NARCliM 1.5 projections and stochastic simulations over the southern basin

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Department reference number: PUB24/331

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Executive summary

The New South Wales Department of Climate Change, Energy the Environment and Water has adopted a risk-based methodology to account for climate variability and change in developing its regional water strategies, whereby climate risk assessment is conducted using stochastically generated long-term sequences that reflect potential climate patterns beyond those contained within the instrumental record (Leonard et al. 2022). A pilot analysis of precipitation trends in southern New South Wales found statistically significant evidence of non-stationarity in multiple weather variables and found that this non-stationarity is broadly consistent with expectations resulting from climate change projections (Devanand et al. 2020). As such, the application of climate risk assessment to this region needs to account for the identified non-stationarity in the observed climate record.

This report complements the pilot analysis by documenting historical biases and future changes associated with 6 model variants from NARCliM 1.5 simulations of the southern region, focusing on the hydrologically relevant attributes of precipitation, temperature and evapotranspiration. This analysis has been undertaken for 2 future time windows centred on 2030 and 2070, for scenarios RCP 4.5 and RCP 8.5.

NARCliM 1.5 is evaluated for model ensemble averages with respect to gauged data in the southern region for 2 cases:

- GCM runs forced with historical greenhouse gas forcings ('historical runs') over the period 1951–2005
- reanalysis runs ('evaluation runs') for the period 1979–2013.

The results of this evaluation show that the ensemble averaged NARCliM 1.5 simulations contain large positive biases in annual totals (+32% and +37% for the historical and evaluation runs, respectively) and seasonal totals. The simulations also identified biases in the number of wet and heavy precipitation days, with ensemble mean biases in the annual number of wet days of +35% and +32% and the number of heavy precipitation days of +32% and +26% for the historical and evaluation runs, respectively. These and related results suggest that biases in annual and seasonal totals are mostly associated with the overestimation of precipitation frequency rather than the amount of precipitation when it occurs.

Turning to other variables, the simulations underestimate maximum daily temperature and overestimate minimum daily temperature. In the historical run, the negative biases in maximum daily temperature are enhanced ($-2.1 \degree$ C to $-2.5 \degree$ C) compared to the evaluation run ($-1.3 \degree$ C to $-1.8 \degree$ C), while the positive biases in minimum daily temperature are lower. Morton potential evapotranspiration is underestimated with annual biases of -8% to -11%.

The NARCliM 1.5 projections were analysed for two 30-year time windows centred on 2030 and 2070, respectively. The range of grid-level future changes projected by the NARCliM 1.5 ensemble mean are not outside the ranges projected by other sources of climate projections.

• Future simulations show decreases on average in annual total precipitation across the region, with significant variability such that some model configurations show increases. The magnitude of decreases in ensemble average precipitation is higher in the RCP 8.5 simulations. There are significant differences between the NARCliM model variants, indicating that variability in projections is an important source of uncertainty.

- Seasonal precipitation totals exhibit decreases on average during MAM, JJA and SON. The highest magnitude of decreases is in SON. The changes in DJF precipitation show mixed patterns (decreases and increases). There are decreases in the number of wet and heavy precipitation days annually and during MAM, JJA and SON, while the mean precipitation intensity during wet/heavy precipitation days exhibits a mixed pattern of changes (increases and decreases) annually and seasonally.
- Annual and seasonal totals/means of potential evapotranspiration and temperature (minimums and maximums) exhibit increases in the future simulations.

Scaling relationships are developed at each gauge location to modify stochastic simulations of the southern basin region so that they conform to projections of future climate. A method of seasonal simple scaling is compared to daily quantile scaling, with the latter adopted due to its ability to better represent changes in precipitation occurrence attributes. A longer historical baseline, 1951–2005, was adopted in preference to a shorter baseline due their similar performance relative to overall uncertainty, and due to the improved representativeness that comes by utilising the full NARCliM 1.5 historical period.

The 6 model variants of NARCliM 1.5 simulations produce patterns significantly different from each other (some showing decreases, others showing increases). These differences in patterns may influence precipitation-runoff models differently from an ensemble average 'best' estimate. Therefore, it is desirable to enable subsequent analyses to investigate impacts of model variants, but it is not pragmatic to provide 10,000-year future climatic time series for each model configuration and climate scenario due to the lengthy simulation time of hydrological models (that is, eWater Source). Therefore, two 10,000-year stochastic time series have been derived for each point location, corresponding to the 2 future climate time windows (centred on 2030 and 2070, respectively). Each time series comprises a single record with contiguous blocks of 833 years for each of the 6 NARCliM variants and 2 representative concentration pathways. This approach means that a single 10,000-year simulation for a given time window can be used to generate streamflow to be analysed either in terms of replicates of an ensemble average or according to specific model configurations or concentration pathways.

1 Introduction

The department has adopted a risk-based methodology to account for climate variability and change in developing the regional water strategies for multiple basins in New South Wales. The method involves the use of stochastically generated long-term sequences of climate data to characterise the current climate, and the application of scaling factors to stochastic data to generate future climate projections. The stochastic modelling uses historical (observed/reconstructed) records of daily precipitation, evapotranspiration and temperature as the basis for generating synthetic data for 10,000 years that reflect variability over the observed record and provides insights beyond the available observations.

This report is focused on the southern basin region, which includes the Murrumbidgee, Murray and Snowy catchments as well as regions of Victoria and South Australia. The project has been conceived according to 3 stages, with Stage 1 documented separately and this report documenting Stage 2 and Stage 3.

- Stage 1 (Leonard et al. 2022) Stochastic simulations based on the historical record under stationarity assumptions, adopting a consistent methodology with earlier stochastic generation work and maintaining correlations with previously generated stochastic sequences.
- Stage 2 (this report) Assessment of future changes from NARCliM 1.5 data for a range of key climate attributes, and qualitative comparison with projected changes from other sources of information on climate change projections. This stage determines a set of scaling factors based on best-available understanding of likely change in the southern basin.
- Stage 3 (this report) Stochastic simulations outlined in Stage 1 are translated to future climates consistent with a historical baseline and scaling factors identified in Stage 2.

The application of risk assessment to the southern region needs additional consideration, beyond that for other regions, because several key hydrometeorological variables in this region are reported to exhibit non-stationary changes in the recent past. In particular, increases in temperature and decreases in the number of wet days and total precipitation during the cool season have been reported, and these changes have at least partly been attributed to anthropogenic influences (Karoly & Braganza 2005; CSIRO 2012; Jones 2012; Hope et al. 2017).

Based on the recommendation of an expert panel review of the climate risk method applied in the northern New South Wales regions, the department commissioned a pilot assessment to understand the implications of this non-stationarity for stochastic data generation and future climate scaling in the southern basin region. The results of the pilot assessment recommended approaches to account for non-stationarity in the climate risk assessment of the southern region (Devanand et al. 2020). The recommendations rely primarily on the selection of a representative 'baseline climate', and then adjust this baseline to produce estimates of possible future changes. The pilot assessment also indicates that the future scaling method used in the southern region should account for changes in multiple attributes of precipitation (for example, number of wet days, seasonal totals, extremes), in addition to seasonal and annual totals that are more commonly considered in scaling studies.

Thus, to account for non-stationarity in the southern basin region, it is necessary to generate a stochastic dataset that is representative of the same historical baseline climate that is used to calculate the future climate change factors. This poses a challenge because historical baselines used in future climate assessments tend to be approximately 20 years long, which is too short for

stochastic generation to estimate the parameters of a stochastic model accurately. A baseline of at least 30 years is recommended to capture the natural climate variability of south-east Australia (WMO 1989; Potter et al. 2016). The NARCliM project produces ensembles of regional climate projections over south-east Australia and contains 2 sets of released projections, namely NARCliM 1.0 (released 2014) and NARCliM 1.5 (released 2020). The longer length of the historical baseline of the NARCliM 1.5 dataset (compared to the NARCliM 1.0 dataset) makes it desirable for use in the department's climate risk method for the southern basin region.

This report documents future changes in the relevant attributes of precipitation, temperature, and evapotranspiration over the southern region for selected future time windows from the NARCliM 1.5 dataset to facilitate the application of the department's climate risk method in this region. Table 1 summarises the methodology and analyses documented in this report for conforming stochastic simulations to projections of future climates.

Modelling aspect	Requirement
Model configurations and RCP scenarios (Section 2.1)	Identify a reliable set of models as the basis for comparison
Spatial representation (Section 2.2)	Attributes at grid points from model outputs need to be translated to point locations for sites of interest
Future time windows (Section 2.3)	Scenarios and time windows should be relevant to the department's application needs
Climate attributes to evaluate (Section 2.4)	Should cover representative features of precipitation, potential evapotranspiration and temperature
Analysis against observations (Section 3.1)	Analyse climate model performance
Analysis of future periods (Section 3.2)	Analyse strength and consistency of climate signal
Generation of stochastic time series (Section 4)	Determine historical baseline, method for modifying stochastic sequences, representation of uncertainty across model configurations and scenarios

Table 1 Summary of modelling decisions addressed in this report for analysing climate projections and conforming stochastic simulations to climate projection attributes

2 Method for evaluating NARCliM and generating climate projections

2.1 NARCliM 1.5 overview

Summary

NARCliM 1.5 simulations are used in preference to NARCliM 1.0 due to the latter model having a baseline that is insufficient for hydrological risk assessments.

Six different model variants are considered (3 CMIP5 GCMs for boundary forcing each with 2 variants of the Weather Research and Forecasting (WRF) RCM.

The NARCliM project produces ensembles of regional climate projections over Australia at resolutions of 10 km and 50 km. The 50 km resolution simulations are performed on the Coordinated Regional Climate Downscaling Experiment (CORDEX) Australasia domain that covers the entire country. The finer 10 km resolution simulations are performed over a smaller domain that covers south-east Australia, and this is referred to as the NARCliM domain.

The first set of model outputs from the project, named the NARCliM 1.0 dataset, was released in 2014 (Evans et al. 2014). An updated version of the dataset based on new climate simulations, named the NARCliM 1.5 dataset, was completed in 2020. One of the key differences between the 2 datasets is the length of the simulations. The NARCliM 1.0 dataset contains simulations that are 20 years long, corresponding to selected time windows from the historical and future periods: the historical baseline of this dataset spans 1990–2009. Thus, selection of an alternative baseline and future periods is not possible with this dataset. In contrast, the NARCliM 1.5 dataset contains continuous simulations for the historical and future periods, together spanning 1951–2100.

The NARCliM project recommends using the NARCliM 1.5 dataset in conjunction with the NARCliM 1.0 dataset to understand the impacts of climate change (DPIE and UNSW 2020). However, due to the shorter length of the NARCliM 1.0 simulations, this dataset is not recommended for use in hydrological applications that are highly sensitive to multiyear variability. Therefore, the analysis presented in this report is based only on the NARCliM 1.5 dataset. The longer length of these simulations is beneficial for application to the southern region because it makes it possible to:

- use baselines of length greater than or equal to 30 years, which is necessary to capture the high natural climatic variability in this region
- use alternative baseline periods to explore sensitivity of results on baseline selection
- calculate change factors for selected future time windows of interest using the continuous simulations into the 21st century.

