentile high flows compared to the 95^{th} percentile high flows. The observed-climate high flows were inside the reanalysis-climate uncertainty bounds for all cases of the 95^{th} percentile flow, and also for Echunga for the 99^{th} percentile high flows. In contrast, the 99^{th} percentile observed flow for Scott Creek and Houlgrave Weir were outside the reanalysis-climate uncertainty bounds.
- GCM results
  - At Scott Creek, three GCMs underestimated observed-climate 95^{th} percentile flows, one overestimated observed-climate 95^{th} percentile flows, and was equal to observed-climate flows. In contrast, GCM-climate 99^{th} percentile flows were below observed climate flows in all cases, and the uncertainty bounds of GFDL21 and CSIRO-MK3.5 did not span the observed flows, while they did for the remaining GCMs.
  - The Houlgrave Weir results were consistent with the Scott Creek results. For the 99^{th} percentile flow, the observed-climate flows were outside the GCM-climate uncertainty bounds for all GCMs.
  - For Echunga Creek, the high flows were much better simulated than the reanalysis data, and were within the uncertainty bounds in all cases.

4.6 Summary

This section described the performance of the reanalysis-climate flows relative to observed-climate flows, as well as the GCM-climate flows obtained from five CMIP3 GCMs. Of these, the reanalysis-climate results deserve particular attention, as the large-scale climate variables used as predictors to the NHMM algorithm are estimates of the historical climate conditions, so that the evaluation specifically tests the capacity of the NHMM to simulate the statistics of historical rainfall and PET.

The reanalysis-based results show that the model typically underestimates annual average flows by between 8 and 25%, although the uncertainty bounds are also wide with some simulations leading to annual average flows that are higher than the observed-climate flows. Examination of various percentiles of the flow duration curve suggest that the primary reason for underestimation of annual flows is due to the underestimation of very high flow days, particularly for flows around the 99 percentile of the flow duration curve. As described in Section 3, these high flows are a significant portion of the total annual water balance, and thus are capable of influencing annual flow statistics. The coefficient of variation is a useful statistic for catchment yield estimates, and reanalysis-climate CV values were typically lower than observed-climate CV values, although the observed-climate CV values were within the reanalysis-climate uncertainty bounds. Finally, the reanalysis-climate low flows (measured as the 10th percentile of the flow duration curve) were typically higher than the observed-climate low flows, with potential implications for environmental flow allocation.

The GCM-climate flows exhibited some variability across all the flow statistics, but generally the results were reasonably consistent with the reanalysis-climate flows. Biases in annual average flows were typically less severe compared to reanalysis-climate flows, except for three GCMs at Houlgrave Weir. The most pronounced biases were associated with the 99th percentile flows, however the magnitude of underestimation was slightly lower than for the reanalysis-climate flows.

5 Assessment of Simulations from the CMIP 5 Archive

The analysis presented in Section 4 is now repeated using 15 general circulation models from the CMIP 5 archive, which are described in Table 4. The statistics are provided for Scott Creek (Figure 8), Echunga Creek (Figure 9) and Houlgrave Weir (Figure 10) catchments. As before, 100 daily resolution NHMM simulations were provided by CSIRO at each catchment, and the box-and-whisker plots produced in the figures depict the 5, 25, 50 and 75 and 95 percentile values of each statistic across all the 100 simulations.

Table 4: List of CMIP5 climate models used for the analysis

Climate model ID	Climate Modelling Group	Country
ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology	Australia
ACCESS1-3	Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology	Australia
BCC-CSM1-1-M	Beijing Climate Centre, China Meteorological Administration	China
CanESM2	Canadian Centre for Climate Modelling and Analysis	Canada
CNRM-CM5	Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	France
CSIRO-Mk-3.6	Commonwealth Scientific and Industrial Research Organisation, Queensland Climate Change Centre of Excellence	Australia
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory	USA
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	USA
INM-CM4	Institute for Numerical Mathematics	Russia
IPSL-CM5A-LR	Institut Pierre-Simon Laplace	France
IPSL-CM5B-LR	Institut Pierre-Simon Laplace	France
MIROC.ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	Japan
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	Japan
MRI-CGCM3	Meteorological Research Institute	Japan
NorES1-M	Norwegian Climate Centre	Norway

The median of the NHMM results are summarised in Table 5, showing areas of consistent over- and underestimation of the GCM-climate flows relative to the observed-climate flows. The conclusions are summarised in Sections 5.1-5.6 below.

Table 5: Percentage difference between the median reanalysis/GCM-climate flow and the observed-climate flows. GCM results are presented as a range for the five CMIP3 GCMs. Negative sign means the reanalysis/GCM-climate flows underestimate observed flows, whereas positive sign means the reanalysis/GCM-climate flows overestimate observed flows.

Simulation/Statistic	**Catchment**		
	Scott Creek	**Echunga Creek**	**Houlgrave Weir**
GCM			
Average annual flows	-9% to +7%	-8% to +25%	-10% to 0%
CV of annual flows	-7% to +29%*	-26% to +35%	-27%* to +9%
Low (10%ile) daily flows	+2% to +24%*	-7% to +29%	-5% to +7%
Median (50%ile) daily flows	-20% to +14%	+9% to +63%*	-8% to +8%
High (99%ile) daily flows	-17%* to -2%	-16% to +18%	-21%* to -9%

* means that at least one of the observed-climate flows are outside the 90% uncertainty interval of the NHMM flows.

