

Evaluation and Future Projections of Hourly Precipitation Extremes from ERA5- and CMIP6-Driven Regional Climate Simulations of over Australia

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Abstract

Hourly precipitation extremes are a key driver of flash flooding but remain less understood than daily extremes due to long-term observational uncertainty and climate model limitations. This study evaluates and projects annual mean and annual maximum of daily maximum hourly precipitation (prhmax) across Australia using ERA5- and CMIP6- driven regional climate simulations from the CORDEX-Australasia ensemble, benchmarked against MSWEP (Multi-Source Weighted-Ensemble Precipitation) data, and assesses future changes under low- and high-emissions scenarios.

Overall, the ERA5-driven simulations reproduce the observed spatial distribution, seasonal cycle, and interannual variability of hourly precipitation, although model performance declines for annual maxima and the rarest events. BARPA-ACS and NARClIM2.0-R3 show the best agreement with observations, highlighting the importance of regional model configuration for simulating hourly precipitation extremes. Differences between simulations indicate that structural model uncertainty (emission scenarios, driving GCMs, different RCMs) remains a major source of uncertainty in future projections.

Under SSP1-2.6, projected changes are generally weak and inconsistent among models. In contrast, SSP3-7.0 produces robust and spatially coherent increases in hourly precipitation extremes across Australia. Although changes in annual mean prhmax are modest and model dependent, annual maximum prhmax increases consistently across all simulations, particularly over northern and eastern Australia. All simulations also project more frequent extreme hourly precipitation events, with the largest absolute increases over northern Australia. Relative increases become progressively larger for rarer events, with ensemble-mean changes of 9.0% K⁻¹, 18.8% K⁻¹, and 31.1% K⁻¹ for events exceeding 10, 20, and 30 mm hr⁻¹, respectively. These results indicate that climate warming will substantially intensify the frequency and magnitude of Australia's most extreme hourly precipitation events, while substantial uncertainties remain for the magnitude of the most intense events. The findings highlight the importance of emission reductions, multi-model ensembles and rigorous evaluation of sub-daily precipitation extremes to improve confidence in climate impact assessments and future flood risk projections.

1. Introduction

Flooding is one of the most frequent and damaging natural hazards in many regions of Australia (Johnson et al. 2016), driven largely by extreme precipitation events that occur across a wide range of climatic regimes, from tropical monsoonal systems to intense convective storms and east-coast lows in the southeast. Both historical records and recent events demonstrate that floods are a recurrent feature of the Australian climate, with substantial impacts on communities, infrastructure, agriculture, and ecosystems. In 2025, major flood events across the states of Eastern Australia where most of the population resides have resulted in \$3.5 billion in economic losses and insurance claims (<https://insurancecouncil.com.au/resource/extreme-weather-cost-3-5-billion-in-2025/>), placing sustained pressure on disaster response systems and the insurance sector. These impacts highlight the urgent need for reliable projections of extreme precipitation characteristics that directly drive flooding.

Increasing flood risk is likely to place upward pressure on insurance premiums in flood-prone areas, raising concerns about the long-term affordability and sustainability of insurance coverage for households and businesses in these locations.

Extreme precipitation is a key driver of flooding, yet its impacts depend strongly on precipitation intensity, duration, and timing, as well as geographic factors (Westra et al., 2014). While daily precipitation extremes are closely linked to riverine flooding and catchment-scale responses (Breinl, et al. 2021), short-duration extremes such as maximum hourly precipitation are critical for flash flooding, urban drainage exceedance, and infrastructure failure (Huang et al., 2022). Hourly precipitation extremes often govern peak runoff generation and flood onset, particularly in small and urban catchments, and are therefore highly relevant for flood risk assessment, engineering design standards, and emergency management (Fowler et al. 2021). Whilst the Clausius–Clapeyron relationship suggests that atmospheric moisture-holding capacity increases by approximately 7% per degree global warming (Trenberth et al. 2003), potentially leading to more intense precipitation extremes, the magnitude and spatial patterns of precipitation change are also strongly influenced by dynamic processes, including changes in atmospheric circulation, moisture transport, and storm dynamics. Importantly, recent studies suggested that sub-daily precipitation extremes may intensify more rapidly under warming than daily totals (e.g., Ayat et al., 2022; Förster and Thiele, 2020), increasing the likelihood of short-lived but highly destructive flood events (e.g., Blenkinsop et al., 2021; Pietras and Pырc, 2025).

Many studies have examined daily extreme precipitation, both globally and over Australia, using observations and climate model simulations (e.g., Li et al. 2021; Herold et al. 2021). Previous studies based on Coupled Model Intercomparison Project (CMIP) Phase 5 (CMIP5) and Phase 6 (CMIP6) global climate model (GCM) ensembles have documented projected increases in the intensity and frequency of daily precipitation extremes, despite considerable regional variability and inter-model spread (e.g., Li et al. 2021; Zhang et al., 2024). In Australia, analyses of daily extreme precipitation indices have shown increases in the proportion of heavy precipitation events in many regions with implications for flood risk (e.g., Herold et al, 2021; Eccles, et al. 2025; Ji et al., 2022, 2026a). However, these studies also highlighted persistent model biases in simulating daily precipitation extremes, emphasizing the importance of systematic evaluation before using projections for impact assessments (Evans et al., 2016).

In contrast, hourly precipitation extremes have received comparatively less attention, largely due to limited long-term observations and the coarse temporal resolution of many climate model outputs (Acharya, et al. 2020). This gap is particularly important in Australia, Southeast Asia, and many urban regions globally, where short-duration, high-intensity precipitation is increasingly linked to flash flooding and drainage exceedance, resulting in substantial economic losses and disruption (e.g., Fowler et al. 2021; Chitwatkulsiri and Miyamoto 2023; Wasko et al. 2024). Evaluation of hourly rainfall distributions against station observations in the Sydney area showed generally good agreement for the simulations considered (Khadke et al 2026). However, these simulations represent only a subset of those analysed here, and the evaluation was limited to a relatively small geographic area. The availability of high-

resolution gridded products such as MSWEP (Multi-Source Weighted-Ensemble Precipitation) (Beck et al. 2019) and the Integrated Multi-satellite Retrievals for the Global Precipitation Measurement (GPM) Mission (IMERG) dataset (Huffman et al., 2020), which provide spatially and temporally consistent hourly precipitation estimates, offers new opportunities to evaluate model performance at sub-daily timescales (Cheung et al. 2025). At the same time, the latest generation of CMIP6 GCMs, when used to drive downscaled regional climate simulations produced by multiple Australian modelling groups (e.g., Howard et al., 2024; Di Virgilio et al., 2025a, 2025b; Ji et al., 2024; Schroeter et al., 2024; Chapman et al., 2023, 2024), enables a more comprehensive assessment of uncertainty in hourly extreme precipitation projections at regional scales.

Given the high socioeconomic cost of flooding and the growing exposure of infrastructure and populations to flood risk, there is a clear need to assess how well the latest regional climate simulations represent the magnitude and variability of both annual mean and annual maximum prhmax (daily maximum hourly precipitation), and how these extremes may change in the future. This study therefore evaluates and projects prhmax using the CORDEX (Coordinated Regional Climate Downscaling Experiment) Australasia ensemble, which includes five regional climate models (RCMs) driven by both the fifth-generation European Centre for Medium-Range Weather Forecasts Reanalysis (ERA5; Hersbach et al., 2020) and the selected Coupled Model Intercomparison Project Phase 6 (CMIP6) global climate models (GCMs) (e.g. Di Virgilio et al. 2022; Grose et al. 2020). By explicitly evaluating and comparing their performance in simulating prhmax, this study aims to improve understanding of model skill, quantify uncertainty in future projections, and provide more robust information to support flood risk assessment, infrastructure planning, and climate adaptation in Australia.

2. Data and Method

2.1 Regional climate models and experiment design

CORDEX is an international initiative of the World Climate Research Programme designed to produce, evaluate, and disseminate high-resolution regional climate projections for climate change research and impact assessment (<https://cordex.org/>).

Four Australian modelling groups have produced five regional climate projections for the CORDEX Australasia domain (Table 1). They are BARPA-ACS (Bureau of Meteorology Atmospheric Regional Projections for Australia – Australian Climate Service)(Howard et al., 2024), NARcliM2.0-R3 (NSW and Australian Regional Climate Modelling Project, Version 2.0 -R3) and NARcliM2.0-R5 (NSW and Australian Regional Climate Modelling Project, Version 2.0 -R5) (Di Virgilio et al., 2025a,b), CCAM-ACS (Conformal Cubic Atmospheric Model – Australian Climate Service) (Schroeter et al., 2024), and QldFCP-2 (Queensland Future Climate Projections Phase 2) (Chapman et al., 2023, 2024). These simulations were driven by ERA5 reanalysis and the selected CMIP6 GCMs boundary conditions (See details in Table 2).