Table 2 lists the simulations available from the NARCliM 1.5 dataset. The dataset contains 4 sets of simulations corresponding to past and future periods. The simulations employ 2 configurations of the WRF model that differ in the convective parameterisation scheme used. The evaluation run uses boundary conditions from the ERA-Interim reanalysis data for the period 1979–2013 for the 2 regional model configurations and contains 2 ensemble members. The historical simulations

and future projections use boundary forcings from 3 CMIP5 GCMs, resulting in a total of 6 ensemble members. The 3 CMIP5 GCMs are reported to be selected for satisfactory model performance based on literature, independence of model errors, and span of future simulated changes complementary to the GCM spread of the models used for NARCliM 1.0 (DPE 2020). The future changes simulated by the forcing GCMs are (DPE 2020):

- annual mean precipitation changes of -25% to 0.3% between 2060-2079 and 1990-2009
- annual mean temperature changes of 3.19 °C to 3.72 °C between 2060–2079 and 1990–2009.

Simulation name	Global forcing	Regional models	Period	Action
Evaluation	ERA-Interim reanalysis data	Two configurations of the WRF model	1979–2013	Compare to observed data
Historical	CCCMa-CanESM2 CSIRO-ACCESS1.0 CSIRO-ACCESS1.3	Two configurations of the WRF model (WRF360J and WRF360K)	1951–2005	Compare to observed data and calculate future changes
Future projections RCP 4.5, RCP 8.5	CCCMa-CanESM2 CSIRO-ACCESS1.0 CSIRO-ACCESS1.3	Two configurations of the WRF model (WRF360J and WRF360K)	2006–2100	Calculate future changes

Table 2 NARCliM 1.5 simulations

Given the recency of the NARCliM 1.5 simulations, only a few publications are available to describe the NARCliM results. The first of these is by Di Virgilio et al. (2019), who documents the evaluation of the 50 km resolution reanalysis driven CORDEX regional model outputs over Australia through comparison with gridded observations. The key results indicate that the simulations exhibit cold biases in maximum temperature, warm biases in minimum temperature, and overestimates in precipitation. All the RCMs show statistically significant cold biases in maximum temperature (exceeded -5 °C for some simulations), and the biases are much higher in winter compared to summer.

These biases are noted to be particularly characteristic of the WRF RCM configurations. The cold biases in mean annual temperature maximums are more intense in the eastern regions of the country. Their results show warm biases in annual mean temperature minimums, and wet biases in mean annual precipitation over New South Wales. The maximum temperature cold bias is thought to be linked to soil moisture biases driven by the precipitation biases.

A recent reference by Nishant et al. (2021) introduces the 10 km resolution NARCliM 1.5 simulations. The NARCliM 1.5 simulations are reported to exhibit lower precipitation biases than NARCliM 1.0; moreover, the seasonal patterns and magnitudes of precipitation are represented better. Nevertheless, the NARCliM 1.5 simulations exhibit wet biases in precipitation and cold biases in maximum temperature. Nishant et al. (2021) also analysed the future simulations and report that the NARCliM 1.5 dataset projects a hotter and drier future compared to NARCliM 1.0.

2.2 Spatial domain for comparison

Summary

When comparing to observations, gridded values from NARCliM 1.5 are averaged using an inverse distance-squared method of weighting centred on the gauge location.

When comparing to other published studies from literature, the model domain from this study is different, but has considerable overlap.

Figure 1 shows the location of the observed gauges in the southern basin that are used for stochastic data generation. The observed data contain a total of 284 precipitation, 160 Morton wet (Mwet) evaporation, 17 Morton potential evaporation (Mpot), and 100 temperature (55 maximum temperature, Tmax; 45 minimum temperature, Tmin) gauges that span many regions, including the Murrumbidgee, Murray, Lower Darling, Wimmera-Mallee, Snowy, Ovens and Mount Lofty regions. The historical and evaluation simulations from NARCliM 1.5 are compared with observed data from these gauges to quantify the biases in attributes of precipitation, evaporation, and temperature listed in Table 3. An additional 92 precipitation sites identified subsequent to this analysis are included in the generation of change factors. A further 237 potential evapotranspiration sites identified in the southern region utilise other formulations, including the SILO FAO56, SILO Morton Lake and IQQM variants. These variants are primarily colocated at sites with Morton wet time series and not used for NARCliM comparison. The derivation of stochastic time series for future time series is nonetheless required at these sites, and the scaling identified from NARCliM analysis will be applied to these time series.



Figure 1 Location of observation gauges in the southern basin region

2.2.1 Method of relating point locations to model grid

NARCliM 1.5 projections cover an area defined by a 0.1 degrees by 0.1 degrees (~10 km) resolution grid having 135 by 77 cells. Comparison with observations requires a relationship between the gridded values and the point location of each gauge. Previous studies involving NARCliM 1.0 used an inverse distance-squared weighting technique available via the NCL function rcm2points, (pers. comm. D. Dutta, Department of Planning and Environment, 30 May 2022). The same technique has been adopted for this study, which was replicated using a script in R. The algorithm assumes that all latitudes and longitudes refer to a spherical earth rather than an ellipsoid (with distances calculated via the haversine formula).

2.2.2 Comparison with alternative lines of evidence

The changes in annual and seasonal climate variables projected by NARCliM 1.5 are compared with available estimates from alternative sources of evidence. The primary other sources of future climate projections used for comparison are:

- Climate Change in Australia (CCIA) Murray sub-cluster (Timbal et al. 2015)
- Loddon Campaspe, Goulburn, Ovens and Murray regions from Victoria Climate Projections 2019 (VCP19) (Clarke et al. 2019).

Figure 2 shows the regions used for reporting future changes by the alternative sources of climate projections. The projections from these sources are compared with the range of grid-level changes from the NARCliM 1.5 ensemble mean data. The dashed boxes in Figure 2 indicate the broad area over which the range of changes projected by NARCliM 1.5 are summarised for comparison with other projections. The black and red dashed boxes, which include most of the observation precipitation/evapotranspiration and temperature gauges, respectively, show the data domains used in this study for comparison.



This report summarises the range of grid-level future changes from NARCliM 1.5 over the black dashed box for precipitation and evapotranspiration and red dashed box for temperature, which include most of the observation gauges.

Figure 2 The regions used for reporting future changes by different sources of projections, CCIA and VCP19, and the location of the observation gauges that are used for stochastic data generation in the southern region

2.3 Timelines for comparison

Summary

The NARCliM 1.5 historical period (1951–2005) and reanalysis period (1979–2013) are used to assess biases in the climate model simulations.

When comparing with observations, periods identical to the climate model simulation are used.

NARCliM 1.5 historical simulations are considered over 2 baseline periods, a 30-year period, 1976–2005, representing the most recent simulation period available, and the full historical period, 1951–2005.

A minimum 30-year period is preferred for hydrological comparison. This study uses 30-year periods that encompass the 20-year periods available from other studies for the historical baseline and future time windows.

Figure 3 provides a comparison of periods used for calculation of attributes from climate projections. Wherever there is a comparison to attributes from observed time series a commensurate period was used to match the specific projection.



Figure 3 Periods used for analysis of climate projections

2.3.1 Periods for evaluation of climate model performance

Regional climate simulations typically exhibit biases due to errors in the global boundary forcing data used for the simulations and errors in the representation of processes within the regional model. The NARCliM 1.5 dataset contains 2 sets of simulations that can be used to quantify these biases:

- 'evaluation runs' that use boundary forcing from 'perfect-boundary' reanalysis data
- 'historical runs' that use boundary forcing from historical GCM simulations.

The former provides a measure of the biases induced specifically by the regional downscaling analysis, whereas the latter combines 3 sources of uncertainty: RCM uncertainty; GCM uncertainty; and additional stochastic uncertainty given that the GCM simulations are not designed to simulate the temporal evolution of historical climate. Therefore, it is necessary to compare climate attributes from the 2 sets of simulations with observations at the gauges to quantify the biases. The period of record for reanalysis runs is 1979–2013 and the period for historical runs is 1951–2005.

2.3.2 Periods for comparison with alternative lines of evidence

The historical and future time windows used by CCIA and VCP19 are only 20 years. The near term (2030s) from both CCIA and VCP19 corresponds to the years 2020 to 2039 and the long term (2070s) corresponds to the years 2060 to 2079. Both datasets calculate future changes with respect to a 20-year historical baseline from 1986 to 2005. Time windows centred on 2030 and 2070 are chosen in this study to enable comparison to other studies. Thirty-year periods are preferred over 20-year periods for hydrological analysis, especially for extreme values.

2.3.3 Periods for scaling of stochastic simulations

The future projections from the NARCliM 1.5 dataset have continuous simulations from 2006 to 2100. We use the dataset to calculate projected changes in selected climate attributes (outlined in

Section 3) for two 30-year time windows corresponding to the near term (centred on 2030) and long term (centred on 2070).

The changes are documented with respect to 2 historical baselines:

- using the full available historical simulation from 1951 to 2005
- using a 30-year baseline from 1976 to 2005.

The 1976–2005 period represents the most recent 30-year baseline that can be selected from the historical NARCliM simulation. These numbers provide the scaling factors for the different attributes that are to be applied to the generated stochastic dataset for future climate risk assessment.

2.4 Climate attributes

Summary

All attributes used for evaluation and scaling are calculated on a seasonal basis.

There are 8 precipitation attributes and 1 attribute each for mean potential evapotranspiration, minimum temperature and maximum temperature.

Quantitative comparisons to historical attributes are conducted site-wise at the point locations of gauges in the study domain and gridded plots are used for visual inspection.

The attributes of precipitation, evapotranspiration and temperature used for the analysis are listed in Table 3. These are hydrologically relevant climate attributes that were used in the pilot assessment to understand the implications of non-stationarity for stochastic generation (Devanand et al. 2020). Here we evaluate these attributes from the NARCliM 1.5 simulations with respect to observations and quantify their projected future changes for application to the southern basin.

Variable	Attribute	Definition
Precipitation	Total	Total annual and seasonal (DJF, MAM, JJA and SON) precipitation (mm)
Precipitation	Wet day precipitation	Mean annual and seasonal wet day (P >= 1 mm) precipitation (mm/day)
Precipitation	Number of wet days	Annual and seasonal number of wet days (P > = 1 mm) (days)
Precipitation	Heavy day precipitation	Annual and seasonal heavy day (P >= 10 mm) precipitation (mm/day)
Precipitation	Number of heavy precipitation days	Mean annual and seasonal heavy day (P >= 10 mm) precipitation (mm/day)
Precipitation	Mean dry spell duration	Annual mean number of consecutive days with precipitation less than 1 mm (days)
Precipitation	Maximum dry spell duration	Annual maximum number of consecutive days with precipitation less than 1 mm (days)
Precipitation	Extreme intensity	Annual mean precipitation during days with precipitation greater than the 95th percentile (mm/day)
Evapotranspiration	Total evapotranspiration	Total annual and seasonal (DJF, MAM, JJA and SON) evapotranspiration (mm)
Temperature	Minimum temperature	Annual and seasonal (DJF, MAM, JJA and SON) mean daily minimum temperature
Temperature	Maximum temperature	Annual and seasonal (DJF, MAM, JJA and SON) mean daily maximum temperature

Table 3 Attributes of hydroclimatic variables used for the analyses

2.4.1 Comparison with alternative lines of evidence

The CCIA simulations are based on the CMIP5 model archive and incorporate climate model results from all available (up to 40) global climate simulations. The VCP19 estimates are based on simulations using a 5 km resolution model (CCAM) and the corresponding GCM results for Victoria. The NARCliM simulations used here consist of 6 ensemble members with boundary conditions from 6 CMIP5 GCMs. If the ranges from the CCAM simulations are smaller than comparable GCM runs, the GCM results have been used to expand the range as specified in the VCP19 usage directions. Precipitation comparison is focused on precipitation totals and does not extend to other attributes. There is a difference in the type of evapotranspiration estimates available from the datasets. The CCIA and NARCliM 1.5 numbers are based on Morton potential evapotranspiration, whereas VCP19 is based on pan evaporation.