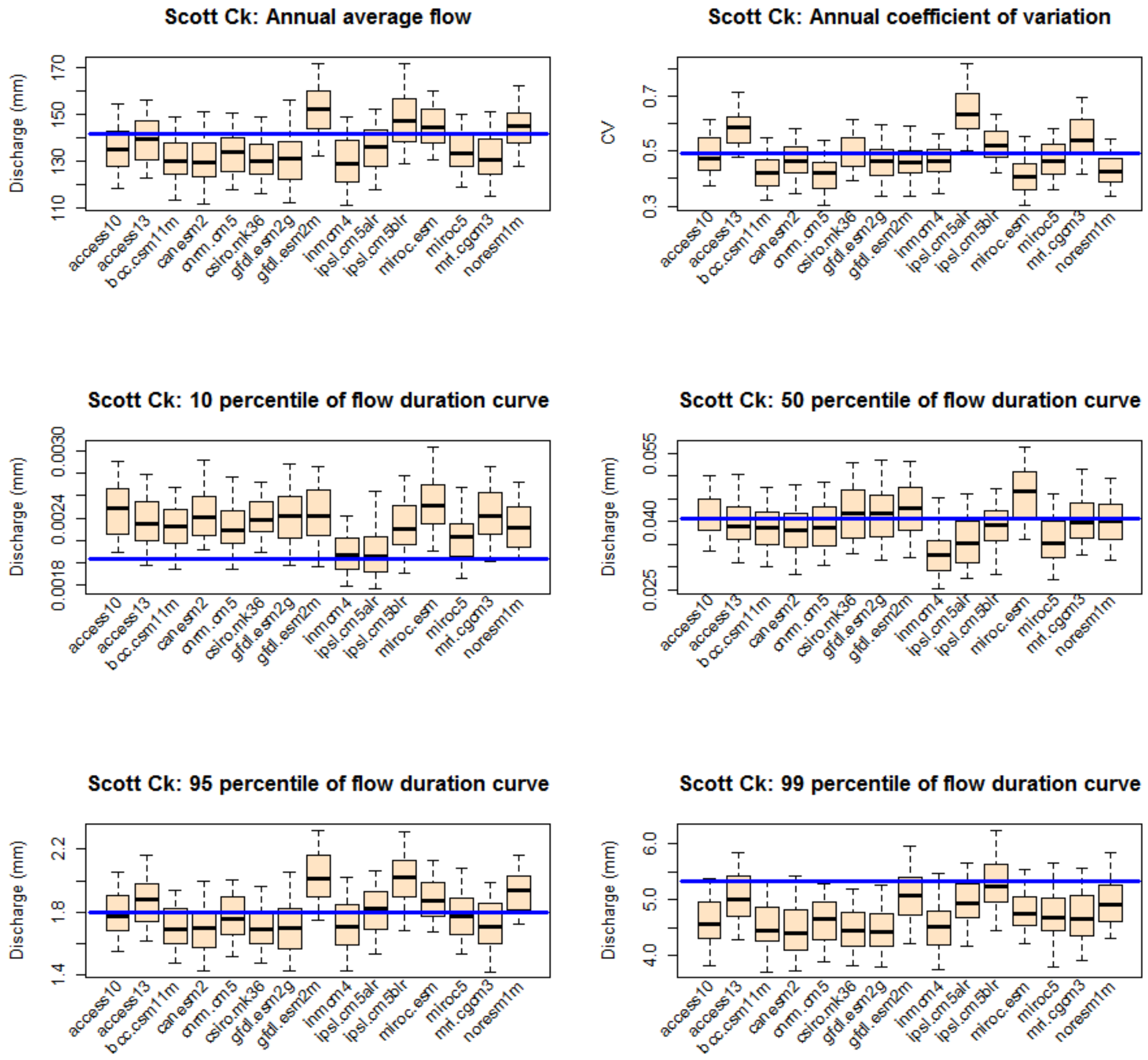

Figure 8: Box and whisker plots of average annual flow, and the 5, 50 and 99 percentiles of the flow duration curve based on models from the CMIP5 archive, for Scott Creek catchment.

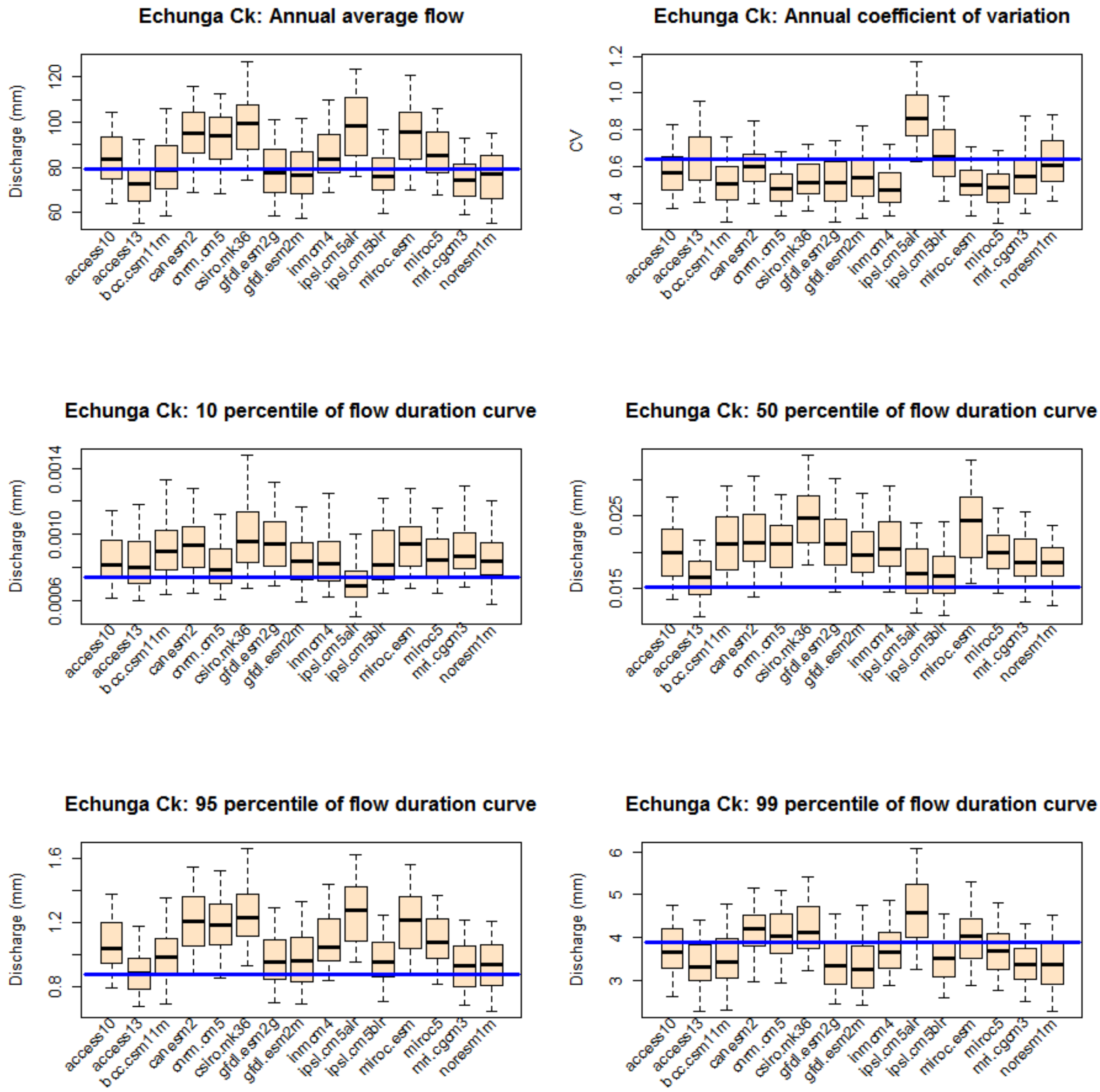

Figure 9: As per Figure 8 but for Echunga Creek catchment.