Table 1
Summary of the regional climate models used in this study

RCM	Institute	Dynamical core	Horizontal resolution	Key characteristics	References
BARPA-ACS	Bureau of Meteorology	BARPA (based on the UK Met Office Unified Model)	0.15° (~ 12–15 km)	UM coupled with JULES; GA7 physics with updated convection and surface parameterisations; 63 vertical levels; limited-area model forced by ERA5 or CMIP6 GCMs; upper-level dynamical nudging of winds and temperature	Howard et al. (2024); Su et al. (2022)
NARClIM2.0-R3	NSW Department of Climate Change, Energy, the Environment and Water	WRF v4.1.2	0.18° (~ 20 km)	Noah-MP land-surface model; MYNN2 PBL scheme; 45 vertical levels; driven by ERA5 and selected CMIP6 GCMs	Di Virgilio et al. (2025a, b)
NARClIM2.0-R5	NSW Department of Climate Change, Energy, the Environment and Water	WRF v4.1.2	0.18° (~ 20 km)	Same as R3 except using the ACM2 hybrid local–nonlocal PBL scheme	Di Virgilio et al. (2025a, b)
CCAM-ACS	CSIRO / Australian Climate Service	CCAM	0.11° (~ 12.5 km)	CCAM coupled with CABLE and inline ocean model; stretched-grid configuration; 54 vertical levels; spectral nudging above 850 hPa; moisture evolves freely	Schroeter et al. (2024); Thatcher and McGregor (2011)
QldFCP-2	University of Queensland / Queensland Government	CCAM	0.11° (~ 10 km)	CCAM coupled with CABLE; stretched-grid configuration; 35 vertical levels; spectral nudging of temperature, winds and surface pressure at large scales	Chapman et al. (2023, 2024); Ma et al. (2025)

Table 2

Sparse matrix of downscaled GCM-RCM simulation pairs. This table includes the QldFCP-2 ocean-coupled simulations, labelled with 'oc' which are not directly assessed in this paper. Table entries indicate the CMIP6 variant ID of the selected driving experiment, following Trancoso et al. (2022), Grose et al. (2023) and Di Virgilio et al. (2022). (adopted and modified from Jiang et al. 2025)

CMIP6 GCM	Resolution	QldFCP-2	NARClIM2.0		CCAM-ACS	BARPA-ACS
			R3	R5		
ACCESS-CM2	1.875° × 1.25°	r2i1p1f1 (oc)			r4i1p1f1	r4i1p1f1
ACCESS-ESM1.5	1.875° × 1.25°	r6i1p1f1 r20i1p1f1 (oc) r40i1p1f1 (oc)	r6i1p1f1	r6i1p1f1	r6i1p1f1	r6i1p1f1
CESM2	1.25° × 0.9°				r11i1p1f1	r11i1p1f1
CMCC-ESM2	1.25° × 0.9°	r1i1p1f1			r1i1p1f1	r1i1p1f1
CNRM-CM6.1-HR	0.5° × 0.5°	r1i1p1f2 r1i1p1f2 (oc)				
CNRM-ESM2-1	1° × 1°				r1i1p1f2	
EC-Earth3	0.8° × 0.8°	r1i1p1f1			r1i1p1f1	r1i1p1f1
EC-Earth3-Veg	0.8° × 0.8°		r1i1p1f1	r1i1p1f1		
FGOALS-g3	2.5° × 2.5°	r4i1p1f1				
GFDL-ESM4	1° × 1°	r1i1p1f1				
GISS-E2-1-G	2.0° × 2.5°	r2i1p1f2				
MPI-ESM1-2-HR	0.9° × 0.9°		r1i1p1f1	r1i1p1f1		r1i1p1f1
MPI-ESM1-2-LR	1.9° × 1.9°	r9i1p1f1				
MRI-ESM2-0	1.125° × 1.125°	r1i1p1f1				
NorESM2-MM	1° × 1°	r1i1p1f1 r1i1p1f1 (oc)	r1i1p1f1	r1i1p1f1	r1i1p1f1	r1i1p1f1

CMIP6 GCM	Resolution	QldFCP-2	NARClIM2.0		CCAM-ACS	BARPA-ACS
			R3	R5		
UKESM1-0-LL	1.875° × 1.25°		r1i1p1f2	r1i1p1f2		

The RCMs differ in their dynamical cores, physical parameterisations, spatial domains, horizontal and vertical resolutions, simulation periods, and use of spatial nudging. Recent studies by Ma et al. (2026), Eccles et al. (2025), and Jiang et al. (2025) have comprehensively evaluated and compared the performance of these CORDEX-CMIP6 simulations in reproducing observed mean climate and climate extremes for ERA5- and GCM-driven experiments. Overall, the simulations exhibit comparable performance and demonstrate good skill in capturing the broad spatial patterns of mean climate and climate extremes. However, systematic biases remain, particularly in the representation of dry spells and the intensity of extreme rainfall.

Collectively, these modelling efforts provide a coordinated ensemble of high-resolution CMIP6 downscaled projections for the Australasian region, supporting climate change assessment and impact studies across Australia and neighbouring regions. A summary of the RCM configurations, including key model characteristics and experimental design, is provided in Table 1.

- **BARPA-ACS**

The BARPA-ACS model is based on the UK Met Office Unified Model coupled with the Joint UK Land Environment Simulator (JULES) land-surface scheme. It follows the Global Atmosphere and Land (GAL) GA7 physics configuration with updated parameterisations to improve convection and suppress grid-point storms (Walters et al., 2019; Tucker et al., 2022; Su et al., 2022; Howard et al., 2024). BARPA-ACS is configured on a regular latitude–longitude grid at approximately 0.15° (~ 12–15 km) resolution with 63 vertical levels extending to about 41 km. The model is run as a limited-area regional climate model forced by ERA5 reanalysis or selected CMIP6 GCMs, with lateral and sea surface temperature boundary conditions supplied by the driving dataset. Dynamical nudging of winds and temperatures in the upper atmosphere is applied to maintain consistency with the large-scale circulation.

- **NARClIM2.0 (R3 and R5)**

NARClIM2.0 employs two configurations of the Weather Research and Forecasting (WRF v4.1.2) model (R3 and R5), which were selected from an initial ensemble of 78 RCMs, each using different combinations of physics parameterisations (Di Virgilio et al., 2025a). Both configurations are run over CORDEX-Australasia at 20 km resolution with 45 vertical levels and use the Noah-MP land-surface model (Di Virgilio et al., 2025a). The only difference between the two configurations is the planetary boundary layer (PBL) scheme: R3 uses the Mellor–Yamada–Nakanishi–Niino (MYNN2) turbulent kinetic energy-based local closure scheme, whereas R5 adopts the Asymmetric Convective Model version 2 (ACM2), a hybrid local–nonlocal PBL scheme designed to enhance convective boundary-layer mixing. Simulations

are forced by ERA5 reanalysis and five carefully selected CMIP6 GCMs based on their performance, independency and possible future changes in precipitation and temperature over Southeast Australia (Di Virgilio et al., 2022). NARClIM2.0 provides climate projections over the CORDEX Australasia domain at 20 km resolution and over southeastern Australia at 4 km resolution, representing Australia's only convection-permitting climate-length regional climate simulation. Compared with previous NARClIM generations, NARClIM2.0 substantially reduces temperature and precipitation biases and improves the simulation of climate extremes (Di Virgilio et al., 2019; Ji et al., 2024, 2026b; Di Virgilio et al., 2025a).

- **CCAM-ACS**

The CCAM-ACS model, developed by CSIRO and the Australian Climate Service, is based on CCAM coupled with the Community Atmosphere Biosphere Land Exchange (CABLE) land-surface model and an inline ocean model. The model employs a variable-resolution stretched C384 grid with approximately 12.5 km resolution over Australia and 54 atmospheric vertical levels. Large-scale atmospheric circulation is constrained through spectral nudging of winds, temperature and pressure above 850 hPa to ERA5 or CMIP6 GCMs, while atmospheric moisture evolves freely (Thatcher and McGregor, 2011). Ocean coupling improves the representation of coastal sea surface temperatures while maintaining consistency with the driving data at synoptic scales through spectral nudging (Thatcher et al., 2015).

- **QldFCP-2**

The QldFCP-2 system, developed through the Queensland Future Climate Science Program, also uses CCAM coupled with the CABLE land-surface model. It employs a stretched C288 grid providing approximately 10 km resolution over Australia with 35 atmospheric vertical levels. ERA5-driven simulations use three-hourly boundary conditions, with spectral nudging applied to winds and temperature above 850 hPa and surface pressure at scales larger than approximately 3000 km, while moisture remains unconstrained. In addition to ERA5 simulations, QldFCP-2 downscaled eleven CMIP6 GCMs using an atmosphere-only configuration, with five models also simulated using a coupled atmosphere–ocean configuration (Chapman et al., 2023; Schroeter et al., 2024; Eccles et al., 2025).