3 Results of NARCliM analysis

3.1 Comparison of NARCliM 1.5 with observations

Summary

Consistent with literature: positive biases are seen in precipitation totals driven by biases in precipitation frequency; and in evaluation runs positive biases are observed in temperature minimums and negative biases are observed in temperature maximums.

Tables 4–6 shows the mean of the climate attributes at all gauge locations, the corresponding values derived from the NARCliM 1.5 dataset, and biases in the simulations in both absolute terms and percentage terms (except for temperature). The key results for all the variables are summarised below. Spatial figures of the ensemble mean and the observation points are shown in Appendix A for precipitation, Appendix B for temperature and Appendix C for potential evapotranspiration.

3.1.1 Precipitation comparison

The simulations show positive biases in annual and seasonal totals and the number of wet and heavy precipitation days in both the evaluation and historical runs; the signs of these biases are consistent with all the ensemble members (not shown). The magnitude of the biases in totals and wet/heavy days are the highest in summer and lowest in winter. The ensemble member from the GCM–RCM combination CSIRO BOM ACCESS1.3–UNSW-WRF360K generally exhibits lowest biases in precipitation totals and number of wet/heavy days. The biases in mean wet/heavy day precipitation intensities are low.

Therefore, the biases in the annual/seasonal totals appear to be associated with an overestimation of precipitation frequency rather than intensity, consistent with analysis of 50 km resolution runs documented by Di Virgilio et al. (2019). Consistent with the overestimation of precipitation days, the simulations underestimate the annual dry spell durations. The precipitation biases in the historical run and the evaluation run are qualitatively similar, indicating that the processes within the regional models are the dominant contributors of the biases.

3.1.2 Temperature comparison

The evaluation simulations reveal an underestimation of temperature maximums (Tmax) and overestimation of temperature minimums (Tmin), consistent with analyses documented by Di Virgilio et al. (2019). In the ensemble mean of the evaluation run, the magnitude of the biases in Tmax (–1.3 to –1.8 °C) are typically higher than that in Tmin (+0.6 to +1.8 °C), except during MAM. The biases in Tmax and Tmin are consistent in sign across both ensemble members of the evaluation run. Since the evaluation runs are forced with the relatively unbiased reanalysis data, the differences in the sign of biases in Tmin and Tmax can be inferred to be caused by processes simulated within the regional model. In the ensemble mean of the historical run, the negative biases in Tmax are higher than that in the evaluation run (–2.1 to –2.5 °C), while the biases in Tmin are much lower (–0.2 to 1.0 °C). The differences in the range of temperature biases between the

evaluation and historical runs indicate that the GCM boundary conditions propagate uniform cold biases in temperature to both Tmin and Tmax – which enhances the cold biases in Tmax and reduces the warm biases in Tmin. Due to the differences in the magnitude of the biases introduced by the different GCMs in the historical run, the biases in Tmin in the ensemble members are not consistent in sign. Generally, simulations forced with the ACCESS GCMs are positively biased (closer to the evaluation runs) while those forced with CanESM2 are negatively biased (not shown). Table 4 Attributes of precipitation from observations (mean of 284 gauges) and simulations from NARCliM 1.5 data (mean of 284 corresponding grid points and ensemble members), and percent biases in the simulations

Attribute	Season	Historical (GCM forced) run: 1951–2005	Historical (GCM forced) run: 1951–2005	Historical (GCM forced) run: 1951–2005	Evaluation (reanalysis forced) run: 1979–2013	Evaluation (reanalysis forced) run: 1979–2013	Evaluation (reanalysis forced) run: 1979–2013
		Sim. ensemble mean	Obs. mean	Bias (%)	Sim. ensemble mean	Obs. mean	Bias (%)
Precipitation total (mm)	Annual	1,001.6	760.1	32	990.5	722.5	37
Precipitation total (mm)	MAM	216.9	169.9	28	206.4	151.1	37
Precipitation total (mm)	JJA	290.6	240.3	21	252.9	235.4	7
Precipitation total (mm)	SON	271.0	208.4	30	289.5	193.1	50
Precipitation total (mm)	DJF	223.6	141.7	58	241.9	144.7	67
No. of wet days (days)	Annual	115.2	87.2	32	110.8	82.4	35
No. of wet days (days)	MAM	24.2	18.5	31	22.5	16.6	35
No. of wet days (days)	JJA	34.6	29.8	16	30.6	29.1	5
No. of wet days (days)	SON	33.0	24.4	35	33.1	22.5	47
No. of wet days (days)	DJF	24.3	14.4	69	25.4	14.3	77
No. of heavy precipitation days (days)	Annual	30.4	24.1	26	30.1	22.9	32
No. of heavy precipitation days (days)	МАМ	6.5	5.3	23	6.3	4.8	32
No. of heavy precipitation days (days)	AII	8.9	7.6	17	7.7	7.4	3
No. of heavy precipitation days (days)	SON	8.5	6.7	28	9.1	6.1	49
No. of heavy precipitation days (days)	DJF	6.7	4.5	47	7.2	4.6	56

Wet day rain intensity (mm/day)	Annual	8.1	8.3	-3	8.4	8.4	0
Wet day rain intensity (mm/day)	МАМ	8.4	8.6	-3	8.6	8.6	0
Wet day rain intensity (mm/day)	JJA	7.6	7.5	1	7.6	7.5	1
Wet day rain intensity (mm/day)	SON	7.8	8.1	-3	8.3	8.1	3
Wet day rain intensity (mm/day)	DJF	8.4	9.4	-10	8.8	9.5	-7
Heavy day rain intensity (mm/day)	Annual	20.4	20.2	1	21.0	20.2	4
Heavy day rain intensity (mm/day)	МАМ	21.1	20.8	1	21.4	20.5	4
Heavy day rain intensity (mm/day)	ALL	19.1	18.7	3	19.5	18.6	5
Heavy day rain intensity (mm/day)	SON	19.6	19.4	1	20.4	19.6	4
Heavy day rain intensity (mm/day)	DJF	21.6	21.5	0	22.3	21.7	3
Extreme intensity (mm/day)	Annual	33.7	35.4	-5	35.6	35.4	0
Mean dry spell duration (days)	Annual	4.2	6.5	-35	4.5	6.8	-33
Max dry spell duration (days)	Annual	12.9	32.6	-60	13.4	32.8	-59

A subset of 284 precipitation gauges was used for the analysis of NARCliM 1.5 based on a preliminary set of sites provided by the department. An updated list was provided during development of the stochastic model to encompass 375 precipitation gauges. The final set of scaled time series is provided for 375 gauges.

Attribute	Season	Historical (GCM forced) run: 1951–2005 Sim. ensemble mean (°C)	Historical (GCM forced) run: 1951–2005 Obs. mean (°C)	Historical (GCM forced) run: 1951–2005 Sim. minus obs. (°C) [#]	Evaluation (reanalysis forced) run: 1979–2013 Sim. ensemble mean (°C)	Evaluation (reanalysis forced) run: 1979–2013 Obs. mean (°C)	Evaluation (reanalysis forced) run: 1979–2013 Sim. minus obs. (°C) [#]
Tmin average	Annual	6.0	5.7	0.3	7.1	6.0	1.1
Tmin average	MAM	7.1	6.2	1.0	8.1	6.3	1.8
Tmin average	JJA	1.2	1.0	0.2	2.1	1.2	0.9
Tmin average	SON	4.9	5.1	-0.2	6.1	5.5	0.6
Tmin average	DJF	10.8	10.8	0.0	12.1	11.2	0.9
Tmax average	Annual	15.2	17.5	-2.4	16.3	17.9	–1.7
Tmax average	MAM	16.1	18.2	-2.1	17.2	18.5	–1.3
Tmax average	JJA	7.2	9.9	-2.7	8.4	10.2	–1.8
Tmax average	SON	14.8	17.0	-2.2	15.9	17.6	–1.7
Tmax average	DJF	22.7	25.2	-2.5	23.9	25.6	–1.8

Table 5 Attributes of temperature from observations, historical and evaluation simulations from NARCliM 1.5 data and biases in the simulations in absolute terms

Note, small discrepancy in 'sim minus obs' due to rounding

3.1.3 Evapotranspiration comparison

Both the observations and the NARCliM dataset contain estimates of evapotranspiration calculated using Morton's formulation (Morton 1983). Each uses different estimates from the formulation, which needs to be considered when comparing them. Morton potential evapotranspiration (Mpot) estimates are available from the NARCliM 1.5 dataset. The observations contain evapotranspiration estimates corresponding to the Morton wet (Mwet) formulation at 160 sites, and estimates corresponding to the Morton potential (Mpot) formulation at 17 sites.

Under water limiting conditions, Mpot is higher than Mwet; the maximum Mpot is equal to 2 × Mwet at zero water availability. Mpot decreases linearly and is equal to Mwet under unlimited water availability (Morton 1983). The Mwet formulation thus corresponds to evapotranspiration from a saturated soil-plant surface with no limitations on the availability of water (Morton 1983). Therefore, Mpot may be greater than or equal to Mwet depending on the ambient conditions. The comparison of the evaluation and historical simulations with observations presented here uses only 17 observed Mpot sites to maintain consistency in the evapotranspiration formulations. It is to be noted that the observation gauges at which Mpot observations exist are not evenly distributed in the southern basin but are located in the south-western part of the region.

There are negative biases in annual and seasonal Mpot in the NARCliM simulations in both the evaluation and the historical runs. This underestimation of evapotranspiration is consistent with the cold biases in Tmax in the simulations. The biases are lowest in SON in both sets of simulations (-1% and -4%). The biases in the annual estimates and during other seasons range from -11% to -16% (historical run), and -7% to -12% (evaluation run).

Table 6 Total evapotranspiration from observations (mean of Mpot at 17 gauges) and simulations from NARCliM 1.5 data (mean of 17 Morton CRAE potential evapotranspiration at corresponding grid points and ensemble members) and differences in the simulations in absolute and percentage terms

Season	Historical (GCM forced) run: 1951– 2005 Sim. ensemble mean (mm)	Historical (GCM forced) run: 1951– 2005 Obs. mean (mm)	Historical (GCM forced) run: 1951– 2005 Bias (%)	Evaluation (reanalysis forced) run: 1979–2013 Sim. ensemble mean (mm)	Evaluation (reanalysis forced) run: 1979–2013 Obs. mean (mm)	Evaluation (reanalysis forced) run: 1979–2013 Bias (%)
Annual	1,298	1,460	–11	1,328	1,444	-8
MAM	259	308	-16	268	303	-12
JJA	136	153	-11	139	150	-7
SON	375	389	-4	381	386	-1
DJF	528	611	-14	541	604	–10

3.2 Comparison of NARCliM 1.5 future projections

Summary

Precipitation shows negative changes in annual total precipitation across the region:

- 2030 window: -10% to 0% in the RCP 4.5; -15% to 0% in the RCP 8.5
- 2070 window: -20% to 0% in the RCP 4.5; -30% to 0% in the RCP 8.5.