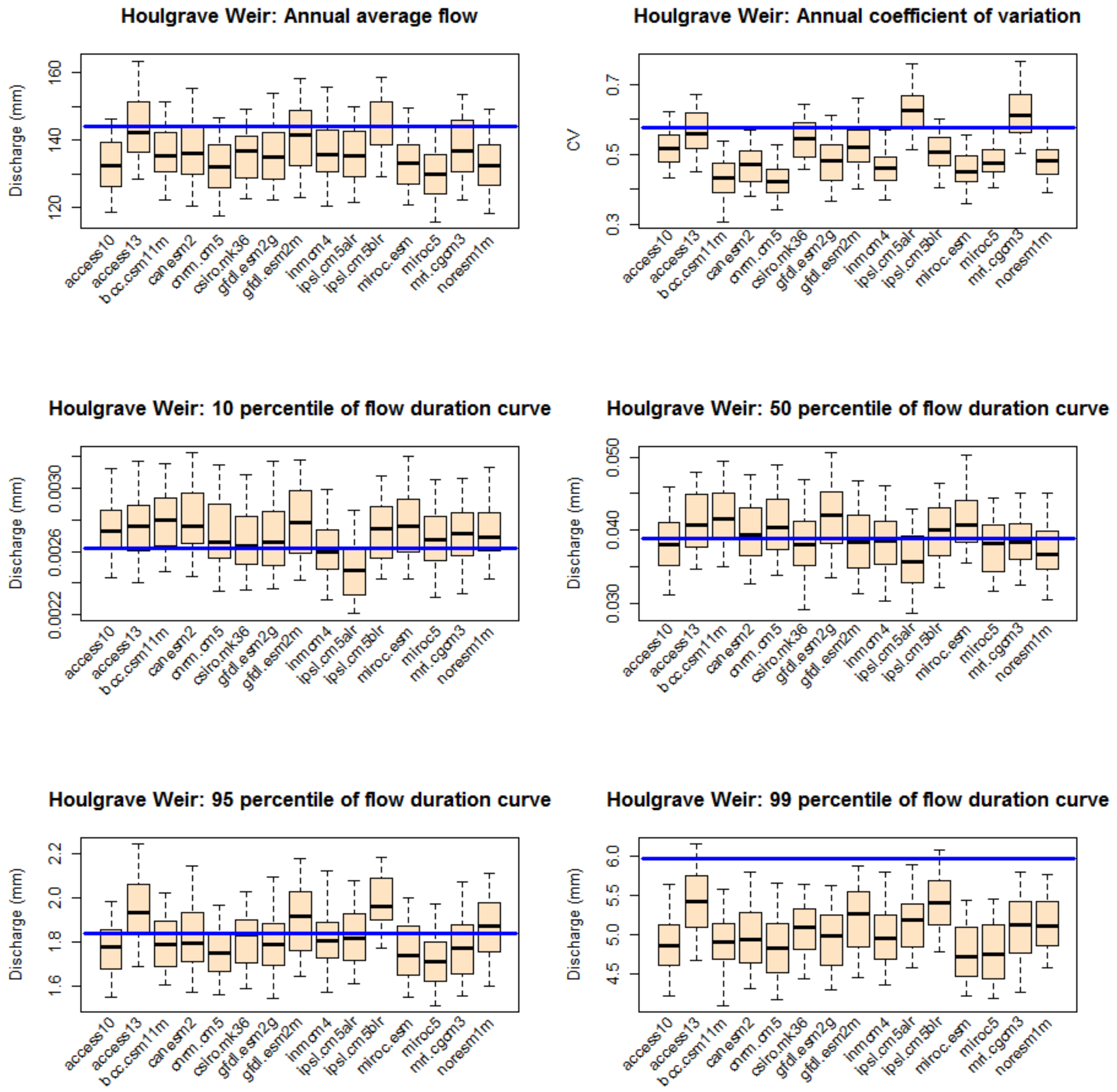

Figure 10: As per Figure 8 but for Houlgrave Weir catchment.

5.1 Annual flow volume

The results for annual flow volumes (top left panel in Figure 8-Figure 10) are summarised as follows:

- Scott Creek: The median GCM-climate flow from 11 out of the 15 models was lower than the observed-climate flow, with the median of the remaining four models being higher than the observed discharge. In all cases the observed-climate flow volume was within the uncertainty bounds of simulation results, with the observed-climate flows being within the interquartile range (i.e. between the 25 and 75 percentile simulated results) for seven out of the 15 models, as would be expected by random chance. The model with the greatest difference between median simulated flow and observed-climate flow (INM-CM4) underestimated annual flow by 9.2%.

- Echunga Creek: The median GCM-climate flow from eight out of the 15 models was greater than the observed flow, with the observed-climate flow being within the interquartile range for 10 out of the 15 models. The model with the strongest difference (CSIRO-Mk-3.6) overestimated flows by 25%.
- Houlgrave Weir: The median flow from all models was lower than the observed-climate flow, except for IPSL-CM5B-LR which had median flow equal to the observed flow. Of these, the interquartile range was below the observed flow for 11 of the 15 models, suggesting the potential for a systematic underestimation of observed flow. The greatest underestimation was for MIROC5, with the median flow being 10% lower than the observed-climate flow.

5.2 Coefficient of Variation (CV)

The results for annual coefficient of variation (top right panel in Figure 8-Figure 10) are summarised as follows:

- Scott Creek: The median GCM-climate CV was lower than observed-climate CV for 10 models, higher for four models, and equal to the observed-climate CV for one model. The observed-climate CV values were within the interquartile range for eight out of the 15 models, as would be expected by random chance. Observed-climate CV values were outside the 90 percent confidence interval for only a single model (INM-CM4).
- Echunga Creek: The median GCM-climate CV was lower than observed-climate CV for 13 models, higher for two models, and equal to the observed-climate CV for one model. The observed-climate CV values were within the interquartile range for six out of the 15 models, as would be expected by random chance. Observed-climate flows were inside the 90 % uncertainty interval in all cases.
- Houlgrave Weir: The median GCM-climate CV was lower than observed-climate CV for 13 models and higher for two models. The observed-climate CV values were within the interquartile range for four out of the 15 models, which is less than would be expected by random chance, suggesting that the GCM-climate CV values underestimate variability. Observed-climate flows were outside the 90 % uncertainty interval for six models.

5.3 Daily low flows (10th percentile flows)

The results for the daily low flows (middle left panel in Figure 8-Figure 10) are summarised as follows:

- Scott Creek: The median GCM-climate 10th percentile flow was greater than the observed-climate 5th percentile flow for all of the 15 models, with the observed flow being outside the interquartile range for 13 of these models. This suggests a systematic overestimation of low flows. The greatest overestimation was for model MIROC.ESM with the median flow being 18% greater than observed.
- Echunga Creek: The median 10th percentile flow was greater than the observed-climate 10th percentile flow for 14 out of the 15 models, and observed-climate flows were only outside of the interquartile range for seven models, as would be expected by random chance. The greatest overestimation was for model CSIRO-Mk-3.6, with median simulated flow being 29% greater than the observed-climate flow.
- Houlgrave Weir: Similar to Scott Creek and Echunga Creek, there was a systematic overestimation of low flows, with the median simulated flow being greater than the observed flow for all but two models (INM-CM4 and IPSL-CM5A-LR). The observed-climate flow was inside

the interquartile range for 12 of the 15 models, with the greatest overestimation being for model BCC-CSM1-1-M, and with median flow being 7% greater than observed flow.

5.4 Daily median flows (50th percentile flows)

The results for the daily median flows (middle right panel in Figure 8-Figure 10) are summarised as follows:

- Scott Creek: The median GCM-climate 50 percentile flow was greater than the observed-climate 50 percentile flow for four out of the 15 models, with the remaining models having median flows equal to or lower than observed. The observed-climate flow was inside the interquartile range for all but four models. The maximum underestimation of flows was for INM-CM4, with simulated median flow being 20% lower than observed flow.
- Echunga Creek: The median GCM-climate 50 percentile flow was greater than the observed-climate 50 percentile flow for all of the 15 models, with the observed-climate flow being inside the interquartile range for only three of the models. The model with the greatest overestimation was CSIRO-Mk-3.6, with the median flow being about 63% greater than observed.
- Houlgrave Weir: Unlike the Echunga Creek results, the simulated results at Houlgrave Weir were consistent with observations, with seven models having median flows greater than observed and eight models having median flows less than observed. The observed-climate flow was within the interquartile range for all models, with the greatest discrepancy between median simulated flow and observed-climate flow being an overestimation of 8% for model GFDL-ESM2M.