Although both QldFCP-2 and CCAM-ACS are based on the CCAM regional climate model, they differ substantially in their experimental design. QldFCP-2 uses bias-adjusted GCM sea surface temperatures and a lower-resolution configuration (C288, 35 levels), whereas CCAM-ACS follows the CORDEX-Australasia framework with higher resolution (C384, 54 levels). The ensembles are also driven by different sets of GCMs, with 11 GCMs in QldFCP-2 and seven in CCAM-ACS. Consequently, despite sharing the same underlying model, the two datasets are treated as distinct regional climate model ensembles.

2.2 Observations

Long-term observations of hourly precipitation are available at only a limited number of stations across Australia (Su et al., 2025), making them insufficient for a comprehensive evaluation of simulated hourly precipitation extremes.

AGCD (Australian Gridded Climate data) is the most used gridded dataset for evaluating RCMs in Australia (Evans et al., 2020), the temporal resolution is daily which is not sufficient for the study. Hence, we use MSWEP (Multi-Source Weighted-Ensemble Precipitation), although it has lower resolution (0.1 degree) as compared to AGCD (0.05 degree).

The MSWEP dataset provides global precipitation estimates from 1979 to the present by merging gauge, satellite, and reanalysis observations, thereby improving performance across a range of climatic regimes (Beck et al., 2019a). MSWEP has been extensively evaluated against the Stage-IV gauge-radar dataset over the United States (Beck et al., 2019b) and gauge observations worldwide (Beck et al., 2017), consistently demonstrating among the highest levels of performance of available precipitation products. The latest version, MSWEP V3, retains the 0.1° spatial resolution of previous versions while providing hourly precipitation estimates and improved accuracy (Wang et al., 2026), making it well suited for evaluating sub-daily precipitation extremes.

2.3 Evaluation and projection methods

MSWEP and the five sets of simulations are at different resolutions. For both the evaluation and projection analyses, they are remapped into the common resolutions (0.1°) using first-order conservative interpolation. ERA5-driven simulations are assessed and compared for their performance, and CMIP6 driven simulations are used for future projections. ERA5-driven simulations are from 1979 to 2020, the first year is taken as a spin-up period, so evaluations are undertaken in 1980–2020 (41-years). We assess performances of five simulations not only for annual mean, but also for seasonal mean, annual maximum prhmax and frequency of extreme events with three categories (prhmax exceeding 10, 20 and 30 mm hr⁻¹).

The period of 1985–2014 was selected as the historical reference period and 2071–2100 as the late-century future period. These 30-year periods provide robust climatological samples, reducing the influence of interannual variability associated with the El Niño–Southern Oscillation, the Indian Ocean Dipole, and the Southern Annular Mode. They are also broadly consistent with the baseline and future assessment periods used in recent climate change assessments, including IPCC Sixth Assessment Report (IPCC 2021). We present future projections for individual simulations and their ensemble mean (CORDEX-AUS) across simulations. As GCM driven simulations started at different years across the four modelling groups, we use the overlapped period (1961–2100) to analyse inter-annual variability across the simulations.

To calculate the relative change per degree of global warming, we first estimated the global mean temperature increase for 2071–2100 relative to 1985–2014 for each GCM used in the CORDEX Australasia simulations produced by the four modelling groups (Table S1). We then calculated the weighted mean global temperature increase for each modelling group (Table S2). The scaling factor (i.e., the relative change in prhmax and frequency of extreme events per degree of global warming) was obtained by dividing the relative change in prhmax and frequency of extreme events by the weighted mean global temperature increase.

RCM performance is assessed using annual and seasonal spatial bias metrics. Domain-mean bias (DMB) and root mean square error (RMSE) are used to quantify spatial agreement with the reference dataset, while the coefficient of variation (CV; calculated using standard deviation divided by the mean) is used to evaluate temporal variability. We also use NRM (Natural Resource Management) regions to geographically average RCM time series (Clarke et al., 2015) to compare simulations, the model skill, and projections of RCMs by region (Fig. 1).

The statistical significance of mean annual and seasonal biases compared to the reference data was calculated for each grid cell. Given the non-normality of precipitation data, the Mann–Whitney U test at a confidence level of 95% was applied.

We use the signal-to-noise ratio to assess where the climate change signal emerges over the ‘noise’ for each climate model ensemble considered. Here, we consider the noise as the standard deviation across all models in each ensemble. Stippling is shown on the ensemble mean and median change maps where the signal-to-noise ratio is > 1.0 , as this is a commonly adopted threshold used in the literature (Eccles et al., 2025).

3. Results

3.1 Evaluation of annual mean and annual maximum prhmax

This section evaluates spatial differences in annual mean and annual maximum prhmax between five ERA5-driven simulations and MSWEP using spatial bias patterns, DMB, and RMSE.

MSWEP shows strong spatial gradients in annual mean prhmax across Australia (Fig. 2), with the highest values over northern Queensland and the tropical Northern Territory, associated with convective and monsoonal rainfall, and lower values across central and southern inland regions. The continental mean is 0.44 mm hr^{-1} . Annual maximum prhmax exhibits a similar spatial distribution but with substantially larger magnitudes, with maxima concentrated over northern and northeastern Australia due to intense convective systems, tropical cyclones, and monsoonal activity. The continental mean annual maximum prhmax is 17.92 mm hr^{-1} .

All simulations reproduce the observed broad spatial patterns of annual mean prhmax, with small domain-mean biases (DMB ranging from -0.16 to 0.14 mm hr^{-1}) and RMSE values below 0.30 mm hr^{-1} . BARPA-ACS shows a modest wet bias (DMB = 0.14 mm hr^{-1}), while NARClIM2.0-R3 is nearly unbiased overall (DMB = -0.05 mm hr^{-1}) but exhibits a north-south dipole with dry biases over northern Australia and slight wet biases elsewhere. NARClIM2.0-R5 has a relatively stronger dry bias (DMB = -0.16 mm hr^{-1}) and the highest RMSE (0.27 mm hr^{-1}), mainly due to underestimation of precipitation over northern Australia. CCAM-ACS provides the best overall performance (DMB = 0.02 mm hr^{-1} and RMSE = 0.17 mm hr^{-1}), followed by QldFCP-2 (DMB = -0.07 mm hr^{-1} and RMSE = 0.19 mm hr^{-1}). Both WRF simulations

(NARClIM2.0-R3 and NARClIM2.0-R5) and both CCAM simulations (CCAM-ACS and QldFCP-2) share similar bias patterns individually. Overall, most simulations underestimate annual mean prhmax over tropical northern Australia, whereas BARPA-ACS is generally wetter.

Simulating annual maximum prhmax is more challenging, with substantially larger biases and RMSE values (3.53–7.14 mm hr⁻¹). BARPA-ACS performs best, with the lowest RMSE (3.53 mm hr⁻¹) and a small wet bias (DMB = 0.91 mm hr⁻¹). NARClIM2.0-R3 moderately underestimates extremes (DMB = -1.73 mm hr⁻¹), whereas NARClIM2.0-R5 exhibits the largest dry bias (DMB = -5.53 mm hr⁻¹) and highest RMSE (7.14 mm hr⁻¹), mainly due to strong underestimation of extreme events. CCAM-ACS shows a wet bias over eastern Australia (DMB = 3.24 mm hr⁻¹), while QldFCP-2 underestimates annual maximum prhmax (DMB = -3.45 mm hr⁻¹).

Overall, all simulations capture the broad spatial distribution of prhmax, with better agreement for annual mean than annual maximum prhmax. The larger uncertainties in annual maximum prhmax reflect the greater difficulty in simulating rare, high-intensity hourly rainfall events associated with convective systems and other extremes. Among the simulations, BARPA-ACS and NARClIM2.0-R3 provide the most realistic representation of prhmax variability across Australia.

- **Biases in the seasonal mean of prhmax.**

Figure 3 presents seasonal mean prhmax from MSWEP and biases in the five ERA5 driven RCM simulations. MSWEP shows a strong seasonal cycle, with continental mean prhmax decreasing from 0.92 mm hr⁻¹ in DJF to 0.17 mm hr⁻¹ in JJA before increasing to 0.30 mm hr⁻¹ in SON. The highest values occur over northern Australia and northeastern Queensland during DJF, associated with monsoonal and convective activity.

All simulations reproduce the observed seasonal cycle and spatial distribution, with highest values in DJF and lower values in cooler seasons. Biases are generally largest in DJF, particularly over tropical northern Australia, indicating greater challenges in simulating warm-season precipitation extremes. Outside DJF, domain-mean biases are mostly within ± 0.1 mm hr⁻¹.