Precipitation shows decreases in MAM, JJA and SON. The highest magnitude of decreases is in SON and there are mixed patterns of changes during DJF.

Precipitation shows decreases in the number of wet and heavy precipitation days and increases in dry spell durations.

Temperature shows positive changes in annual and seasonal means:

- 2030 window: 0.5 to 1.5 °C
- 2070 window: 1 to 4 °C.

PET shows positive changes in annual and seasonal totals:

- 2030 window: up to +3% in annual total
- 2070 window: up to +10% in annual total.

The future changes in the selected climate attributes calculated for 30-year time windows corresponding to short-term (2015–2044) and long-term (2055–2084) periods are presented in Tables 7–9. The tables show the range of changes calculated from the NARCliM 1.5 data with respect to the full historical baseline (1951–2005) for the regions marked using dashed boxes in Figure 2. Appendix D provides spatial visualisation of all attributes over the model domain.

3.2.1 Precipitation comparison

Figure 4 provides an illustration of changes in the ensemble mean of the future simulations for the 2030 window, showing decreases in annual total precipitation across the region for RCP 4.5 and RCP 8.5 scenarios. Table 7 further examines the range of future changes in the precipitation across the wider range of attributes. Changes in the individual ensemble members are not shown here but are available in Appendix D and are further discussed in Section 4 when determining scaling factors.





From Table 7, the ensemble mean of the future simulations shows decreases in annual total precipitation across the region. Spatially, the magnitudes range from -10% to 0% in the RCP 4.5 run and from -15% to 0% in the RCP 8.5 run for a future 30-year window centred on 2030. For a future window centred on 2070, the magnitude of decreases is higher and ranges from -20% to 0% in the RCP 4.5 run and from -30% to 0% in the RCP 8.5 run. Most ensemble members exhibit decreases in annual totals in the long term. Seasonal precipitation totals exhibit decreases during MAM, JJA and SON, with the highest magnitude of decreases in SON. The ranges of the magnitude of changes during SON are: for the 2030 window, RCP 4.5 -20% to 0% and RCP 8.5 -30% to 0%; and for the 2070 window, RCP 4.5 -30% to 0% and RCP 8.5 -40% to -10%.

The decreases in spring precipitation are consistent in sign across most of the ensemble members. The changes during MAM and JJA show mixed signs between the ensemble members in the short term (2030 window). In the longer term (2070 window), the decreases in MAM precipitation are consistent in sign in most of the ensemble members; the changes in JJA precipitation are of mixed signs between the ensemble members. The changes in DJF precipitation show mixed patterns (decreases and increases) in both the short and long terms.

The number of wet and heavy precipitation days in the ensemble mean shows decreases annually and during MAM, JJA and SON. The decreases during SON are larger in magnitude and consistent in sign compared with most of the ensemble members for both the short and long terms. The long-term decreases in wet and heavy precipitation days annually are also consistent between the ensemble members. During DJF, the number of wet and heavy precipitation days shows mixed patterns (both increases and decreases) in the short and long terms. The mean precipitation intensity during wet/heavy precipitation days exhibits mixed patterns of changes (increases and decreases) annually and seasonally.

The length of dry spell durations shows positive changes in both the near term and long term. The sign of changes is more consistent between the ensemble members in the long term.

Considering an alternative shorter historical baseline of 30 years (1976–2005) for the calculation of future changes, the sign/range of changes in the ensemble mean is generally consistent with the changes estimated using the full historical baseline, except for a few attributes. The attributes that show some differences are the number of heavy precipitation days, and some of the seasonal totals. These attributes/seasons are asterisked and shaded in Table 7.

Table 7 The range of future changes in precipitation attributes (in percentage) from NARCliM 1.5

Attribute	Season	Short term (2015 to 2044) Ensemble mean changes RCP 4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP 8.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 4.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 8.5 (%)	Description of the spatial patterns of changes in the short term	Description of the spatial patterns of changes in the long term
Precipitation total (mm)	Annual	–10 to 0	–15 to 0	-20 to 0	-30 to 0	Decreases across the region. There is a spatial gradient in the magnitude of percentage changes from south- east (lower) to north-west (higher) areas of the region.	Same as short term.
Precipitation total (mm)	МАМ	–10 to 10	-20 to 0	-20 to 0	-30 to 0	Decreases across the region. There is a spatial gradient in the percentage of changes from south-east (lower) to north-west (higher).	Same as short term.
Precipitation total (mm)	JJA	–10 to 0	–10 to 10	–20 to 0	–30 to 10*	Mixed. Primarily decrease in RCP 4.5. The mixed pattern is more prominent in RCP 8.5. There is a spatial gradient in the pattern of changes from south (lower) to north (higher).	Decreases. There is a spatial gradient in the pattern of changes from south (lower) to north (higher).
Precipitation total (mm)	SON	-20 to 0	-30 to 0*	-30 to 0	-40 to -10	Decreases across the region.	Same as short term.
Precipitation total (mm)	DJF	–15 to 15	–15 to 15	–20 to 20*	–20 to 20	Mixed. Decreases in the east, increases in the west	Same as short term.
No. of wet days (days)	Annual	-10 to 0	-10 to 0	-20 to 0	-10 to -30	Decrease. There is a spatial gradient in the magnitude of percentage changes from south-east (lower) to north-west (higher), similar to the annual total.	Same as short term.
No. of wet days (days)	MAM	-10 to 0	–15 to 0	–20 to 10	-30 to 0	Decrease. There is a gradient in spatial pattern from south-east (lower) to north-west (higher).	Same as short term.

Attribute	Season	Short term (2015 to 2044) Ensemble mean changes RCP 4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP 8.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 4.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 8.5 (%)	Description of the spatial patterns of changes in the short term	Description of the spatial patterns of changes in the long term
No. of wet days (days)	AII	-10 to 0	-10 to 5	-20 to 0	-20 to 0	Mixed positive/negative signals, especially in RCP 8.5.	Decreases. There is a spatial gradient in the pattern of changes from south (lower) to north (higher).
No. of wet days (days)	SON	-20 to 0	-20 to 0	−30 to −10	–10 to –40*	Decreases across the region.	Same as short term.
No. of wet days (days)	DJF	–15 to 10	–10 to 5	–20 to 10	–20 to 10	Increases in the east, decreases in the west.	Same as short term.
No. of heavy days (days)	Annual	−20 to 0*	-20 to 0	-20 to 0	-30 to 0	Decrease. There is a spatial pattern in the magnitude of changes from south- east (lower) to north-west (higher).	Same as short term.
No. of heavy days (days)	MAM	–10 to 0*	-20 to 0	−30 to 0*	-30 to 0	Predominantly decreasing.	Decrease. There is a spatial pattern in the magnitude of changes from south-east (lower) to north-west (higher).
No. of heavy days (days)	JJA	-20 to 0*	-20 to 20	-25 to 0	–25 to 25	Mixed signals in RCP 8.5.	Predominantly decreases.
No. of heavy days (days)	SON	−30 to 0*	-30 to 0	-40 to 0*	–40 to −20*	Changes are prominent. Most grid points show changes of at least – 10%.	Changes are prominent. Most grid points show changes of at least – 20%.
No. of heavy days (days)	DJF	–20 to 20*	-20 to 20*	-20 to 20	-20 to 20	East/west pattern of decrease/increase	Same as short term.
Wet day rain intensity (mm/day)	Annual	-3 to 3	-6 to 3	-5 to 10	–5 to 10	Mixed pattern of minor increases/decreases.	Same as short term.

Attribute	Season	Short term (2015 to 2044) Ensemble mean changes RCP 4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP 8.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 4.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 8.5 (%)	Description of the spatial patterns of changes in the short term	Description of the spatial patterns of changes in the long term
Wet day rain intensity (mm/day)	МАМ	-5 to 10	-10 to 5	–15 to 5	-10 to 5	Mixed spatial pattern of increases/decreases.	Same as short term.
Wet day rain intensity (mm/day)	JJA	–5 to 5	-10 to 10	-10 to 10	–10 to 10	Mixed spatial pattern of increases/decreases.	Same as short term.
Wet day rain intensity (mm/day)	SON	-6 to 3	-9 to 3	-10 to 10	–15 to 5	RCP 4.5 shows mixed pattern, RCP 8.5 primarily decreases.	Same as short term.
Wet day rain intensity (mm/day)	DJF	0 to 10	–5 to 10	-5 to 10	–10 to 10	Mixed pattern; RCP 4.5 predominantly increases.	Same as short term.
Heavy day rain intensity (mm/day)	Annual	0 to 5	-2.5 to 5	-3 to 9	-3 to 9	RCP 4.5 shows increases; RCP 8.5 shows mixed patterns.	Primarily increases across the region; more spatially coherent in the RCP4.5 run.
Heavy day rain intensity (mm/day)	МАМ	–5 to 10	-5 to 5	–10 to 15	–10 to 15	Mixed pattern.	Same as short term.
Heavy day rain intensity (mm/day)	JJA	-5 to 5	–5 to 10	–5 to 10	–5 to 15	Mixed pattern.	Mixed in RCP 4.5; RCP 8.5 primarily increases.
Heavy day rain intensity (mm/day)	SON	-7.5 to 7.5	-7.5 to 7.5	-5 to 15	–5 to 10	Mixed pattern.	Same as short term.
Heavy day rain intensity (mm/day)	DJF	0 to 10	0 to 10	0 to 15	–5 to 15	Mixed pattern; more increases than decreases.	Same as short term.

Attribute	Season	Short term (2015 to 2044) Ensemble mean changes RCP 4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP 8.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 4.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 8.5 (%)	Description of the spatial patterns of changes in the short term	Description of the spatial patterns of changes in the long term
Extreme intensity (mm/day)	Annual	–5 to 10) –5 to 10	0 –5 to 10	–5 to 15	Mixed pattern; more increases than decreases.	Same as short term.
Mean dry spell duration (days)	Annual	0 to 5	5 0 to 5	5 0 to 20*	0 to 40	Increases across the region.	Increases across the region; the magnitude increases from south- east to north-west.
Max dry spell duration (days)	Annual	0 to 7.5	0 to 7.5	5 0 to 10	0 to 15	Increases across the region.	Increases across the region; highest in the south-east.

* Asterisked, shaded cells indicate the attribute where the range of future changes calculated using a shorter 30-year historical baseline differ from these ranges by more than 5%. The estimates are the grid-level changes in the ensemble mean with respect to the full historical baseline (1951 to 2005) over the area marked by black dashed box in Figure 2. The shading indicates attributes/seasons that exhibit differences if a shorter historical baseline of 30 years is used for the calculation.

3.2.2 Evapotranspiration comparison

Table 8 examines the range of future changes in evapotranspiration. The Morton potential evapotranspiration available from the NARCliM dataset exhibits increases at annual and seasonal timescales during all seasons in both the short-term and long-term analyses. The magnitude of grid-level increases are up to 3% in the short term and up to 10% in the long term. There are no major differences in the range of future changes calculated using a shorter historical baseline of 30 years (not shown).