5.5 Daily high flows (99th percentile flows)

The results for the daily high flows (bottom panels in Figure 8-Figure 10) are summarised as follows:

- Scott Creek: the median GCM-climate 99 percentile flow was less than the observed-climate 99 percentile flow for all of the 15 models, with observed-climate flow being within the interquartile range for only three models. The greatest underestimation of median flow relative to observed-climate flow was approximately 17% for model CanESM2, with CSIRO-Mk-3.6 and GFDL-ESM2G performing similarly.
- Echunga Creek: the median GCM-climate 99 percentile flow was less than the observed-climate flow for 10 of the 15 models, and greater than observed-climate flow for five models. The observed-climate flows were within the interquartile range for five models, indicating that the climate model outputs provide a reasonable estimate of model spread. The greatest discrepancy was for model IPSL-CM5A-LR, with median flows being approximately 18% below above observed-climate flows.
- Houlgrave Weir: Similar to Scott Creek but unlike Echunga Creek, the median 99 percentile flow was less than the observed-climate 99 percentile flow for all of the 15 models. Furthermore, the observed-climate flow was not only outside the interquartile range for all models, but was also outside the uncertainty bounds for 13 of the 15 models. This indicates a significant difference in simulation of high flows at Houlgrave weir. The median of the simulated flow was up to 21% below the observed-climate flow (model MIROC.ESM).

5.6 Summary of CMIP5 results

The results from the CMIP5 downscaled model runs were similar to the results from the CMIP3 model runs that were summarised in Section 4. Observed-climate flows were typically within the uncertainty bounds of GCM-climate NHMM simulations, although there were also some areas of consistent bias between GCMs, particularly relating to an underestimation of high flows and overestimation of low flows at Scott Creek and Houlgrave Weir catchment, and an overestimation of median flows at Echunga Creek catchment.

The models that yielded the greatest discrepancy between the observed flow and the median of the simulated flow for at least one of the catchments and flow metrics were the GFDL models (GFDL-ESM2G and GFDL-ESM2M) the MIROC models (MIROC.ESM and MIROC5), CSIRO-Mk-3.6 and INM-CM4. Nevertheless, visual inspection of the results for all the simulations and catchments showed that any underestimation or overestimation by these models was generally consistent with the remaining models from the CMIP5 simulations. This means that no clear 'outlier' models (i.e. models that performed consistently worse than other models) were identified for removal or further scrutiny.

In some cases, the within-model variability (indicated by the interquartile range and 90 % uncertainty interval) was wider than the between-model variability. However as will be shown in the third volume of this report, the between-model variability becomes substantially higher when considering future GCM-derived projections. For this reason, we do not recommend using a single model or small subset of models to develop future climate projections.

The issue of consistent underestimation of high flows is important, as a significant proportion of the total annual flow occurs in a small number of wet days. (see Table 6) Therefore, in the following section we investigate the possible reasons for these biases and how they contribute to biases in the total flow volume.

6 Investigation of Biases in NHMM Runs

Based on results from the reanalysis-climate and GCM-climate flows using both the CMIP3 and CMIP5 archives, there is a tendency for hydrological simulations forced by NHMM data to underestimate high flows and overestimate low flows, with the net effect being that average annual flows are underestimated. We now further investigate simulations from the reanalysis run to identify reasons for the observed biases.

6.1 Bias correction of daily rainfall distribution using quantile correction

We first examine the distribution of Scott Creek catchment average precipitation for the reanalysis-climate flows (Figure 11 and Figure 12). The reanalysis-based precipitation is typically lower than observed precipitation for high non-exceedance probability events, with the absolute magnitude of the difference between simulated and observed being as much as 20% lower for high precipitation events. The remainder of the distribution shows better performance, and in almost all cases except for very low precipitation events, the observed precipitation is within the range of simulated values. The discrepancy for precipitation below 1 mm is due to the definition of 'dry days' in the NHMM algorithm being days with less than 1 mm precipitation, whereas observed rainfall is measured at a resolution of 0.2 mm.

Simulated evapotranspiration generally shows close correspondence to observed evapotranspiration (Figure 13) across all exceedance probabilities, with the range of simulated values being small. Therefore, biases in precipitation are more likely to account for possible biases in flow compared to possible biases in potential evapotranspiration.

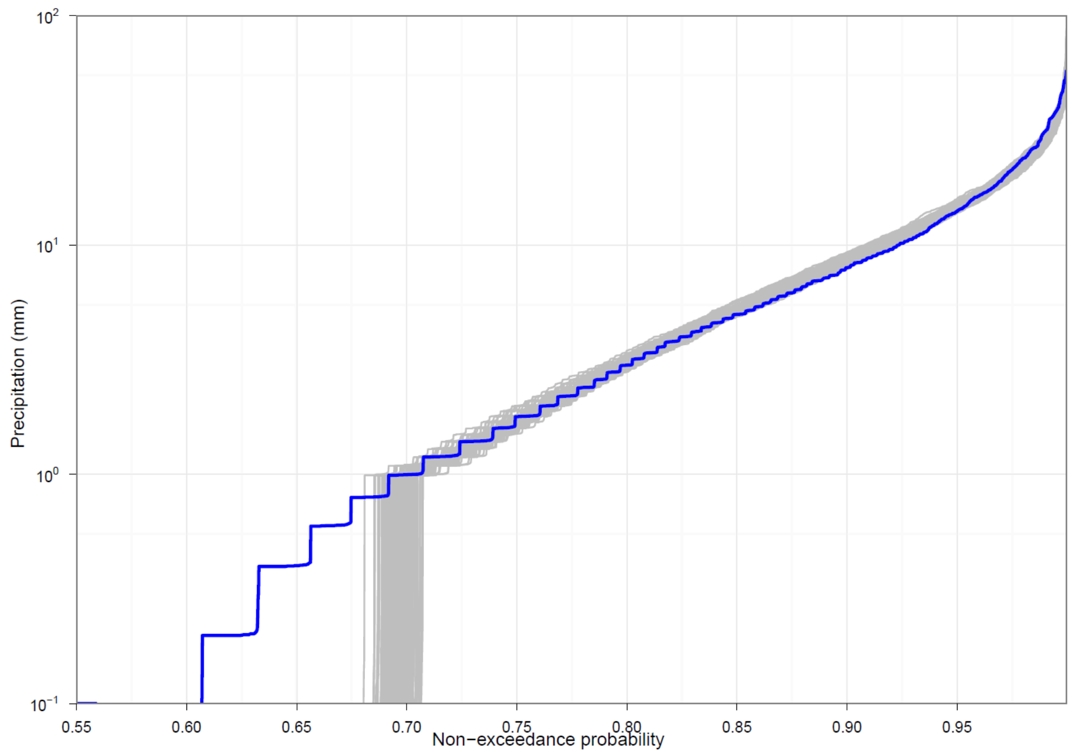

Figure 11: Non-exceedance probability plot of catchment-average precipitation at Scott Creek catchment. Both observed data (blue line) and NHMM simulated reanalysis data (grey lines) are presented.