Model differences are most apparent during DJF. BARPA-ACS shows a wet bias in DJF (+0.23 mm hr⁻¹) and SON (+0.24 mm hr⁻¹), indicating overestimation of warm-season intensity. NARClIM2.0-R3 performs well overall but has a moderate DJF dry bias in the north (-0.27 mm hr⁻¹), while NARClIM2.0-R5 shows the largest DJF dry bias (-0.47 mm hr⁻¹) and the highest RMSE. QldFCP-2 also underestimates DJF precipitation, mostly in the north, whereas CCAM-ACS exhibits the most consistent performance with small seasonal biases. Both WRF simulations and both CCAM simulations also demonstrate similar spatial bias patterns individually.

Overall, all simulations capture the seasonal cycle of prhmax, with BARPA-ACS and CCAM-ACS showing better agreement with MSWEP.

- **Coefficient of variation (CV) of annual mean and annual maximum prhmax**

The CV is a useful metric for assessing whether regional climate simulations reproduce observed interannual rainfall variability. Underestimating CV may lead to reduced confidence in projections of drought and flood risks by weakening the representation of wet and dry year variability.

MSWEP shows moderate spatial variability in CV for both annual mean and annual maximum prhmax, with higher values over central Australia and lower values in southern and coastal regions (Fig. 4). The domain-mean CV is 0.37 for annual mean prhmax and increases to 0.43 for annual maximum prhmax, indicating greater variability in extreme hourly precipitation.

All simulations broadly reproduce the observed spatial patterns, including higher variability over central Australia and larger CV values for annual maximum than annual mean prhmax (Figure S1). However, differences exist in the magnitude of biases (Fig. 4). For annual mean prhmax, BARPA-ACS and NARClIM2.0-R3 show the closest agreement with MSWEP, with small biases (DMB = - 0.06 and - 0.02) and low RMSEs (0.09 and 0.08). NARClIM2.0-R5 also performs well, while CCAM-ACS and QldFCP-2 underestimate variability over inland Australia.

For annual maximum prhmax, all simulations capture the observed spatial pattern of interannual variability but generally overestimate its magnitude. BARPA-ACS performs best, with a relatively small bias (DMB = - 0.04) and the lowest RMSE (0.11), whereas NARClIM2.0-R5 exhibits the largest overestimation (DMB = + 0.16; RMSE = 0.25). Overall, the simulations reproduce the spatial distribution of interannual variability reasonably well but tend to underestimate variability in annual mean prhmax while overestimating variability in annual maximum prhmax. The comparatively better performance of BARPA-ACS, CCAM-ACS, and QldFCP-2 in representing annual maximum prhmax variability may be partly related to the use of spectral nudging in these simulations, which constrains the large-scale atmospheric circulation and may improve the representation of year-to-year variability. In contrast, neither NARClIM2.0-R3 nor NARClIM2.0-R5 employs spectral nudging, which may contribute to their larger biases in the magnitude of interannual variability.

3.2 Evaluation of extreme events: Days with prhmax exceeding 10, 20 and 30 mm hr⁻¹

This section evaluates the ability of ERA5-driven simulations to reproduce the frequency of extreme hourly precipitation events, defined as days with prhmax exceeding 10, 20, and 30 mm hr⁻¹. MSWEP shows strong spatial concentration of extreme events over tropical northern Australia, with lower frequencies across inland and southern regions (Fig. 5). The observed mean annual frequencies decrease substantially with increasing thresholds, from 3.30 days yr⁻¹ (> 10 mm hr⁻¹) to 0.69 days yr⁻¹ (> 20 mm hr⁻¹) and 0.18 days yr⁻¹ (> 30 mm hr⁻¹). All simulations capture these broad spatial patterns.

To enable comparison among thresholds with different occurrence frequencies, normalized RMSE (NRMSE), calculated by dividing RMSE by the observed mean frequency, is used (Jolliffe and Stephenson, 2012). For events exceeding 10 mm hr⁻¹, NRMSE ranges from 0.55 to 1.23 (Table S1).

BARPA-ACS performs best (NRMSE = 0.55), primarily because it most accurately reproduces the frequency of extreme events over northern Australia, where other simulations generally exhibit substantial negative biases. In contrast, NARcliM2.0-R5 (1.23) and QldFCP-2 (1.18) show the largest relative errors due to substantial underestimation over northern Australia. NARcliM2.0-R3 and CCAM-ACS show intermediate performance. Despite their poorer performance over northern Australia, the two NARcliM2.0 simulations and QldFCP-2 generally produce smaller biases than BARPA-ACS and CCAM-ACS over southeast Australia, highlighting regional differences in model performance.

For the 20 mm hr^{-1} threshold, absolute biases decrease relative to 10 mm hr^{-1} , with domain-mean biases generally within ± 0.5 days yr^{-1} . However, due to the lower observed frequency (0.69 days yr^{-1}), NRMSE remains high (0.87–1.33). BARPA-ACS again shows the lowest error (0.87), whereas NARcliM2.0-R5 and QldFCP-2 have the largest errors. Spatially, BARPA-ACS and NARcliM2.0-R3 reproduce the observed frequency more accurately, while NARcliM2.0-R5 and QldFCP-2 continue to underestimate event frequency over northern Australia and CCAM-ACS exhibits relatively larger biases over eastern Australia.

For the rarest events (> 30 mm hr^{-1}), all simulations show small domain-mean biases and similar RMSE values (0.21–0.27 days yr^{-1}). However, NRMSE increases to 1.17–1.50 because the observed frequency is only 0.18 days yr^{-1} , indicating persistent spatial uncertainties. NARcliM2.0-R3 achieves the lowest NRMSE (1.17), followed by BARPA-ACS (1.28), while QldFCP-2 performs poorest. As for the 20 mm hr^{-1} threshold, BARPA-ACS and NARcliM2.0-R3 more accurately reproduce the spatial distribution of these rare events, while NARcliM2.0-R5 and QldFCP-2 show substantial underestimation over northern Australia and CCAM-ACS exhibits larger biases over eastern Australia.

Overall, model errors shift from larger absolute but smaller relative errors for moderate extremes to smaller absolute but larger relative errors for rare extremes. Although agreement improves for domain-mean frequencies at higher thresholds, accurately representing the spatial distribution of very rare hourly precipitation extremes remains challenging. BARPA-ACS consistently shows the best overall performance, while NARcliM2.0-R3 substantially outperforms NARcliM2.0-R5, demonstrating the influence of model configuration on extreme precipitation simulation.

3.3 Future projection of annual mean and annual maximum prhmax

Under SSP3-7.0, projected changes in annual mean prhmax are modest but generally indicate increased hourly precipitation intensity across Australia (Fig. 6). Domain-mean changes range from -0.007 to $+0.078$ mm hr^{-1} . Most simulations project increases over northern and eastern Australia, with decreases mainly in parts of southwestern and southeastern Australia. BARPA-ACS and QldFCP-2 produce the largest increases, while CCAM-ACS shows moderate increases but localized decreases in the north. NARcliM2.0 exhibits weaker responses, with R3 showing increases mainly over northern Australia and decreases elsewhere, and R5 a slight overall decrease. In contrast to the two ACS simulations, which exhibit robust increases over southeastern and central-western Australia, the projected changes in the

NARClIM2.0 simulations and QldFCP-2 are generally smaller than the interannual variability across most regions, indicating a weak climate change signal (low SNR). The CORDEX-AUS ensemble projects a weak but spatially coherent increase across most of Australia.

In contrast, annual maximum prhmax exhibits a much stronger and more consistent response under SSP3-7.0 (Fig. 6). All simulations project increases in extreme hourly precipitation across most of Australia, with the largest changes occurring over northern and eastern regions. The robust signal of increase in annual maximum prhmax is consistent across simulations, especially for southeast Australia. Domain-mean increases range from + 1.53 mm hr⁻¹ in QldFCP-2 to + 3.91 mm hr⁻¹ in BARPA-ACS. CCAM-ACS (+ 3.85 mm hr⁻¹) and NARClIM2.0-R3 (+ 3.33 mm hr⁻¹) also simulate substantial intensification, while NARClIM2.0-R5 (+ 2.02 mm hr⁻¹) and the CORDEX-AUS ensemble mean (+ 2.74 mm hr⁻¹) show more moderate but spatially consistent increases. Compared with annual mean prhmax, projections of annual maximum prhmax show substantially stronger agreement among simulations, with decreases limited to small, isolated areas. This indicates that intensification of short-duration extreme precipitation is a robust response under SSP3-7.0. The two ACS simulations (BARPA-ACS and CCAM-ACS), which share six of seven driving GCMs, and the two NARClIM simulations, which use the same GCMs, project similar spatial patterns of change in annual maximum prhmax, suggesting that the driving GCMs exert a strong influence on projected changes.