Season	Short term (2015 to 2044) Ensemble mean changes RCP4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP8.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP8.5 (%)
Annual	0 to 3	1 to 3	2.5 to 7.5	5 to 10
МАМ	0 to 4	2 to 6	3 to 6	6 to 12
JJA	0 to 4	0 to 6	0 to 10	0 to 10
SON	1 to 5	1 to 5	3 to 9	6 to 12
DJF	–1 to 3	0 to 4	0 to 6	4 to 8

Table 8 The range of future changes in annual and seasonal evapotranspiration in total mm from NARCliM 1.5

The estimates are the grid-level changes in the ensemble mean with respect to the full historical baseline (1951–2005) over the area marked by black dashed box in Figure 2.

3.2.3 Temperature comparison

Table 9 examines the range of future changes in temperature maximums and minimums. Tmax and Tmin exhibit increases with respect to the historical baseline with no specific spatial pattern in the short or long term. The increases in summer are slightly higher than the other seasons in the near term. In the long term, the increases are of similar magnitudes during all seasons. There are no major differences in the range of future changes calculated using a shorter historical baseline of 30 years (not shown).

Attribute	Season	Short term (2015 to 2044) Ensemble mean changes RCP 4.5 (%)	Short term (2015 to 2044) Ensemble mean changes RCP 8.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 4.5 (%)	Long term (2055 to 2084) Ensemble mean changes RCP 8.5 (%)
Tmax mean (°C)	Annual	0.5 to 1.5	1 to 1.5	1 to 3	2 to 4
Tmax mean (°C)	MAM	0.5 to 1.5	1 to 1.5	1 to 2	2 to 4
Tmax mean (°C)	JJA	0.5 to 1.5	0.5 to 1.5	1 to 3	2 to 4
Tmax mean (°C)	SON	0.5 to 1.5	0.5 to 1.5	2 to 3	2 to 3
Tmax mean (°C)	DJF	1 to 1.5	1 to 1.5	2 to 3	2 to 4
Tmin mean (°C)	Annual	0.5 to 1.5	0.5 to 1.5	1 to 2	2 to 3
Tmin mean (°C)	MAM	0.5 to 1.5	1 to 1.5	1 to 2	2 to 3
Tmin mean (°C)	JJA	0.5 to 1.5	1 to 1.5	1 to 2	2 to 3
Tmin mean (°C)	SON	0.5 to 1.5	0.5 to 1.5	1 to 2	1 to 3
Tmin mean (°C)	DJF	1 to 1.5	1 to 1.5	1 to 3	2 to 3

Table 9 The range of future changes in annual and seasonal temperature from NARCliM 1.5

The estimates are the grid-level changes in the ensemble mean with respect to the full historical baseline (1951 to 2005) over the area marked by the red dashed box in Figure 2.

3.2.4 Comparison of future projections with other sources

The range of grid-level future changes projected by the NARCliM 1.5 ensemble mean is compared with estimates from other sources of projections: the CCIA estimates available for the Murray sub-cluster (Timbal et al. 2015) and regional projections available from VCP19. The future changes in annual and seasonal mean/total of precipitation, evapotranspiration and temperature are compared. There are some differences in the periods and variables available from the different datasets, as summarised below. Nevertheless, this comparison provides an indication of the similarity/differences in the range of changes projected by the different datasets.

Tables 10a-h compare the range of grid-level changes in the ensemble mean from the NARCliM 1.5 data with the projections from the other 2 sources. The results show that the changes in annual and seasonal total precipitation projected by NARCliM 1.5 are within the bounds projected by the alternative sources. The higher decline in SON totals and the mixed sign in DJF totals are consistent between the different datasets. The future changes in evapotranspiration projected by NARCliM 1.5, especially in the bounds indicated by CCIA. The VCP19 estimates are much higher than CCIA and NARCliM 1.5, especially in the long term. This could be because these projections are based on pan evaporation estimates, which differs from the other 2 datasets, although further investigation would be required to understand the different underpinning assumptions between the alternative approaches. The increases in Tmax and Tmin projected by the NARCliM 1.5 ensemble mean are within the bounds indicated by the other projections.

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Annual	-2	-1	-4	-4	-6	-10	-9	-11	-10 to 0	15 to 0
Annuai	(–9 to 5)	(–11 to 5)	(–10 to 6)	(–12 to 4)	(–12 to 4)	(–16 to 4)	(–16 to 3)	(–18 to 3)	-10 10 0	-13 10 0
54454	-1	-1	-3	-4	-6	-3	-6	-4	10 to 10	20 to 0
IVIAIVI	(-24 to 12)	(–21 to 12)	(–19 to 23)	(–21 to 21)	(–19 to 16)	(–21 to 13)	(–21 to 13)	(–24 to 13)	-10 10 10	-20 10 0
114	-3	-5	-8	-7	-9	-10	-10	-12	10 to 0	10 to 10
JJA	(–15 to 8)	(–17 to 7)	(–18 to 10)	(–18 to 10)	(–18 to 10)	(–19 to 7)	(–17 to 7)	(–21 to 7)	-10 10 0	-10 10 10
CON	-3	-6	-6	-8	-9	-15	–15	–18	20 to 0	20 to 0
SON	(–16 to 12)	(–17 to 7)	(–14 to 24)	(–17 to 13)	(–20 to 4)	(–18 to 7)	(–20 to 7)	(–23 to 7)	-20 10 0	-30 10 0
DIF	0	1	-3	-3	-5	-11	-2	-2	15 += 15	15 += 15
DJF	(–15 to 13)	(–9 to 16)	(–11 to 14)	(–11 to 15)	(–13 to 12)	(-23 to 18)	(–25 to 18)	(–20 to 14)	-15 to 15	-15 to 15

Table 10a Future changes to total precipitation for near term (2030s) projected by NARCliM 1.5 compared with projections from other sources

Table 10b Future changes to total precipitation for far term (2070s) projected by NARCliM 1.5 compared with projections from other sources

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Annual	-4	-4	-8	-8	-10	-11	–12	-15	20 to 0	20 to 0
Annual	(–18 to 8)	(–22 to 8)	(–21 to 5)	(–21 to 5)	(–21 to 5)	(–25 to 5)	(–28 to 5)	(–28 to 5)	-20 10 0	-50 10 0
	-4	-4	-5	-8	-9	-12	–17	-17	-20 to 0 -30	20 += 0
IVIAIVI	(–19 to 20)	(–25 to 19)	(–30 to 16)	(–32 to 16)	(–32 to 16)	(–30 to 17)	(–33 to 17)	(–36 to 17)		-30 10 0
114	-4	-8	-7	-7	-9	-20	-20	-24	20 to 0	20 to 10
JJA	(–22 to 7)	(–25 to 2)	(–20 to 8)	(–19 to 8)	(–21 to 8)	(–31 to 5)	(–30 to 5)	(–31 to 5)	-20 to 0	-30 to 10
CON	-5	-8	-14	–13	-15	-12	–15	–19	201.0	40 to 10
SON	(–28 to 7)	(–32 to 8)	(–28 to 4)	(–28 to 4)	(–28 to 4)	(–41 to 6)	(–41 to 6)	(–41 to 6)	-30 to 0	-40 to - 10
DIF	2	4	5	7	3	-2	2	9	20 1 - 20	20 1 - 20
DJF	(–19 to 13)	(–16 to 24)	(–20 to 27)	(–20 to 27)	(–20 to 19)	(–22 to 29)	(–22 to 29)	(–22 to 29)	-20 to 20	-20 to 20

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Annual	3	3	11	10	8	15	13	11	0 to 2	1 to 2
Annual	(1 to 4)	(2 to 5)	(7 to 18)	(7 to 17)	(7 to 15)	(7 to 21)	(8 to 20)	(7 to 17)	0 10 5	1 10 5
NANA	3	4	8	9	8	9	9	8	0 to 1	2 to 6
IVIAIVI	(1 to 6)	(2 to 6)	(-3 to 14)	(-1 to 14)	(0 to 11)	(3 to 20)	(4 to 17)	(5 to 13)	0 10 4	2 10 6
114	5	7	2	2	2	3	3	2	0 to 1	0 to 6
JJA	(2 to 13)	(3 to 12)	(1 to 3)	(1 to 2)	(1 to 2)	(0 to 5)	(1 to 4)	(1 to 3)	0 10 4	0106
CON	3	3	20	18	14	24	21	17	1 to 5	1 to F
SON	(0 to 5)	(0 to 6)	(13 to 26)	(13 to 23)	(11 to 18)	(13 to 29)	(14 to 27)	(11 to 21)	1 10 5	1 10 5
DIF	3	3	15	12	9	19	18	15	1 + - 2	0 += 4
JIF	(1 to 4)	(1 to 5)	(8 to 37)	(8 to 35)	(7 to 32)	(11 to 37)	(10 to 36)	(6 to 33)	- i to 3	U tO 4

Table 10c Future changes to total evapotranspiration for near term (2030s) projected by NARCliM 1.5 compared with projections from other sources

Table 10d Future changes to total evapotranspiration for far term (2070s) projected by NARCliM 1.5 compared with projections from other sources

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Annual	5	9	24	22	17	34	31	25	2.5 to 7.5	E to 10
Annual	(3 to 9)	(5 to 13)	(17 to 25)	(15 to 24)	(12 to 22)	(24 to 55)	(20 to 52)	(14 to 44)		5 10 10
	6	11	15	13	12	22	21	17	2 + 0 6	C to 12
IVIAIVI	(3 to 10)	(7 to 16)	(10 to 24)	(10 to 21)	(8 to 16)	(18 to 37)	(15 to 34)	(10 to 28)	3 10 6	01012
11A	8	18	5	4	3	10	8	6	0 to 10	0 to 10
JJA	(6 to 18)	(11 to 30)	(3 to 7)	(2 to 5)	(2 to 4)	(5 to 14)	(5 to 11)	(4 to 8)	0 to 10	0 to 10
CON	5	7	38	35	28	54	51	42	2 += 0	C to 12
SON	(0 to 8)	(2 to 11)	(25 to 47)	(21 to 42)	(17 to 33)	(34 to 81)	(29 to 74)	(23 to 61)	3 to 9	6 to 12
DIF	5	8	34	31	27	53	46	36	0 +- 0	4 + = 0
DJF	(3 to 10)	(5 to 12)	(21 to 44)	(19 to 39)	(15 to 42)	(36 to 89)	(28 to 89)	(18 to 81)	0 10 6	4 to 8

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Annual	0.9	1.1	1	1.1	1.1	1.4	1.4	1.4	0.5 to 1.5	1 to 1 E
Alliudi	(0.6 to 1.3)	(0.8 to 1.4)	(0.6 to 1.4)	(0.6 to 1.5)	(0.6 to 1.6)	(0.7 to 1.7)	(0.7 to 1.8)	(0.7 to 1.9)	0.5 (0 1.5	1 (0 1.5
МАЛА	0.8	0.9	1	1.1	1.3	1.3	1.4	1.4	05 to 15	1 to 15
IVIAIVI	(0.2 to 1.4)	(0.5 to 1.5)	(0.2 to 1.5)	(0.2 to 1.6)	(0.2 to 1.6)	(0.5 to 1.8)	(0.5 to 1.8)	(0.5 to 1.8)	0.5 (0 1.5	1 (0 1.5
114	0.8	1	0.8	0.8	1	1	1.1	1.2	0 E to 1 E	0 E to 1 E
JJA	(0.5 to 1.2)	(0.7 to 1.4)	(0.4 to 1.1)	(0.4 to 1.1)	(0.4 to 1.1)	(0.5 to 1.5)	(0.5 to 1.5)	(0.5 to 1.5)	0.5 10 1.5	0.5 to 1.5
SON	1	1.1	1.5	1.5	1.5	2	2	1.9	0 E to 1 E	0 E to 1 E
5014	(0.6 to 1.4)	(0.7 to 1.7)	(0.4 to 1.8)	(0.4 to 1.8)	(0.4 to 1.8)	(0.6 to 2.4)	(0.6 to 2.4)	(0.6 to 2.3)	0.5 10 1.5	0.5 to 1.5
DIE	1	1.1	0.9	0.9	1	1.2	1.2	1.2	1 to 1 F	1 to 1 F
DJF	(0.6 to 1.6)	(0.6 to 1.5)	(0.6 to 1.9)	(0.6 to 2.1)	(0.6 to 2.4)	(0.6 to 1.9)	(0.6 to 2.1)	(0.6 to 2.4)	1 to 1.5	1 to 1.5