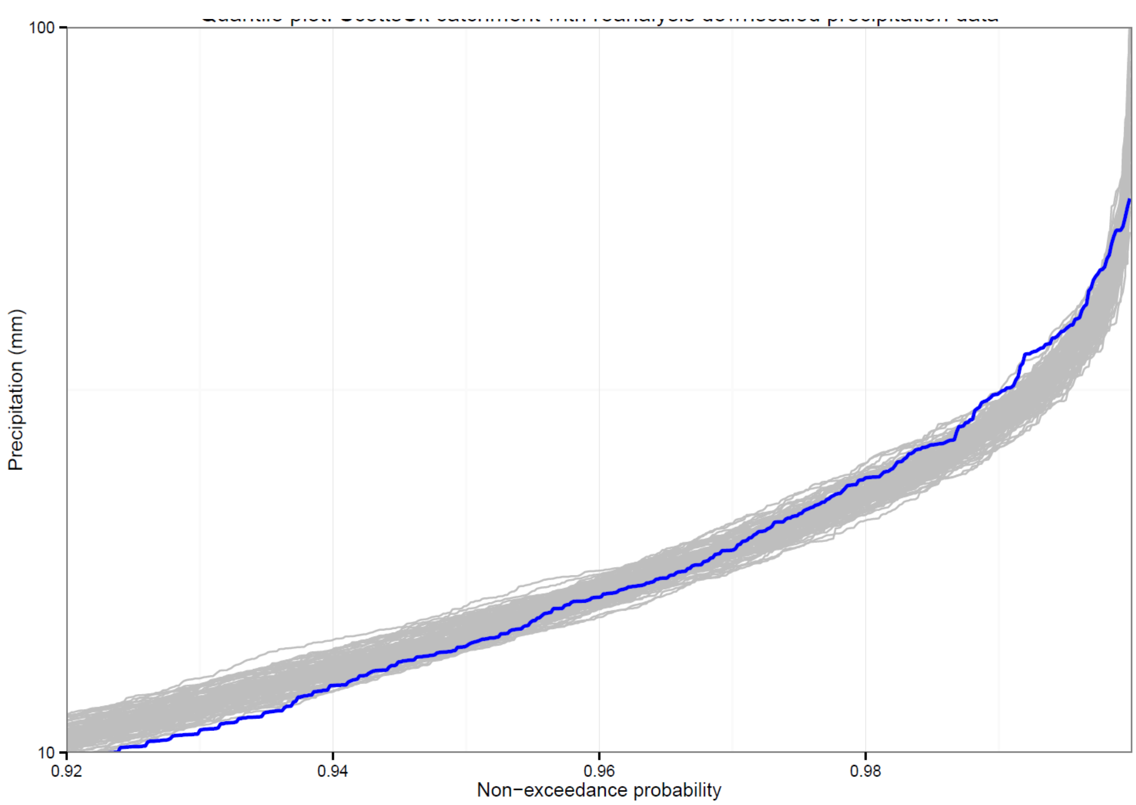

Figure 12: As for Figure 11 for top 8% of rainfall distribution.

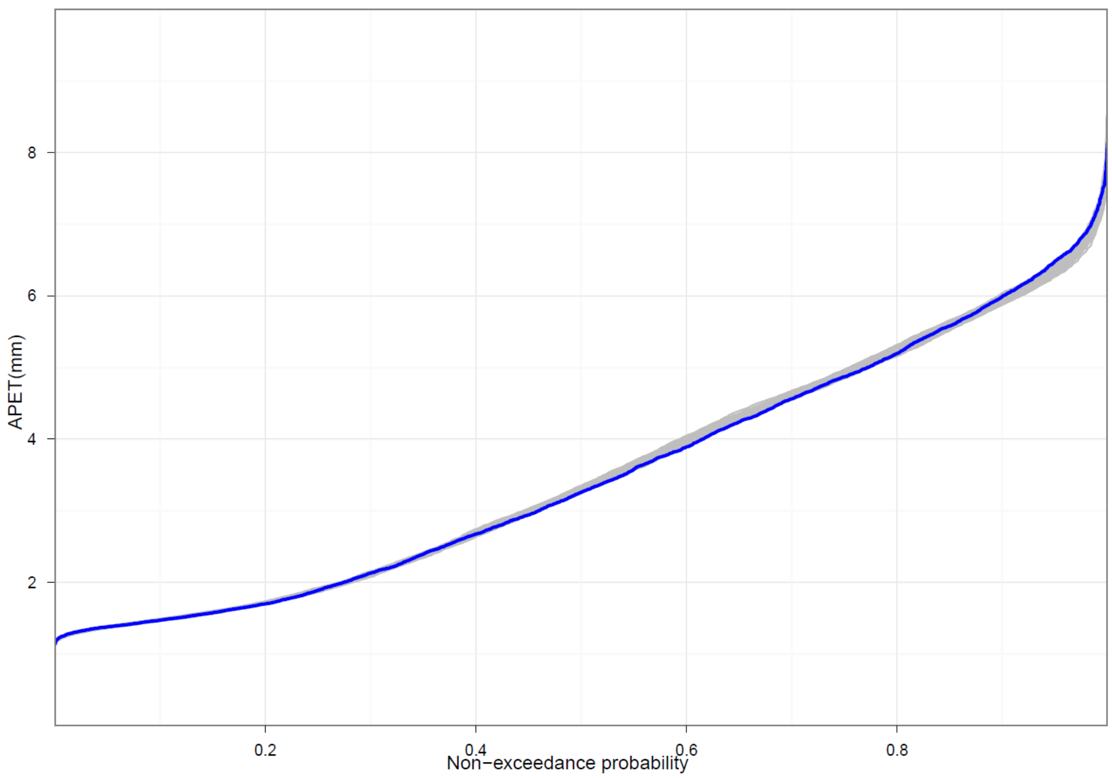

Figure 13: Non-exceedance probability plot of catchment-average potential evapotranspiration at Scott Creek catchment. Both observed data (blue line) and NHMM simulated reanalysis data (grey lines) are presented.

To determine whether possible biases in the precipitation and potential evapotranspiration data lead to the biases in the flow as described in Sections 4 and 5, both variables were quantile-corrected using R package `qmap` [*Gudmundsson et al.*, 2012]. This algorithm matches the empirical cumulative distribution function of the simulated data with that of the observed data using a linear interpolation approach.

The revised marginal distribution of the simulated precipitation and potential evaporation now matches the observations, with precipitation results presented in Figure 14 and evapotranspiration results presented in Figure 15. The exception is for very low precipitation events, however these are unlikely to have a significant impact on annual flow volumes or peak flows.

The flow duration curve obtained when applying GR4J to the quantile-corrected inputs is shown in Figure 16, and can be compared to the flow duration curve without quantile correction (Figure 3). Interestingly, the simulated results still underestimate high flows and overestimate low flows, to a similar degree as the non-quantile-corrected results. The median of the simulated annual flow rates is 124 mm, which is similar to the simulated median without quantile correction, and lower than the median observed flow of 142 mm.