Under SSP1-2.6, projected changes are considerably weaker and show greater inter-model uncertainty (Figure S2). Annual mean prhmax changes are small across all simulations, with domain-mean changes ranging from - 0.032 to + 0.003 mm hr⁻¹. NARClIM2.0 consistently projects slight decreases, whereas BARPA-ACS, CCAM-ACS, and QldFCP-2 show near-neutral or weakly negative changes. For annual maximum prhmax, model responses diverge substantially: BARPA-ACS and CCAM-ACS simulate increases (~ + 1 mm hr⁻¹), while NARClIM2.0-R5 projects a notable decrease (- 0.58 mm hr⁻¹). The ensemble response remains weak, reflecting large structural uncertainty under the lower-emissions pathway.

Overall, SSP3-7.0 produces stronger, more spatially coherent, and more robust increases in both annual mean and annual maximum prhmax than SSP1-2.6, demonstrating the critical role of emission reductions in mitigating future climate change impacts. While model differences remain evident for annual mean prhmax, particularly among NARClIM2.0 configurations, the robust intensification of annual maximum prhmax across all simulations indicates increasing confidence in future increases in hourly precipitation extremes under higher warming scenarios.

Figure 7 shows the relative change of annual maximum prhmax per degree global warming for SSP3-7.0. All models project predominantly positive scaling of hourly precipitation extremes with global warming, with southern Australia and Tasmania consistently exhibiting the strongest increases. Most simulations also indicate super- Clausius–Clapeyron (CC) scaling over parts of central west and southeastern Australia, suggesting that hourly rainfall extremes intensify faster than expected from thermodynamic moisture increases alone. However, substantial differences exist in the magnitude and spatial extent of

the scaling. BARPA-ACS and CCAM-ACS produce the strongest and most spatially coherent increases, while the two NARClIM2.0 configurations, particularly R5, project considerably weaker responses and greater spatial heterogeneity. QldFCP-2 occupies an intermediate position, with stronger scaling over southern Australia but localized decreases along the tropical coasts. Two ACS simulations and two NARClIM simulations show similar spatial patterns of prhmax scaling individually. These differences highlight the sensitivity of projected hourly precipitation extremes to driving GCMs, RCM configurations and physical parameterizations, despite broad agreement on the direction of future change.

3.4 Future projection of the frequency of extreme events

Under SSP3-7.0, all simulations project increases in the frequency of extreme hourly precipitation events, although the magnitude and spatial distribution vary among simulations and thresholds (Figure S3). The largest increases occur over northern Australia, particularly in BARPA-ACS and NARClIM2.0 simulations, while southern and inland regions generally show weaker increases. CCAM-ACS and QldFCP-2 exhibit smaller or more spatially variable changes, including limited decreases in parts of northern Australia. Across all simulations, the domain-mean change decreases with increasing threshold, indicating that the change in frequency of extreme events is weaker for rarer and more intense events.

BARPA-ACS shows the strongest and most widespread increases across all thresholds, followed by CCAM-ACS with a similar but weaker response. NARClIM2.0-R3 and R5 project modest increases (generally < 0.25 days yr^{-1}), with R3 slightly exceeding R5, while QldFCP-2 shows relatively small and spatially patchy changes. Model differences are largest for the 10 mm hr^{-1} threshold and become smaller for higher thresholds, showing greater consistency among simulations for more extreme precipitation events. The CORDEX-AUS ensemble mean indicates increased frequencies of extreme hourly precipitation events, particularly over northern and southeastern Australia.

Relative changes per degree of global warming (Fig. 8) show that all simulations project increases in the frequency of extreme hourly precipitation events, although the magnitude varies substantially among models and thresholds. Changes are relatively modest for events exceeding 10 mm hr^{-1} , with three of the five simulations projecting increases of less than 7% K^{-1} and an ensemble-mean increase of 9.0% K^{-1} . In contrast, all simulations project much larger increases for rarer events, with the ensemble mean rising to 18.8% K^{-1} for events exceeding 20 mm hr^{-1} and 31.1% K^{-1} for events exceeding 30 mm hr^{-1} . The larger relative increases in frequency of extreme events are largest in southern Australia even if their absolute increases are small. This systematic amplification with increasing threshold indicates that the most extreme hourly precipitation events intensify more rapidly with warming than more frequent, lower-intensity events. BARPA-ACS generally projects the largest increases across all thresholds, while the remaining simulations show weaker but broadly consistent positive changes.

In comparison, SSP1-2.6 shows much weaker and less consistent changes (Figure S4). Simulations differ in both the magnitude and sign of projected changes, with BARPA-ACS indicating slight increases, while NARClIM2.0 generally projects decreases. Overall, the stronger forcing under SSP3-7.0 produces a

clearer and more robust increase in the frequency of short-duration extreme precipitation events, with larger absolute increase in Northern Australia but a larger relative increase over Southern Australia.

3.5 Interannual variation of annual maximum prhmax and extreme events across four NRM regions

As shown in Sections 3.3 and 3.4, there is no consistent change in the annual mean prhmax under either SSP1-2.6 or SSP3-7.0, nor in projected changes in extreme events under SSP1-2.6. Therefore, this section focuses on variations in annual maximum prhmax and associated extreme events under SSP3-7.0.

- **Interannual variation of annual maximum prhmax for SSP3-7.0**

Annual maximum prhmax differs markedly between NRM regions and simulations, but several robust features are evident (Fig. 9). Across all regions, most simulations exhibit a gradual increase in extreme hourly precipitation over time, superimposed on substantial interannual variability.

Strong regional contrasts are evident, with Northern Australia showing the highest intensities and variability, often exceeding 30 mm hr^{-1} and occasionally 40 mm hr^{-1} . Eastern Australia also shows relatively high values and a gradual increase, while Southern Australia and the Rangelands remain lower, mostly below $20\text{--}25 \text{ mm hr}^{-1}$ with weaker trends. Across simulations, CCAM-ACS produces the highest values in southern and eastern regions and Rangelands, and strong increases, while BARPA-ACS shows intermediate magnitudes. NARClIM2.0-R3 generally yields higher extremes and variability than R5, particularly in the north, whereas R5 is consistently lower. QldFCP-2 exhibits weak trends and low variability, especially in Northern Australia.

Overall, while the simulations broadly agree on the relative ranking of regions and the presence of increasing extreme hourly precipitation, the spread between simulations remains large, particularly in Northern Australia, indicating substantial model-dependent uncertainty in projected extreme hourly rainfall.

- **Interannual variation of frequency of extreme events for SSP3-7.0**

Under SSP3-7.0, all five simulations project an increase in extreme hourly precipitation events, although the magnitude and regional expression vary among models and thresholds (Figures S5–6 and Fig. 10). Across the 10 , 20 , and 30 mm hr^{-1} thresholds, a consistent pattern is evident: event frequencies decrease with increasing threshold, while the absolute magnitude of projected changes becomes smaller. However, the spatial pattern of intensification remains robust, with the strongest increases in Northern Australia, followed by Eastern Australia, and weaker responses in Southern Australia and the Rangelands.

For events exceeding 10 mm hr^{-1} , most simulations show stable to increasing frequencies across all NRM regions, with the largest increases generally occurring in Northern Australia. BARPA-ACS projects the highest frequencies and strongest increases, followed by CCAM-ACS, while QldFCP-2 shows similar but weaker responses. NARClIM2.0-R3 produces intermediate values, whereas R5 consistently simulates the lowest frequencies and greater interannual variability. Eastern Australia shows moderate increases, while Southern Australia and the Rangelands remain lower but generally increasing.

Similar spatial patterns are observed for 20 mm hr^{-1} events, although frequencies are lower and model spread increases, reflecting greater uncertainty for rarer events. Northern Australia remains the region with the highest occurrence, followed by Eastern Australia, while Southern Australia and the Rangelands exhibit much lower frequencies. BARPA-ACS and CCAM-ACS generally simulate stronger increases, whereas NARClIM2.0-R5 shows weaker responses and larger variability.

For the most extreme events ($> 30 \text{ mm hr}^{-1}$), frequencies are substantially lower but still increase in most regions. Northern Australia remains the hotspot, with some simulations approaching $\sim 1 \text{ day yr}^{-1}$, while Southern Australia and the Rangelands remain rare ($< 0.3 \text{ days yr}^{-1}$). Despite larger inter-model differences at this threshold, all simulations indicate increasing occurrences of very intense hourly rainfall.

Overall, the five simulations consistently indicate future intensification of short-duration extreme precipitation under SSP3-7.0, particularly across northern and eastern Australia. Although uncertainty remains in the magnitude of change, the agreement among simulations supports increased confidence in projections of more frequent intense hourly rainfall events.