Table 10e Future changes to **maximum temperature for near term (2030s)** projected by NARCliM 1.5 compared with projections from other sources

Table 10f Future changes to **maximum temperature for far term (2070s)** projected by NARCliM 1.5 compared with projections from other sources

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Annual	1.8	2.9	2.3	2.3	2.4	3.2	3.4	3.4	1 to 2	2 to 4
Annual	(1.3 to 2.4)	(2.2 to 3.6)	(1.3 to 2.4)	(1.3 to 2.5)	(1.3 to 2.6)	(2.1 to 4.5)	(2.1 to 4.7)	(2.1 to 5)	1 10 5	2 10 4
54454	1.6	2.9	2.2	2.2	2.4	3	3.2	3.3	1 to 2	2 + - 4
IVIAIVI	(1 to 2.4)	(1.9 to 3.6)	(0.9 to 3.1)	(0.9 to 3.2)	(0.9 to 3.2)	(1.8 to 4.6)	(1.8 to 4.8)	(1.8 to 5)	1 10 2	2 10 4
114	1.6	2.7	1.8	1.8	1.9	2.8	2.8	3	1 + - 2	
JJA	(1.1 to 2.1)	(2 to 3.4)	(1 to 2)	(1 to 2.1)	(1 to 2.3)	(1.8 to 3.5)	(1.8 to 3.5)	(1.8 to 3.6)	1 10 3	2 10 4
CON	2	3.2	2.9	2.9	2.9	4.1	4.2	4.3		2 + - 2
SON	(1.2 to 2.8)	(2.3 to 4.2)	(1.1 to 3.3)	(1.1 to 3.3)	(1.1 to 3.1)	(2.5 to 5.6)	(2.5 to 5.7)	(2.5 to 5.7)	2 to 3	2 to 3
DIF	2	2.9	2	2	2.1	3	3	3.1	2 + - 2	2 + - 4
DJF	(1.1 to 2.7)	(2.2 to 4)	(1.3 to 2.9)	(1.3 to 2.9)	(1.3 to 3.1)	(2.3 to 4.5)	(2.3 to 5)	(2.3 to 5.7)	2 (0 3	2 to 4

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
Appual	0.7	0.9	0.7	0.7	0.8	0.8	0.8	0.9	0.5 to 1.5	0 5 to 1 5
Annual	(0.5 to 1)	(0.7 to 1.2)	(0.5 to 1)	(0.5 to 1)	(0.5 to 1)	(0.6 to 1.1)	(0.6 to 1.1)	(0.6 to 1.1)	0.5 10 1.5	0.5 to 1.5
МАЛА	0.7	1	0.6	0.7	0.7	0.8	0.8	1.1	0.5 to 1.5	1 to 15
IVIAIVI	(0.4 to 1.2)	(0.4 to 1.4)	(0.5 to 1.2)	(0.5 to 1.2)	(0.5 to 1.2)	(0.5 to 1.4)	(0.5 to 1.4)	(0.6 to 1.5)	0.5 (0 1.5	1 (0 1.5
114	0.6	0.7	0.5	0.6	0.6	0.5	0.6	0.9	0 E to 1 E	1 to 1 E
JJA	(0.4 to 0.8)	(0.5 to 1)	(0.2 to 0.8)	(0.2 to 0.8)	(0.2 to 0.8)	(0.3 to 1)	(0.4 to 1)	(0.5 to 1.4)	0.5 10 1.5	1 10 1.5
SON	0.7	0.9	0.8	0.8	0.8	1	1	0.7	0 E to 1 E	0 E to 1 E
501	(0.3 to 1.1)	(0.6 to 1.3)	(0.2 to 1.1)	(0.2 to 1.1)	(0.2 to 1.1)	(0.3 to 1.3)	(0.3 to 1.4)	(0.4 to 1)	0.5 10 1.5	0.5 to 1.5
DIF	0.9	1	0.9	0.9	0.9	1	1	1	1 to 1 F	1 to 1 F
UJF	(0.6 to 1.3)	(0.7 to 1.5)	(0.5 to 1.3)	(0.6 to 1.4)	(0.6 to 1.5)	(0.6 to 1.5)	(0.6 to 1.5)	(0.3 to 1.5)	1 to 1.5	1 to 1.5

Table 10g Future changes to minimum temperature for near term (2030s) projected by NARCliM 1.5 compared with projections from other sources

Table 10h Future changes to **minimum temperature for far term (2070s)** projected by NARCliM 1.5 compared with projections from other sources

Season	CCIA median	CCIA median	VCP19	VCP19	VCP19	VCP19	VCP19	VCP19	NARCliM 1.5	NARCliM 1.5
	(10th perc.,	(10th perc.,	median	median	median	median	median	median	range	range
	90th perc.)	90th perc.)	(10th perc.,							
			90th perc.)							
	Murray	Murray	Loddon	Goulburn	Ovens	Loddon	Goulburn	Ovens	Southern Basin	Southern Basin
	cluster	cluster	Campaspe		Murray	Campaspe		Murray	region	region
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 4.5	RCP 4.5	RCP 8.5	RCP 8.5	RCP 8.5	RCP 4.5	RCP 8.5
٨٠٠٠٠٩	1.5	2.5	1.5	1.6	1.6	2.4	2.4	2.5	1 to 2	2 to 2
Annuai	(1.1 to 1.8)	(2.1 to 3.1)	(1.1 to 1.9)	(1.1 to 1.9)	(1.1 to 2)	(2 to 3)	(2 to 3)	(2 to 3.2)	1 10 2	2 10 3
	1.5	2.7	1.5	1.5	1.5	2.4	2.4	2.4	1 + - 2	244.2
IVIAIVI	(1.1 to 2)	(2 to 3.2)	(1 to 2.3)	(1 to 2.4)	(1 to 2.4)	(2 to 3.4)	(2 to 3.4)	(2 to 3.5)	1 10 2	2 10 3
	1.2	2	1.1	1.2	1.3	1.8	1.9	2	1 + - 2	244.2
JJA	(0.8 to 1.6)	(1.7 to 2.5)	(0.7 to 1.6)	(0.7 to 1.7)	(0.7 to 1.8)	(1.6 to 2.4)	(1.6 to 2.4)	(1.6 to 2.4)	1 10 2	2 10 5
CON	1.5	2.5	1.7	1.8	1.8	2.6	2.6	2.7	1 + - 2	1 + - 2
SON	(0.9 to 1.8)	(2 to 3)	(0.7 to 1.9)	(0.7 to 1.9)	(0.7 to 1.9)	(1.8 to 3.1)	(1.8 to 3.2)	(1.8 to 3.4)	1 to 2	1 to 3
DIF	1.7	2.8	1.7	1.7	1.9	2.8	2.9	3	1+- 2	2 + - 2
DJF	(1 to 2.4)	(2 to 3.7)	(1 to 2.5)	(1 to 2.5)	(1 to 2.5)	(2.1 to 3.8)	(2.1 to 3.8)	(2.1 to 3.9)) 1 to 3	2 to 3

4 Generation of stochastic time series

Summary

The 1951–2005 historical baseline is used for scaling as it is comparable to the shorter baseline given climate variability and utilises the full historical NARCliM simulation.

Scaling is provided to each model rather than ensemble mean to maintain physical coherence.

Daily quantile scaling is recommended instead of seasonal simple scaling to better accommodate changes to dry days.

Two 10,000-year time series are generated for each point location corresponding to the 2030 and 2070 windows.

The 10,000-year sequence is carefully structured to enable analysis of uncertainty across all 6 model configurations and 2 RCP scenarios. Partitions of length 833 years are available for each configuration and scenario for replicate analysis.

4.1 Overview of approach to scaling stochastic time series

Reported trends in the historical record for the southern basin (Devanand et al. 2020) create a need to consider the implications of climate non-stationarity with respect to the method of stochastic risk assessment. The stochastic method is calibrated against the historical record with the implicit assumption that the climate is stationary over this period (Leonard et al. 2022).

To modify the stochastic simulations, it is important to balance the strength of the non-stationary climate signal with the underlying variability in the historical record. A key element of this task is to determine a representative baseline. The baseline should be chosen to be consistent with the NARCliM 1.5 simulations (that is, the period 1951 to 2005), but a shorter baseline could be used to more closely align to the present-day climate (with the downside of greater variability arising from the shorter length). As 2 examples, the World Meteorological Organization recommends a minimum baseline length of 30 years (WMO 1989) and guidelines for the Victorian Climate Change Initiative recommend a baseline of at least 40 years, given the high interannual variability in precipitation and runoff in this region (Potter et al. 2016).

Another consideration is the method of relating stochastic simulations to future projections. One approach for scaling is to use seasonal 'change factors', but these do not affect the proportion of 'dry' days¹ and they change extremes by the same factor as seasonal precipitation totals. An alternative is to use a quantile-based approach to jointly change the seasonal totals, wet days and extremes in a manner that reflects the climate projections.

This section analyses alternatives for the baseline period and scaling options and /addresses pragmatic issues of how best to account for uncertainty between models and scenarios given a limited computational budget for hydrological analyses. A final set of time series is recommended for use by the department.

A complication is that dry days are defined here as those with <1 mm precipitation. Thus, multiplication by change factors can influence the proportion of dry days. For example, 0 mm days will remain as 0 mm after scaling but 0.8 mm 'dry' days could be scaled to be greater than 1 mm and thus become 'wet'. This effect is negligible but is mentioned for completeness.

4.2 Selection of historical baseline

Section 3.1 provided a comparison of future climate against two baselines: a longer baseline (1951–2005) that utilises the full record of the NARCliM 1.5 historical period and a shorter baseline (1976–2005) that is potentially more representative of the recent climate yet with sufficient length (30 years) to facilitate analysis of hydrological extremes. In Tables 7–10, asterisked, shaded cells denote attributes and scenarios that differ between the longer and shorter baselines. In most instances the models were in agreement, suggesting no overall significant difference in terms of outcome determined when adopting a baseline. Rather than propagate multiple baselines for use in subsequent analysis, it is convenient to have a single baseline. For this purpose, an additional comparison was undertaken here using the stochastic data to determine variability in change factors for a stationary climate and better compare the climate signal to noise.