Given that there is still a bias in simulated flows even through the marginal distributions of daily precipitation and potential evapotranspiration are accurately reproduced after quantile correction, and that seasonality of the precipitation is also correctly reproduced (Figure 17), there must be another factor that is causing this biases. This is investigated in the next section.

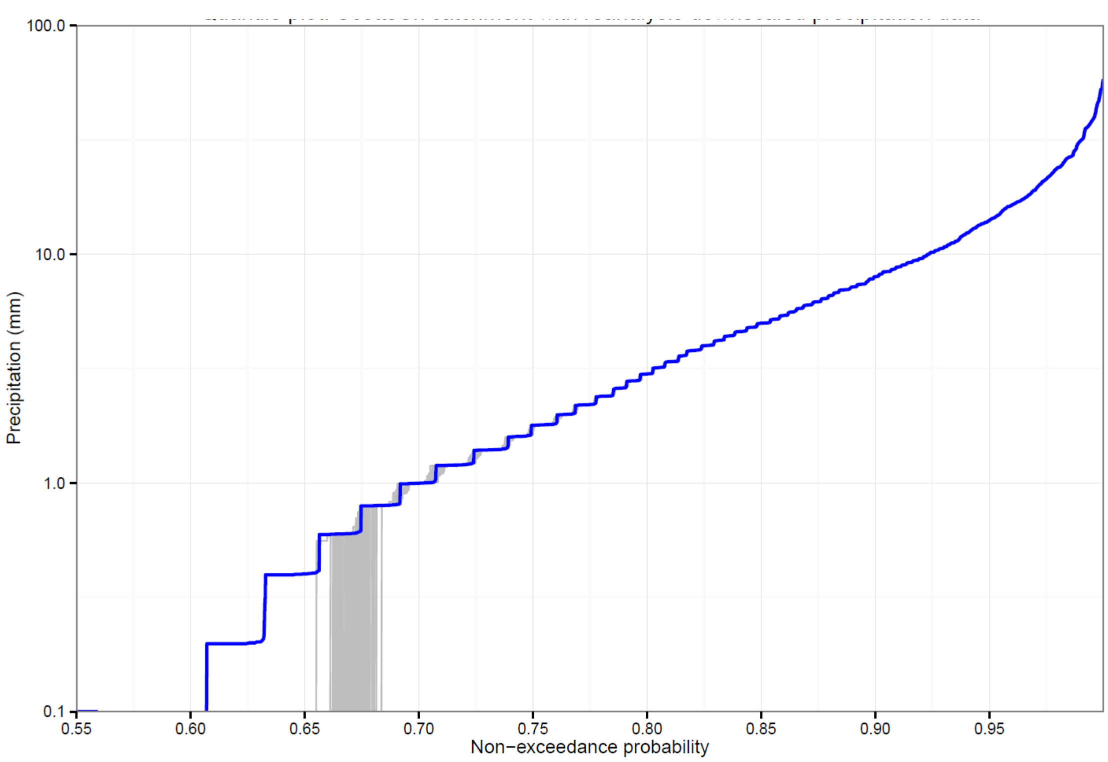

Figure 14: Non-exceedance probability plot of catchment-average precipitation at Scott Creek catchment. Both observed data (blue line) and quantile-corrected NHMM simulated reanalysis data (grey lines) are presented.

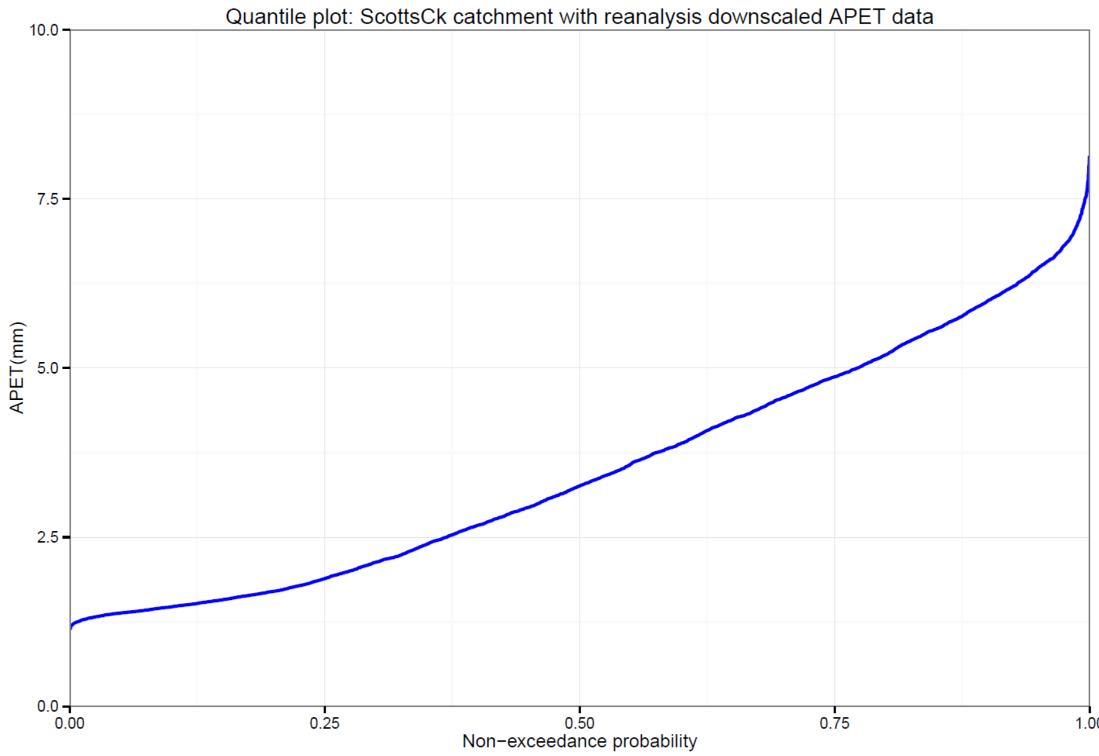

Figure 15: Non-exceedance probability plot of catchment-average potential evapotranspiration at Scott Creek catchment. Both observed data (blue line) and quantile-corrected NHMM simulated reanalysis data (grey lines) are presented.