3. Discussion

This study evaluated five ERA5-driven regional climate simulations in reproducing observed annual mean and annual maximum prhmax, as well as extreme precipitation events. Projected changes simulated by these RCMs when forced by CMIP6 GCMs under the SSP1-2.6 and SSP3-7.0 scenarios were also assessed. Despite differences in model performance and future responses, several consistent patterns emerge across simulations.

1) Model evaluation: annual mean versus annual maximum prhmax All simulations reproduce the broad spatial distribution of observed prhmax, with higher intensities along northern and eastern Australia and lower values inland. However, model performance declines for rarer and more intense events, with annual maximum prhmax showing substantially larger biases than annual mean prhmax. This scale-dependent degradation reflects the challenges in representing hourly precipitation extremes, particularly convective processes, which remain a major source of uncertainty in climate models. Similar limitations have been reported in CMIP6 and regional modelling systems, where model resolution and parameterised convection can strongly influence extreme precipitation representation (Nishant et al., 2022; Eccles et al., 2025). Convection permitting models (CPMs) have shown added values in simulate

extreme precipitation compared to RCMs (Prein et al. 2013), which could improve performance in simulating annual mean and annual maximum prhmax.

2) Scenario dependence: SSP1-2.6 versus SSP3-7.0 Future changes show a strong dependence on emissions pathways. Under SSP1-2.6, changes in annual mean and annual maximum prhmax are generally small, spatially inconsistent, and often comparable to natural variability. In contrast, SSP3-7.0 produces stronger and more spatially coherent increases, particularly for annual maximum prhmax and high-intensity thresholds. Although inter-model differences remain, uncertainty decreases under SSP3-7.0 as the forced climate signal becomes stronger. Models showing weak or mixed responses under SSP1-2.6 generally converge toward increased extreme precipitation under SSP3-7.0. The contrast between the high- and low-emission scenarios demonstrates that reducing greenhouse gas emissions can substantially limit future impacts of hourly precipitation extremes.

Under higher emission scenario, all simulations also show predominantly positive scaling of hourly precipitation extremes with global warming, with the strongest increases over southern Australia and Tasmania (Fig. 7). Although domain-average scaling remains below the Clausius–Clapeyron (CC) rate of $7\% \text{ K}^{-1}$, several simulations indicate super-CC scaling over central west, and southeastern Australia, suggesting that dynamical effects may amplify thermodynamic moisture increases. The relatively modest domain-average scaling may partly reflect limitations in resolving convective processes at current model resolutions. CPM simulations have shown improved representation of sub-daily precipitation extremes and provide an important direction for future research (Lee et al., 2022; Fowler et al., 2021).

3) Model uncertainty and observational reference Inter-model differences are evident in both historical evaluation and future projections. BARPA-ACS and CCAM-ACS generally simulate stronger extreme precipitation intensity and frequency, whereas NARClIM2.0 configurations tend to underestimate the most intense hourly events (Figs. 2 & 6). Spatial nudging may also contribute to the relatively better performance of BARPA-ACS, CCAM-ACS, and QldFCP-2 in capturing annual maximum prhmax variability compared with NARClIM2.0 simulations (Fig. 4). The differences between NARClIM2.0 simulations highlight the role of planetary boundary layer (PBL) dynamics (Li et al. 2026). These differences likely arise from variations in driving GCMs, RCM configurations, convection parameterisations, land–atmosphere interactions, and numerical formulations. The uncertainty in future precipitation projections is largely driven by inter-model differences, particularly those associated with the choice of GCMs (Narsey et al. 2025), while regional climate models provide a smaller but still significant contribution (Stassen et al. 2025; Narsey et al. 2025; Wootten et al., 2017).

The influence of GCMs and RCMs can be inferred from similarities and differences among the simulations. BARPA-ACS and CCAM-ACS share six out of seven driving GCMs, while NARClIM2.0-R3 and NARClIM2.0-R5 use identical driving GCMs (Table 1). Their projections of annual maximum prhmax exhibit similar spatial patterns of change (Fig. 6), suggesting a strong influence from the large-scale climate response provided by the driving GCMs. They also show broadly consistent changes in annual

mean prhmax, although the magnitude and spatial details differ more substantially, indicating an important contribution from regional model formulation and physical parameterisations (Stassen et al. 2025). QldFCP-2 also uses CCAM but with different model configurations and a larger set of driving GCMs (Chapman et al., 2024) and therefore represents a distinct RCM–GCM combination. Its projected changes in both annual mean and annual maximum prhmax differ from the other simulations (Fig. 6), although they are consistent with the findings of Eccles et al. (2025) for daily extreme and rare precipitation events.

The larger spread in projected annual mean prhmax compared with annual maximum prhmax reflects differences in the processes controlling these metrics. Annual mean prhmax integrates changes across many heavy rainfall events and is therefore sensitive to variations in both rainfall intensity and occurrence, including changes in precipitation frequency, seasonality, circulation patterns, and convective activity. These processes depend on both large-scale thermodynamic and dynamical responses and regional-scale processes represented differently among models. In particular, differences in driving GCMs influence future changes in atmospheric moisture availability and circulation, while RCM formulation introduces additional uncertainty through differences in convection, cloud microphysics, boundary layer processes, and land–atmosphere interactions, which are especially important for hourly precipitation.

Consequently, simulations exhibit different signs of change in annual mean prhmax, indicating substantial uncertainty in the future evolution of the frequency and average intensity of daily hourly rainfall extremes. In contrast, annual maximum prhmax shows a more consistent sign of change across simulations, suggesting a more robust response of the most extreme hourly rainfall events to climate warming (Eccles et al., 2025). This consistency likely reflects the stronger influence of the thermodynamic response, particularly the increase in atmospheric moisture-holding capacity under warmer conditions, which enhances the intensity of the most extreme precipitation events despite differences in model formulation. Therefore, while projections of annual maximum prhmax provide greater confidence in the direction of change, annual mean prhmax remains more uncertain due to the combined influence of GCM differences, RCM processes, and internal climate variability.

Gridded observations of prhmax are unavailable; therefore, the MSWEP dataset was used as the reference dataset. Its suitability was assessed against the Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia (BARRA-C2) (Su et al., 2025) and the Integrated Multi-satellite Retrievals for the Global Precipitation Measurement (GPM) Mission (IMERG) dataset (Huffman et al., 2020). BARRA-C2 shows systematic wet biases in annual mean, annual maximum, and temporal variability of prhmax (Nguyen et al. 2026, in preparation). In contrast, MSWEP and IMERG agree closely in the spatial distribution, magnitude, and interannual variability of annual mean and annual maximum prhmax during their overlapping period. Although IMERG provides an independent satellite-based reference, its record is only available since 2000, limiting its use for long-term evaluation. Therefore, MSWEP was selected as the reference dataset. The strong agreement between MSWEP and IMERG increases confidence in using MSWEP as a benchmark where gridded observations are unavailable.

4) Implications and future research

Despite differences among simulations, all models project increased annual maximum prhmax and frequency of extreme events under future warming, particularly across northern and eastern Australia. In contrast to annual maximum prhmax, the domain-averaged increase in the frequency of extreme hourly precipitation events generally exceeds the Clausius–Clapeyron (CC) scaling rate for events exceeding 10 mm hr⁻¹ and substantially exceeds it for higher-intensity events. Across all simulations, the frequency of the most extreme hourly precipitation events increases more rapidly with warming than that of lower-intensity events, suggesting a disproportionate increase in the risk of flash flooding, urban inundation, soil erosion, and infrastructure damage, even where changes in mean precipitation are relatively modest.

These findings highlight the importance of ensemble-based approaches in climate impact assessments, as the magnitude of projected changes varies considerably among simulations despite a consistent increase in extreme precipitation. Future research should expand multi-model ensembles, improve observations of rare extreme precipitation events, and investigate event-based characteristics, including storm duration, intensity evolution, spatial extent, and event clustering. While this study focused on evaluating and comparing model performance and future projections, it did not investigate the physical processes responsible for the differences among simulations in their historical performance and projected changes. Addressing these mechanisms, including the roles of large-scale circulation, thermodynamic and dynamic processes, convection, and land–atmosphere interactions, would improve understanding of model uncertainty and the robustness of future projections. In addition, the availability of 4 km convection-permitting NARCLiM2.0 simulations provides an important opportunity to quantify the added value of explicitly resolving convection for projecting hourly precipitation extremes and to assess differences between convection-permitting and convection-parameterized regional climate models.