Figure 5 compares seasonal scaling factors for various climate scenarios for pairs of baseline periods: a shorter baseline (1976–2005) and a longer baseline (1951–2005). Each panel represents a different season and has five scenarios for paired comparisons: the stationary climate and each of the RCP and time window scenarios. The stationary climate was sampled from the 10,000-year stochastic time series with independent samples that match the same configuration of baseline (either 55 or 30 years) and time window (30 years set into the future). Figure 5 shows a significant level of climate variability within the stationary record when constructing a change factor between the baseline and future time window. In all instances, the variability of the scaling factors (whether from the stationary period or climate projections) is significantly greater than changes in the median change factor for any given scenario. In other words, the signal of a change in seasonal totals is relatively weak relative to the variability in the climate. The considerable overlap of the scaling factors between the 2 baselines shows it is suitable to use the longer historical baseline of 1951–2005 for deriving future change factors. Results for other attributes are available in Appendix E and similarly lend support to adopting a longer baseline.



MAM (top-left), JJA (top-right), SON (bottom-left), DJF (bottom-right). Stationary data are taken from 200 independent samples of the stochastic time series using a baseline period (either 55 or 30 years) and a future 30-year time window. Other box plot pairs represent each climate scenario and time window from NARCliM 1.5 simulations.

Figure 5 Comparison of seasonal scaling factors across 375 precipitation sites for annual total attribute for long baseline (1951–2005, green, left plots) and short baseline (1976–2005, orange, right plots)

4.3 Comparison of ensemble mean to individual model performance

Given the large number of comparisons, discussion to this point has primarily been summarised according to ensemble mean performance, with variations between models available in the appendixes. Nonetheless, there are significant differences for precipitation between the model variants. For example, Figure 6 shows changes in the annual total precipitation as a difference from the 1951–2005 baseline for the 2030 time window for each model variant (Whereas the ensemble mean (Figure 4) showed a mild decrease on average, some model instances show projected increases to the precipitation (top-left panel) while others show more significant drying than the ensemble mean (top-right panel).

Given that hydrological models typically amplify the impact of climate inputs, variability in the model configurations is likely to be an important factor to quantify in subsequent studies. Furthermore, the average of a function output is not the same as the function output based on an averaged input, especially for nonlinear models such as those used for streamflow production. Lastly, the spatial 'gradient' of the ensemble mean is an abstracted pattern rather than a pattern derived from a physically coherent

simulation (as with an individual model configuration). For these reasons, it is recommended that the method of scaling is applied individually to each model rather than based on a single ensemble average.



Compare with Figure 4 (ensemble mean).

Figure 6 Changes in precipitation – annual total precipitation per model configuration, 2030 window minus baseline

4.4 Simple scaling method

Simple scaling is achieved by calculation of a change factor constructed between the historical baseline and the future climate scenario. For precipitation and potential evapotranspiration, the change factor is the ratio of the seasonal totals and is applied multiplicatively in each season for each year of the stochastic time series. By definition, this method is unable to account for changes in the frequency of zero precipitation occurrences (that is, the proportion of zero precipitation and dry spell durations). In this report, some trivial change is nonetheless observed in reported statistics related to dry occurrence since the threshold for a 'dry' event is taken at 1 mm rather than 0 mm. For temperature, a difference between the seasonal means is applied in each season for each year of the stochastic time series.

4.5 Quantile scaling method

Quantile scaling is an alternative method to simple scaling. It is explored here for scaling precipitation to better account for differences in precipitation frequency and in the extremes relative to the mean. A parametric method was used to achieve quantile scaling at the daily timescale for each season. A gamma distribution was identified as having a good fit to the seasonal distribution of daily precipitation amounts. A modification is made to the distribution to include an additional spike at zero to ensure that the proportion of dry days can be matched. The gamma distribution has two parameters (shape and rate) that are fitted by matching the attributes of 'wet day' precipitation amount and 'heavy day' precipitation amount (defined in Table 3 as the conditional means for days above 1 mm and 10 mm, respectively). The shape and rate parameters are calibrated via optimisation using a sum of squares loss function. The gamma distribution fits well, as can be seen in Figure 7. An additional parameter for the proportion of 'dry' days is exactly matched

by calculating the proportion of the distribution less than 1 mm and taking the difference with the NARCliM attribute.



Each plot is a separate model configuration. RCP 8.5 2070 time window is shown; other climate scenarios (not shown) perform similarly.

Figure 7 Quantile-quantile plot of fitted gamma distribution for each site, future climate vs 1951–2005 historical baseline

To check that the model does not yield a poor fit to extreme values, the extreme precipitation attribute (95th percentile of daily precipitation, defined in Table 3) calculated directly from the NARCliM data at the annual scale was compared to the mixture of gamma models at the seasonal scale (Leonard et al. 2008). This attribute was not used in fitting the model. Figure 8 shows the comparison to extreme values is favourable.



All model configurations RCP 4.5 2030.

Figure 8 Evaluation of 95th quantile from the fitted gamma model at the annual scale compared with the directly calculated attribute from NARCliM simulations for 370 precipitation sites

Using the fitted precipitation distributions, scaling factors are obtained at the daily timescale. Figure 9 summarises the scaling factors, showing the distribution across all sites and model configurations according to a median value and 90% limits. For all quantiles, the scaling factors are either side of 1, indicating that some sites may increase while others may decrease. In the upper tail the median scaling factor is above 1, indicating overall increases in precipitation at these scales. In the lower tail, many sites have quantiles with scaling at or near zero, indicating a change to the frequency of dry days.

The positive scaling factors in the lower tail are variable between the scenarios because of complication with the number of 0 mm days. 'Scaling' a 0 mm day into a non-zero precipitation amount requires an infinite scaling factor; therefore, to bypass this, a non-zero precipitation amount was uniformly randomly sampled less than 1 mm on selected days. The proportion of dry days is varied each year in the stochastic sequence based on observed variability in this statistic (otherwise all years will have an identically dry proportion). The sampling of changes to the dry distribution is made about the parameterised mean value but with correlation to the seasonal total (so that drier years are more likely to have more dry days). This procedure does not guarantee an exact match to the mean; therefore, all days were additionally rescaled to ensure this attribute of the simulation mean was matched exactly.



Different colours represent scaling from each climate scenario.

Figure 9 Daily quantile scaling factor at all sites and model configurations, median (solid line) and 90% confidence interval (dashed line)

4.6 Comparison of scaling methods

The simple scaling and quantile scaling methods were applied to the stochastic time series for precipitation (Tables 11a–e), temperature and potential evapotranspiration (Tables 12a–c). The sites for application are greater than those used for the NARCliM analysis (375 for precipitation, 414 for evapotranspiration and 100 for temperature). The stochastic time series the period 1951–2005 are shown to match the observed attributes over the baseline and are the starting point for applying change factors. The baseline NARCliM and future projections are provided to show the expected magnitude of change for ensemble averages of each attribute. All statistics are an average across all sites in the domain. The simple scaling and quantile scaling methods are compared for each scenario and time window. Both scaling methods are able to reproduce changes to the seasonal totals with good agreement. The quantile scaling method shows better performance on other attributes.

4.7 Integrating multiple sources of uncertainty into the stochastic simulation

This study involves two time windows (2030 and 2070), 2 RCP scenarios (4.5 and 8.5) and 6 climate model configurations. It is, however, potentially unwieldy to have 24 different time series for each location to account for this variety of scenarios. This is especially the case given that some hydrological models can be complicated and cover a large domain, leading to significant computational burden when computing streamflow from climate inputs (that is, eWater Source models for the Murray River). For this reason, a method is developed to enable convenient analysis of scenario uncertainty. A single 10,000-year

simulation can be structured so that each subset of the timeline corresponds to a different model or RCP scenario. This means that only two 10,000-year time series are provided for each site, corresponding to an analysis of either the 2030 or 2070 time window.

Figure 10 provides a schematic of the structure used in all scaled stochastic simulations for model configurations M1 to M6.² Each partition is 833 years long and the last 4 years are trivially added from the last model to complete the record. Record lengths of 833 years provide several replicates (for example, 6×132 -year replicates having the same length as the observed record 1890–2022) per model and climate scenario to enable assessment of within-scenario variability, or composites can be taken to construct averages across scenarios.



M1: CCCma-CanESM2_WRF360J; M2: CSIRO-BOM-ACCESS1.0_UNSW-WRF360J; M3: CSIRO-BOM-ACCESS1.3_UNSW-WRF360J; M4: CCCma-CanESM2_UNSW-WRF360K; M5: CSIRO-BOM-ACCESS1.0_UNSW-WRF360K; M6: CSIRO-BOM-ACCESS1.3_UNSW-WRF360K.a

Figure 10 Schematic allocation of models, time windows and RCPs to a single 10,000-year stochastic sequence

²

Table 11a Comparison of percentage changes in **number of wet days** under future climate scenarios for simple and quantile scaling of stochastic time series at 375 points

Season	Stationa 1951-200	iry 05	Stationary 1951-2005	Stationary 1951-2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observe	d	Stochastic	NARCliM historical	NARCliM	Simple scaling	Quantile scaling	NARCliM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling	NARCliM	Simple scaling	Quantile scaling
	days		days	days	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change
Annual	8	33.6	84.5	5 111.2	2 -5%	-4%	-3%	-5%	-6%	-6%	-10%	-4%	-10%	<i>-</i> 14%	-7%	-9%
МАМ	1	14.1	13.8	3 23.6	5 -2%	3%	1%	-6%	<i>б</i> и 1%	-1%	-8%	3%	-6%	<i>б</i> -14%	5 1%	-13%
JJA	2	25.9	26.2	32.6	5 -3%	-4%	-2%	-1%	-6%	-7%	-9%	-4%	-7%	<i>.</i> -7%	-8%	-13%
SON	2	27.1	28.1	32	2 -12%	-9%	-7%	-11%	-9%	-10%	-20%	-9%	-18%	-26%	-11%	-25%
DJF	1	16.6	16.6	23.9	-3%	-4%	-2%	-1%	-5%	-5%	-3%	-5%	-4%	-8%	-7%	-4%

Number of wet days defined for days > 1 mm rather than 0 mm. The difference in threshold helps to explain why simple-scaling (a multiplicative factor) sees changes to this attribute.