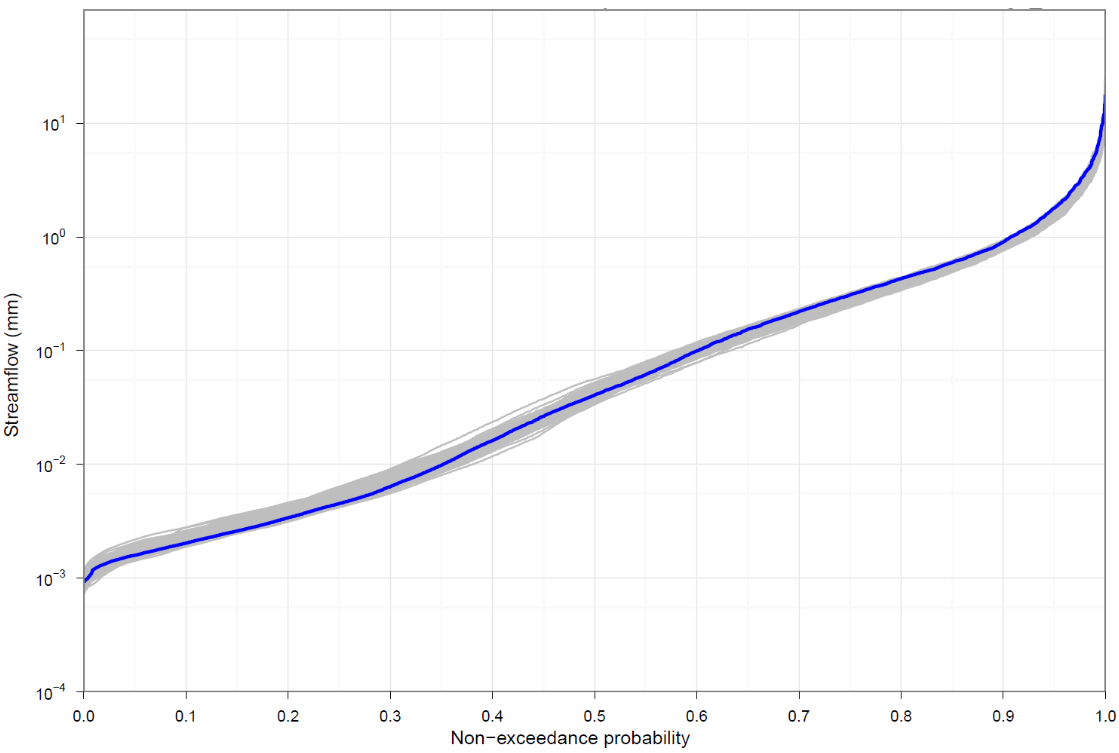

Figure 16: Flow duration curve for Scott Creek, using quantile-corrected reanalysis climate data. Solid blue line represents flows obtained by the standard version of GR4J using observed rainfall

and APET, while grey lines represent 100 realizations of rainfall and APET obtained from reanalysis.

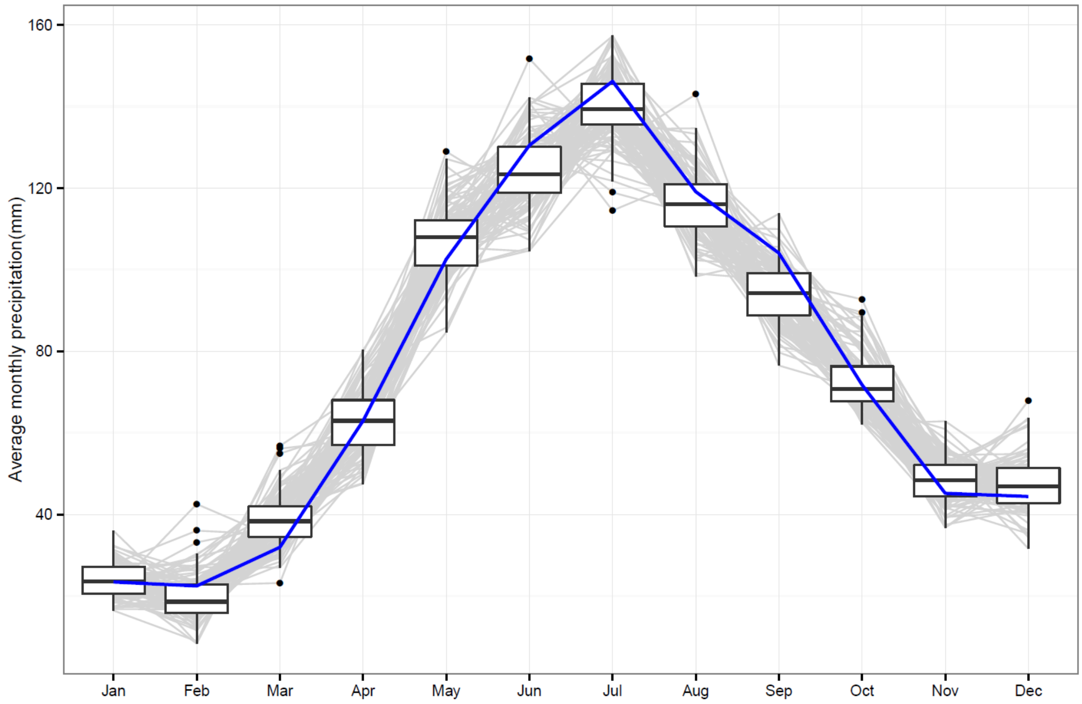

Figure 17: Monthly average precipitation after quantile correction. Grey lines represent 100 realizations of precipitation, and blue line represents the mean from all realisations.

6.2 Biases in multi-day precipitation amounts

In this section we investigate whether poor representation of extreme rainfall intensity across multiple consecutive wet days might explain the observed underestimation in high flows. Typically, a significant degree of day-to-day persistence exists in precipitation time series [*Mehrotra et al.*, 2012], with wet days being more likely to be preceded and followed by other wet days and with rainfall magnitudes correlated across days. Failure to accurately represent extreme rainfall events across multiple days might therefore have a significant impact on the simulation of high flows [*Pathiraja et al.*, 2012].

To investigate whether the persistence is adequately represented in simulated data, the daily precipitation time series was aggregated to different durations ranging from two days through to 14 days. The 95, 99 and 99.8 percentile precipitation depths at each period of aggregation were then extracted from both the simulated and observed series. The 99 percentile rainfall are shown in Figure 18 (results for the 95 and 99.8 percentile are consistent with this figure). Because of quantile correction, the 99 percentile simulated rainfall is identical to the observed rainfall for one day period, however differences emerge with increased levels of aggregation. Importantly, all but one of the 100 NHMM simulations are below the observed precipitation, implying that the day-to-day persistence in rainfall is underestimated.

This result potentially explains the discrepancy between the observed and simulated flow volumes in the Onkaparinga catchment. Table 6 shows that a small number of high flow days make a significant contribution to the total flow volume. For example, for Scott Creek, the top 2% of high flow days contribute 32% of the flow volume, while the top 10% of high flow days contribute 67% to the flow volume. Hence, any errors in the high flow events will impact the annual water balance. Furthermore, the large elasticity of flows in the Onkaparinga (with a 1% change in annual rainfall leading to a >3% change in flow) indicates that small biases in rainfall will be strongly amplified when examining flow time series.