4. Conclusions

This study provides a comprehensive evaluation and future projection of annual mean and annual maximum prhmax across Australia using five regional climate simulations contributing to CORDEX-CMIP6 including its ERA5-forced evaluation simulations. Overall, the ERA5-driven simulations successfully reproduce the observed spatial distribution, seasonal cycle, and interannual variability of prhmax, although model performance declines with decreasing temporal scale and increasing event intensity. Annual maximum prhmax and the rarest hourly precipitation events remain the most challenging to simulate, with uncertainties increasing for higher thresholds despite generally good agreement in the broad spatial patterns. BARPA-ACS and NARCLiM2.0-R3 consistently provide the most realistic representation of prhmax and frequency of extreme events, and CCAM-ACS showing better agreement with MSWEP for seasonal cycle, while the marked improvement of NARCLiM2.0-R3 over R5 demonstrates the strong influence of regional model configuration on simulating extreme precipitation.

Substantial differences among simulations in both historical performance and future projections demonstrate that structural model uncertainties (emission scenario, driving GCMs and different RCMs) remain an important source of uncertainty in projections of hourly precipitation extremes. Simulations sharing the same RCM generally exhibit similar bias characteristics, whereas those driven by the same or similar GCMs tend to project comparable spatial patterns of future change. Notably, models like BARPA-ACS that more realistically reproduce present-day hourly precipitation extremes generally project stronger future intensification, highlighting the importance of rigorous model evaluation and selection for increasing confidence in future climate projections.

Future projections indicate that changes under SSP1-2.6 are generally weak and inconsistent among models, reflecting considerable structural uncertainty under a low-emissions pathway. In contrast, SSP3-7.0 produces robust and spatially coherent increases in annual mean and annual maximum prhmax, and frequency of extreme events across Australia. Although projected changes in annual mean prhmax are generally modest and remain model dependent, annual maximum prhmax increases consistently across all simulations, particularly over northern and eastern Australia, demonstrating a robust intensification of short-duration rainfall extremes under stronger warming. Relative to global warming, all simulations project positive scaling of annual maximum prhmax, with super-Clausius–Clapeyron scaling over parts of southern and southeastern Australia, indicating that the strongest events may intensify faster than expected from thermodynamic moisture increases alone.

All simulations also project more frequent extreme hourly precipitation events under SSP3-7.0, with the largest absolute increases occurring over northern Australia. Although the magnitude of change varies among models, the direction of change is highly consistent. Furthermore, the relative increase in event frequency becomes progressively larger with increasing event intensity, with ensemble-mean changes of 8.9% K⁻¹ for events exceeding 10 mm hr⁻¹, 18.6% K⁻¹ for events exceeding 20 mm hr⁻¹, and 30.6% K⁻¹ for events exceeding 30 mm hr⁻¹. This systematic amplification indicates that the rarest and most intense hourly precipitation events are projected to increase disproportionately with warming, implying greater future risks of flash flooding and other short-duration rainfall hazards.

Overall, despite substantial inter-model differences in the magnitude of change, the consistent intensification of extreme hourly precipitation across all simulations under SSP3-7.0 highlights the importance of ensemble-based assessments for quantifying uncertainty while providing increasing confidence that climate warming will lead to more frequent and more intense hourly precipitation extremes across Australia.

Looking ahead, CPM simulations provide an important pathway for future research into hourly precipitation extremes, allowing assessment of their added value and quantification of differences between RCM- and CPM-based projections of future extreme precipitation changes.

Declarations

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution

Fei Ji: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft. Giovanni Di Virgilio: Project Administration, Conceptualization, Methodology, Investigation, Visualization, Supervision, Writing –Review & Editing. Eugene Tam, Shaoxiu Ma: Methodology, Software, Formal analysis, Investigation, Visualization, Writing – Review & Editing. Jason P. Evans, Jatin Kala, Emma Howard: Formal analysis, Investigation, Validation, Writing –Review & Editing. Julia Andrys, Stephen White: Data Curation, Validation, Writing –Review & Editing. Yue Li, Phuong Loan Nguyen, Youngil Kim, Dipayan Choudhury, Rishav Goyal, Validation, Writing –Review & Editing. Matthew L. Riley: Resources, Funding Acquisition, Writing –Review & Editing.

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Data Availability

The RCM simulation data are published through the Australian National Computational Infrastructure. QldFCP-2 dataset created by QFCSP is available from <https://dx.doi.org/10.25914/h0bx-be42> at 20 km grid-spacing and <https://dx.doi.org/10.25914/2c0z-8t40> at 10 km grid-spacing. CCAM-ACS is available from <https://doi.org/10.25914/rd73-4m38>. NARClIM2.0 is available from <https://doi.org/10.25914/ysxb-rt43>. BARPA-ACS is available from <https://dx.doi.org/10.25914/z1x6-dq28>. CMIP6 data are available through the Earth System Grid Federation at: <http://esgf.llnl.gov/>. Replicated data is available from NCI as ESGF Tier 1 node: <https://dx.doi.org/10.25914/5b98afc88531e>. AGCD data used in this study is the

CSIRO's commercially licensed version of the Bureau's AGCD dataset on NCI (<http://dx.doi.org/10.25914/6009600304b02>). MSWEP was downloaded from GloH2O, and BARRA-C2 is available from <https://doi.org/10.25914/1x6g-2v48>.

Code Availability

The Weather Research and Forecasting (WRF) version 4.1.2 used in NARClIM2.0 is freely available from: <https://github.com/coecms/WRF/tree/V4.1.2>. The underlying code for this study is not publicly available but may be made available to qualified researchers on reasonable requests from the corresponding author.

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Figures

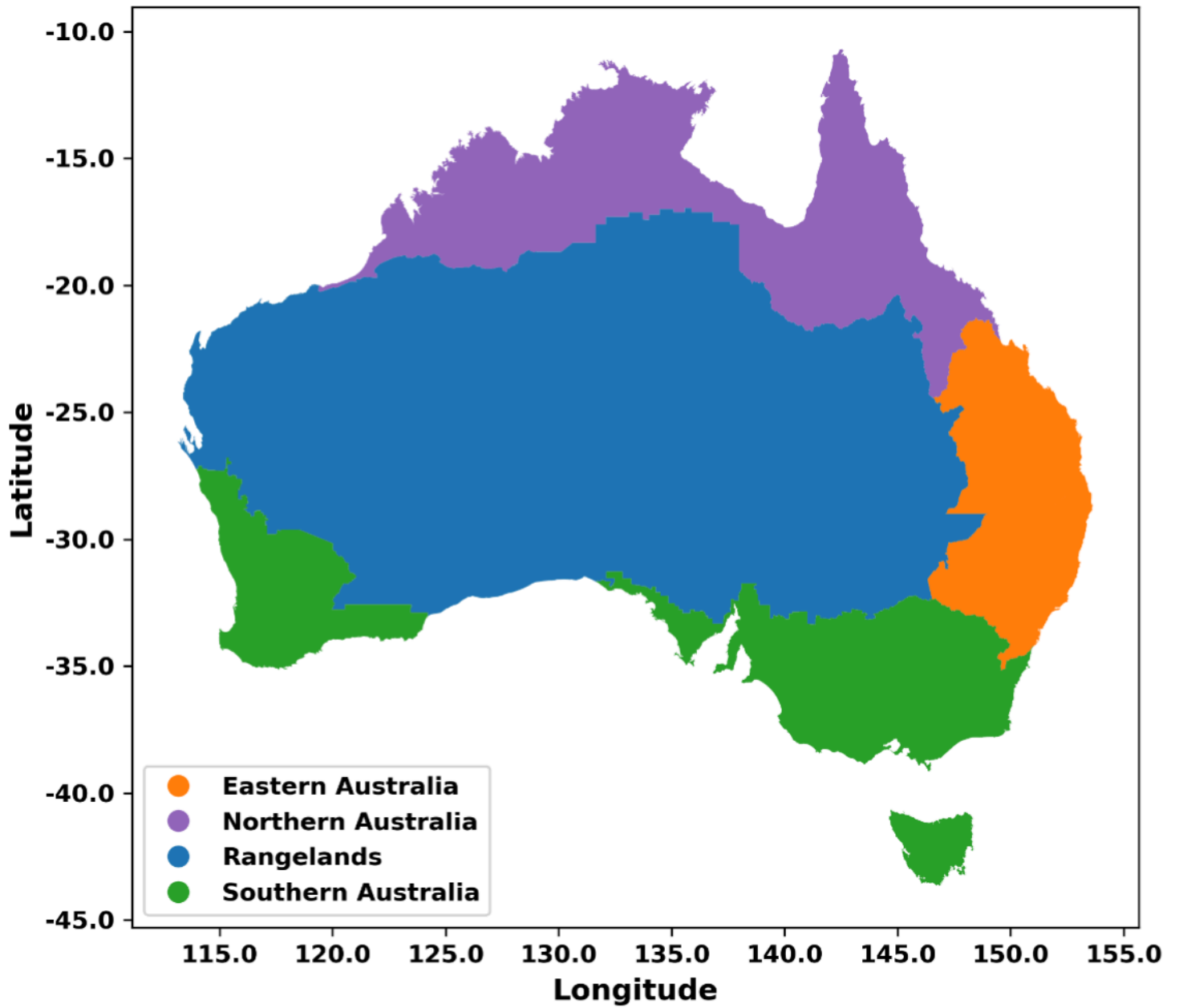


Figure 1

Four Natural resource management (NRM) regions for Australia.