Table 11b Comparison of percentage changes in **number of heavy precipitation days** under future climate scenarios for simple and quantile scaling of stochastic time series at 375 points

Season	Stationary 1951-2005	Stationary 1951-2005	Stationary 1951-2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM historical	NARCIIM	Simple scaling	Quantile scaling	NARCliM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling
	days	days	days	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change
Annual	24.2	2 24	28.1	1 -6%	-8%	-10%	-7%	-14%	-7%	-13%	-8%	-13%	-17%	-19%	-13%
МАМ	4.4	4 4.4	6.1	1 -3%	0%	2%	-10%	-7%	-7%	-13%	0%	-11%	-20%	-5%	-27%
JJA	7.2	2 7.1	7.7	7 -4%	-13%	-10%	-1%	-20%	. 1%	-12%	-11%	-11%	-6%	-25%	-3%
SON	7.5	5 7.4	1 7.9	9 -14%	-12%	-18%	-15%	-15%	-16%	-22%	-11%	-20%	-30%	-23%	-28%
DJF	5.2	2 5.1	6.4	4 0%	-4%	-4%	(0%	-10%	-2%	-2%	-8%	-2%	-8%	-16%	-12%

Table 11c Comparison of percentage changes in **wet-day precipitation intensity** under future climate scenarios for simple scaling and quantile scaling of stochastic time series at 375 points

Season	Stationary 1951-2005	Stationary 1951-2005	Stationary 1951-2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM historical	NARCliM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling	NARCIiM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling
	mm/day	mm/day	mm/day	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change
Annual	8.9	9 9.	1 7.8	3 0%	-4%	-1%	0%	-4%	-3%	0%	-10%	3%	0%	-13%	-2%
МАМ	9.7	7 9.!	5 8.1	0%	-2%	0%	-4%	-8%	-2%	-4%	-11%	-2%	-2%	-17%	0%
ALL	8.2	2 8.3	3 7.2	-1%	-4%	-1%	0%	. 0%	1%	-1%	-10%	-1%	0%	-5%	5%
SON	8.2	2 8.0	5 7.5	5 0%	-12%	0%	-3%	-13%	-1%	0%	-20%	2%	-3%	-27%	-7%
DJF	9.4	4 9.6	5 8.2	2 4%	0%	1%	4%	2%	4%	4%	1%	-1%	2%	-5%	-1%

Table 11d Comparison of percentage changes in **heavy wet-day precipitation intensity** under future climate scenarios for simple and quantile scaling of stochastic time series at 375 points

Season	Stationary 1951-2005	Stationary 1951-2005	Stationary 1951-2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM historical	NARCIIM	Simple scaling	Quantile scaling									
	mm/day	mm/day	mm/day	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change
Annual	21.7	7 22.3	3 20.2	2 1%	-4%	4%	1%	-5%	1%	3%	-9%	1%	3%	-13%	5%
MAM	22.7	7 21.8	3 20.9	9 1%	-2%	0%	-1%	-6%	-2%	5 0%	-8%	4%	5 1%	-14%	5%
JJA	20	20.5	5 18.8	3 1%	-3%	. 1%	3%	s 0%	2%	s 2%	-9%	-4%	4%	-7%	s 2%
SON	19.5	5 21.1	1 19.4	4 2%	-11%	0%	1%	-11%	2%	3%	-20%	2%	3%	-26%	6 0%
DJF	21.3	3 22.5	5 21.4	4 3%	-3%	4%	4%	-1%	3%	5%	-3%	0%	4%	-8%	ő 0 %

Table 11e Comparison of percentage changes in **dry spell duration** under future climate scenarios for simple scaling and quantile scaling of stochastic time series at 375 points

Seasor	Stationary 1951–2005	Stationary 1951–2005	Stationary 1951–2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM historical	NARCliM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling	NARCIIM	Simple scaling	Quantile scaling
	days	days	days	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change	% change
Annua	6.4	4 6.4	4 4.4	4 5%	. 0%	3%	7%	3%	6%	5 14%	6%	ы́ 11%	23%	5%	6 20%
Annua	33	2 3	2 13.7	1 2%	. 0%	3%	3%	3%	5%	5%	5%	5%	8%	3%	6 10%

Table 12a Comparison of percentage changes in **minimum average temperature** under future climate scenarios for simple and quantile scaling of stochastic timeseries at 100 temperature points

Season	Stationary 1951–2005	Stationary 1951–2005	Stationary 1951–2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM baseline	NARCIIM	Simple scaling						
	°C	°C	°C	% change							
Annual	5.4	5.4	6.3	+1	+1	+1	+1	+1.8	+1.8	+2.5	+2.5
MAM	8.3	8.3	7.4	+1	+1	+1	+1	+1.6	+1.6	+2.6	+2.6
AII	1.3	1.3	1.5	+1	+1	+1	+1	+1.7	+1.7	+2.5	+2.5
SON	2.7	2.7	5.3	+0.9	+0.9	+0.9	+0.9	+1.8	+1.8	+2.2	+2.2
DJF	9.1	9.1	11.1	+1.2	+1.2	+1.2	+1.2	+2.1	+2.1	+2.8	+2.8

Table 12b Comparison of percentage changes in **maximum average temperature** under future climate scenarios for simple and quantile scaling of stochastic timeseries at 100 temperature points

Season	Stationary 1951–2005	Stationary 1951–2005	Stationary 1951–2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM baseline	NARCIIM	Simple scaling						
	°C	°C	°C	% change							
Annual	17.5	17.5	16.1	+1.1	+1.1	+1.2	+1.2	+2	+2	+2.9	+2.9
MAM	21.8	21.8	8.4	+1	+1	+1.1	+1.1	+1.9	+1.9	+2.7	+2.7
JJA	11	11	17	+0.9	+0.9	+1.2	+1.2	+1.7	+1.7	+2.8	+2.8
SON	13.9	13.9	15.8	+1.1	+1.1	+1	+1	+2.2	+2.2	+2.8	+2.8
DJF	23.6	23.6	23.5	+1.2	+1.2	+1.3	+1.3	+2.1	+2.1	+3.1	+3.1

Table 12c Comparison of percentage changes in **potential evapotranspiration** under future climate scenarios for simple and quantile scaling of stochastic timeseries at414 PET points

Season	Stationary 1951–2005	Stationary 1951–2005	Stationary 1951–2005	RCP 4.5 / 2030	RCP 4.5 / 2030	RCP 4.5 / 2070	RCP 4.5 / 2070	RCP 8.5 / 2030	RCP 8.5 / 2030	RCP 8.5 / 2070	RCP 8.5 / 2070
	Observed	Stochastic	NARCliM baseline	NARCIIM	Simple scaling						
	mm	mm	mm	% change							
Ann.	1460.3	1460.3	1313.8	(3%)	(3%)	(5%)	(5%)	(3%)	(3%)	(6%)	(6%)
MAM	435.9	435.9	262.3	(2%)	(2%)	(5%)	(5%)	(3%)	(3%)	(7%)	(6%)
JJA	148	148	137.8	(3%)	(3%)	(6%)	(6%)	(4%)	(3%)	(8%)	(8%)
SON	285.8	285.8	380.2	(3%)	(3%)	(5%)	(5%)	(3%)	(3%)	(7%)	(7%)
DJF	590.6	590.6	533.3	(2%)	(2%)	(4%)	(4%)	(2%)	(2%)	(5%)	(5%)

5 Summary

This report assessed future changes of a range of key climate attributes from NARCliM 1.5 projections across the southern region, encompassing the Murrumbidgee, Murray and Snowy catchments as well as regions of Victoria and South Australia. Quantitative analysis was conducted for a set of 6 model configurations according to different periods and climate scenarios as well as qualitative analysis for other published studies. A method of relating stochastic data generated for a historical stationary climate to projected future climates was developed. This method was adopted to facilitate risk-based assessment as part of ongoing development of regional water strategies (across New South Wales by the Department of Planning and Environment.

The application of risk assessment to the southern region needs additional consideration above and beyond prior implementations for other regions, because several key hydrometeorological variables in this region are reported to exhibit non-stationary changes in the recent past (Karoly & Braganza 2005; CSIRO 2012; Jones 2012; Hope et al. 2017). Based on the recommendation of an expert panel review of the climate risk method applied in the northern New South Wales regions, the Department of Planning and Environment commissioned a pilot assessment to understand the implications of this non-stationarity for stochastic data generation and future climate scaling in the southern region (Devanand et al. 2020). The recommendations of this pilot require a representative 'baseline climate' to adjust historical observations from earlier periods to adjust the stochastic model to produce estimates of possible future changes. The pilot assessment also recommended scaling should account for changes in multiple attributes of precipitation (for example, number of wet days, seasonal totals, extremes).

5.1 Analysis decisions

NARCliM 1.5 simulations are selected for 6 different model variants that represent reliable GCM and RCM configurations. The gridded model values are translated to point locations using a weighted distancebased averaging method. To assess biases in the climate model simulations relative to observations, two analyses are considered, each having their own period: a historical period to account for GCM uncertainty (1951–2005) and an evaluation period to account for RCM uncertainty (1979–2013). Future climates are considered relative to 2 baseline periods, a shorter 30-year baseline 1976–2005 commensurate with other studies, and a longer baseline 1951–2005 making full use of the NARCliM 1.5 historical simulation. A wide range of attributes were selected to account for climatic changes: 8 precipitation attributes covering the wet day frequency, amounts and extremes, and 3 attributes respectively for mean potential evapotranspiration, minimum temperature and maximum temperature.

5.2 Comparison to observations

The historical and evaluation runs from the NARCliM 1.5 ensemble are compared with observed data from the gauges in the southern basin and the biases in various attributes of climate are documented. The future changes projected for two 30-year time windows with respect to the full historical baseline are reported.

The simulations show positive biases in annual and seasonal totals and the number of wet and heavy precipitation days in the evaluation and historical runs compared to observed gauge data in the region. The signs of these biases are consistent in all the ensemble members. The ensemble mean exhibits biases of +37% and +32% in the annual total precipitation in the evaluation and historical runs respectively. The ensemble mean biases in the annual number of wet days is +35%/+32% and the number of heavy precipitation days is +32%/+26%. The biases in mean wet/heavy day precipitation intensities are low.

Thus, the biases in the annual/seasonal totals appear to be associated with an overestimation of precipitation frequency rather than intensity. The precipitation biases in the historical run and the evaluation run are qualitatively similar, indicating that the regional models are the dominant contributors of the precipitation biases. Generally, the simulations underestimate Tmax and overestimate Tmin, consistent with reported results (Di Virgilio et al. 2019). In the historical run, the negative biases in Tmax are enhanced (-2.1 °C to -2.5 °C) relative to the evaluation run (-1.3 °C to -1.8 °C), while the positive biases in Tmin are lower. The Morton potential evapotranspiration is underestimated (annual biases of -8% to -11%) in the NARCliM 1.5 simulations.

5.3 Future changes

The range of grid-level future changes projected by the NARCliM 1.5 ensemble mean is generally within the ranges projected by other sources of climate projections. The ensemble mean of the future simulations shows decreases in annual total precipitation across the region. The magnitudes of decreases are higher in the RCP 8.5 simulations. Seasonal precipitation totals exhibit decreases during MAM, JJA and SON, with the highest magnitude of decreases in SON. The decreases in spring precipitation are consistent in sign across most of the ensemble members. The changes in DJF precipitation show mixed patterns (decreases and increases). There are decreases in the number of wet and heavy precipitation days annually and during MAM, JJA and SON, while the mean precipitation intensity during wet/heavy precipitation days exhibits a mixed pattern of changes (increases and decreases) annually and seasonally. Thus, the changes in precipitation totals appear to be primarily associated with a decrease in the frequency of precipitation events. Annual and seasonal totals/means of potential evapotranspiration and temperature (Tmin and Tmax) exhibit increases in the future simulations.

5.4 Generating stochastic simulations

The 1951–2005 historical baseline was selected for scaling as it is comparable to the shorter baseline given climate variability and utilises the full historical NARCliM 1.5 simulation. Both simple scaling and daily quantile scaling are investigated, with daily quantile scaling utilised to derive two 10,000-year time series at each point location, one per 2030 and 2070 time window. Rather than have separate time series for each model configuration and RCP scenario, the number of time series has been restricted to 'averaged' conditions for each time window to minimise subsequent computational expense during hydrological simulations. The 10,000-year sequence is carefully structured to enable analysis of uncertainty across all 6 model configurations and 2 RCP scenarios. Partitions of length 833 years are available for each configuration and scenario. Each partition can be further split into a small number of replicates, depending on chosen replicate length, for analysis of stochastic variability within a specific configuration and scenario.

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