Table 6: Contribution of the high flow days to the total flow volume

Catchment	**Top 10% high flow days**	**Top 2% high flows days**
Scott Creek	67%	32%
Echunga Creek	80%	44%
Houlgraves Weir	70%	35%

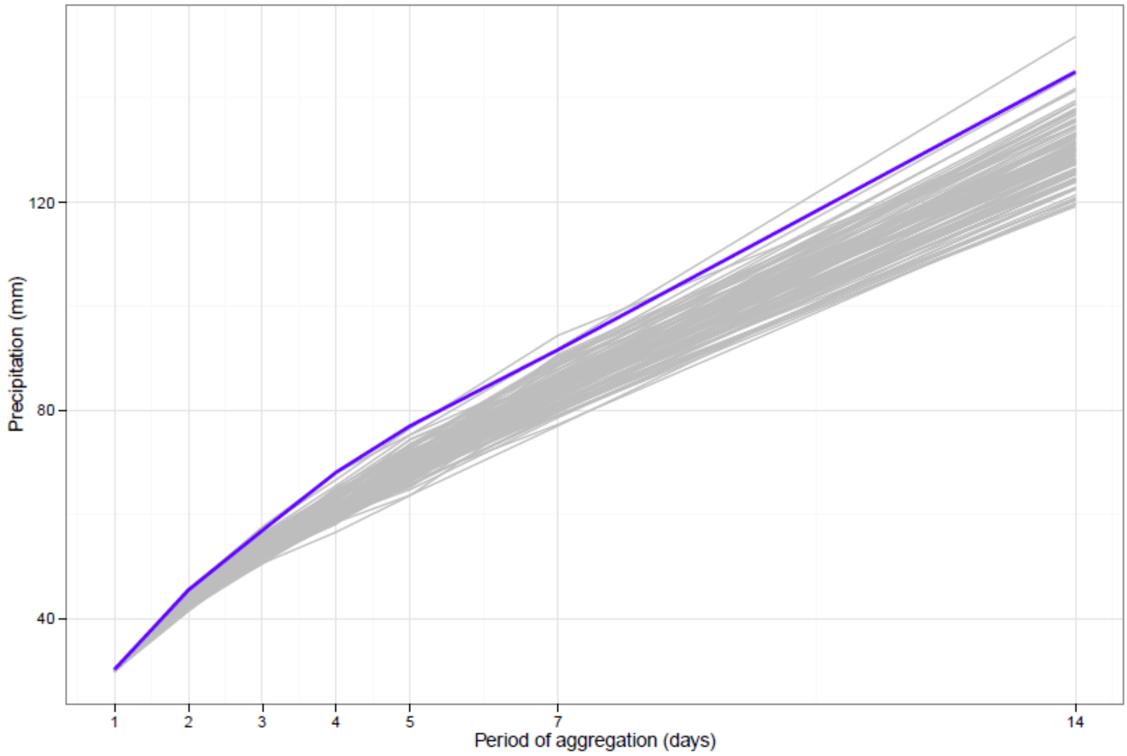

Figure 18: 99th percentile observed (blue) and quantile-corrected simulated (grey) precipitation at Scott Creek at different scales of aggregation.

6.3 Evaluation of options to handle the biases in downscaled data.

The previous analysis showed that quantile correction of the daily rainfall was not able to correct for the biases in the multi-day rainfall accumulations. These biases in the multi-day rainfall accumulations produce underestimations of high flows and hence underestimations of annual flows. Developing approaches to resolve this issue and provide more reliable projections of climate change impacts is not a trivial exercise. The following options were evaluated to handle the biases in the downscaled data:

(1) Improving the NHMM rainfall downscaling method

Improving the ability of the NHMM downscaled approach to better reproduce the multi-day rainfall accumulation amounts would be the best approach to resolve this issue. However, the scope of this component of the Goyder climate change project was to undertake a hydrological evaluation of the downscaling projections, rather than develop improvements to the downscaling approach. In this project, a series of trial improvements to NHMM were provided by CSIRO *[Charles et al, pers com]*, and were evaluated (results not shown) but none were able to produce significant improvements. It is recommended that future research develop approaches to improve the downscaling method to better reproduce the observed distribution of multi-day rainfall accumulations. Once this is achieved the GCM and downscaling approaches can be evaluated using a split-sample approach [*Frost et al.*, 2011], where the historical record is split into two periods, one used to calibrate the GCM and downscaling approaches and the second used to test the approaches. This will provide an assessment of the reliability of the GCM + downscaling approaches.

(2) Utilising the relative change approach to provide climate change projections

Given the existence of these biases, a simple pragmatic approach to develop projections is to adopt a “relative change” approach. This is where the impact of climate change on streamflow is evaluated by comparing the relative change in the streamflow statistics between the historical and future climate periods simulated by the GCM+NHMM-based rainfall and potential evapotranspiration and the hydrological model. The benefits of this approach are that it is easy to implement and is internally consistent because the relative changes are evaluated between the historical and future period using the same GCM, NHMM and hydrological model combination. This approach assumes the biases that exist the historical period are the same in the future climate period. In this sense, it is conceptually similar to undertaking quantile correction of the streamflow. Until the biases in the downscaling method are addressed the relative change approach is a pragmatic method to estimate the impact of climate change on streamflow.

7 Conclusions and Recommendations

A detailed comparison was undertaken of simulated flows using NHMM predictions from reanalysis and climate model simulations against simulated flows based on observed rainfall and PET. The comparison was conducted for three sub-catchments of the Onkaparinga, using the hydrological model GR4J. The emphasis of the evaluation was on the reanalysis-climate runs, as these results provide a more direct reflection of the performance of the NHMM algorithm. Diagnostics considered include:

- Annual flows, including annual averages, the annual coefficient of variations, and low- and high-flow years;
- Monthly average flows; and
- The flow duration curve, calculated over (i) all flow days; (ii) the highest two percent of flow days; (iii) individual seasons; and (iv) rising and falling limbs of the hydrograph.

For the GCM-climate model results, a more limited set of summary statistics was used to facilitate comparison between the five CMIP3 models and 15 CMIP5 models across the three subcatchments in the Onkaparinga catchment.

Generally, observed flows were within the range of simulated flows, indicating that the climate models perform well in capturing a diversity of scenarios representing historical flow. Nevertheless, areas of systematic bias were identified, particularly with relation to high flows at Houlgrave Weir and Scott Creek. These biases impacted on annual flow volumes, since a very large proportion of the overall flow volume comes from a small number of high-flow days. In contrast, low flows were generally overestimated. A review of the reanalysis runs as well as the CMIP3 and CMIP5 archive runs shows that the performance is similar, and thus is more likely to be associated with the NHMM algorithm rather than the forcing GCM.

An investigation into possible causes of systematic biases revealed that the following factors were likely to be important contributors:

(1) The multi-day consecutive wet spell intensity is underestimated, so that biases remain even after quantile-correcting the marginal precipitation and potential evapotranspiration distributions. This can lead to an underestimation in extreme flows, which are a major contributor to the total annual flows; and
(2) The runoff coefficient in the Onkaparinga is low (e.g. 0.14 at Houlgrave Weir), and the flows are highly ‘elastic’, with small changes in rainfall leading to large changes in flow. The implication is that small errors in hydroclimatic forcing variables, and particularly rainfall, are likely to be amplified in the predicted flow.

One of the key recommendations of this report is that future research be conducted to develop improved downscaling techniques that can reproduce this multi-day rainfall amounts, and that these approaches are evaluated using a split-sample procedure.

Until these issues are addressed it is recommended that a “relative change” approach be adopted to assess the impacts of climate change on streamflow in the Onkaparinga catchment. This is approach that will be used in the third volume of this report [*Westra et al.*, 2014].

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The Goyder Institute for Water Research is a partnership between the South Australian Government through the Department of Environment, Water and Natural Resources, CSIRO, Flinders University, the University of Adelaide and the University of South Australia.