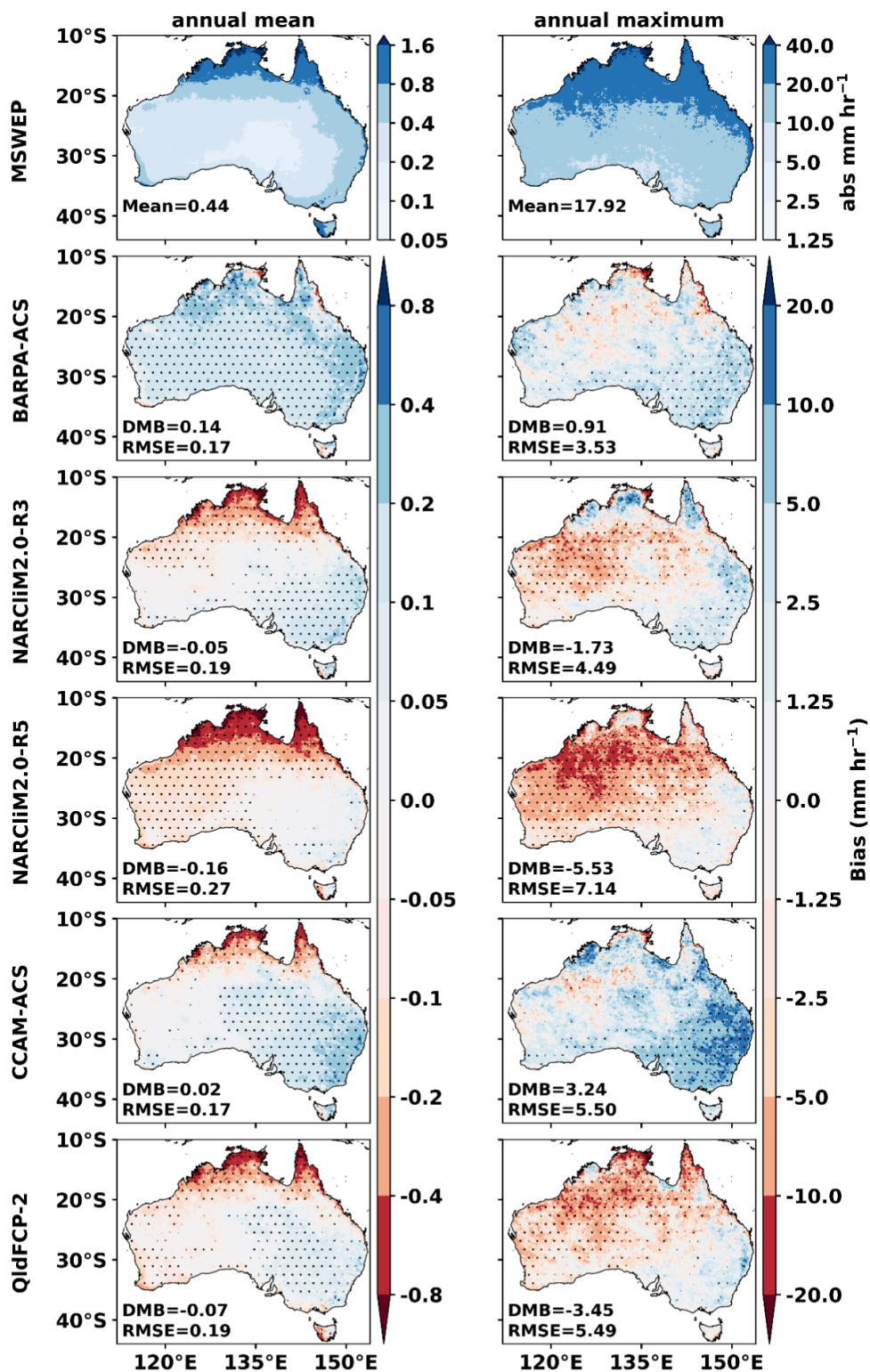


Figure 2

Observed annual mean and annual maximum prhmax and biases in them for five simulations. DMB – domain mean bias and RMSE - Root mean square error. Stippled areas indicate locations where an RCM shows statistically significant bias ($P < 0.05$).

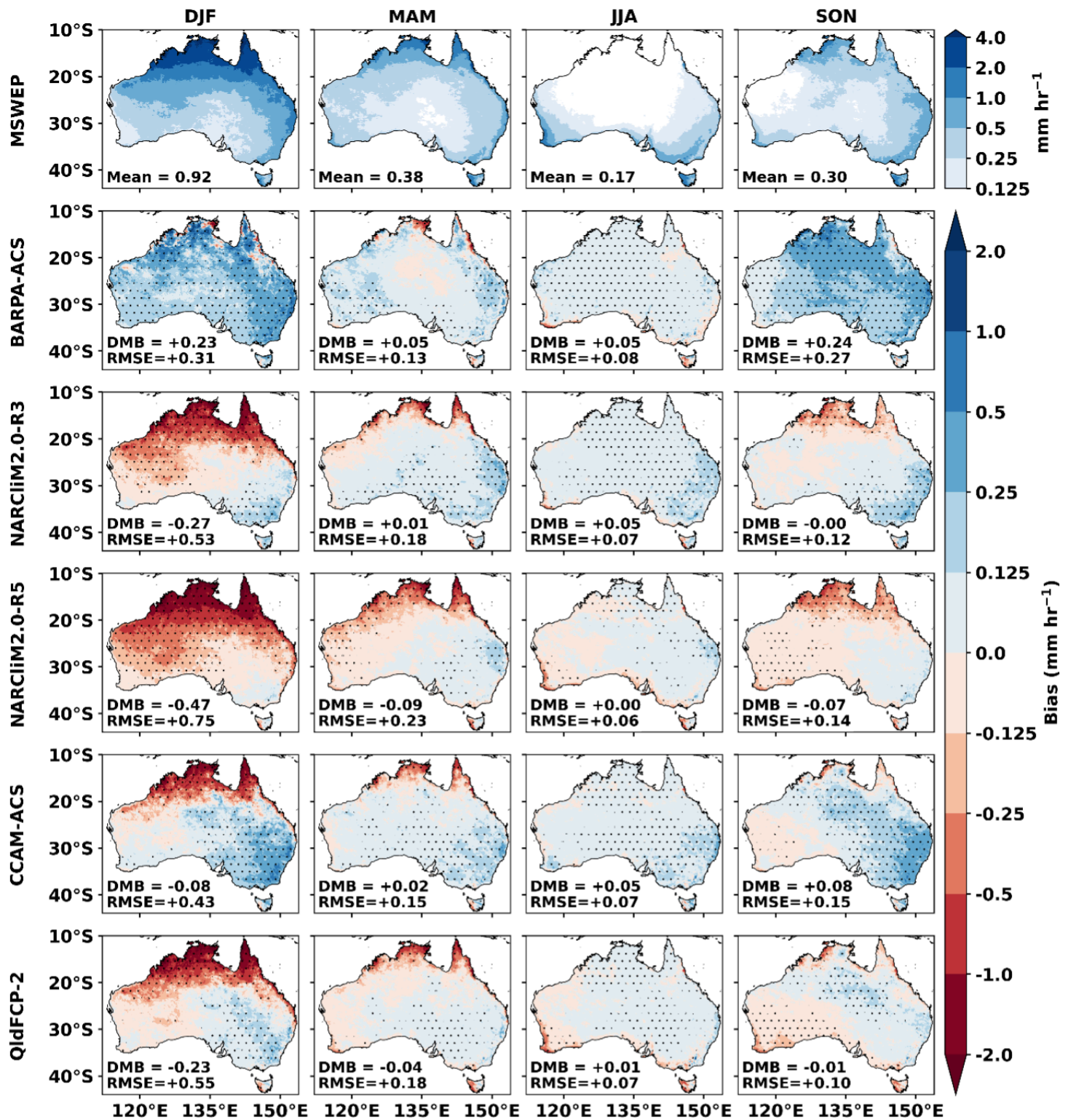


Figure 3

Observed seasonal prhmax and biases in seasonal mean prhmax for five simulations. DM – domain mean and RMSE - Root mean square error. Stippled areas indicate locations where an RCM shows statistically significant bias ($P < 0.05$).

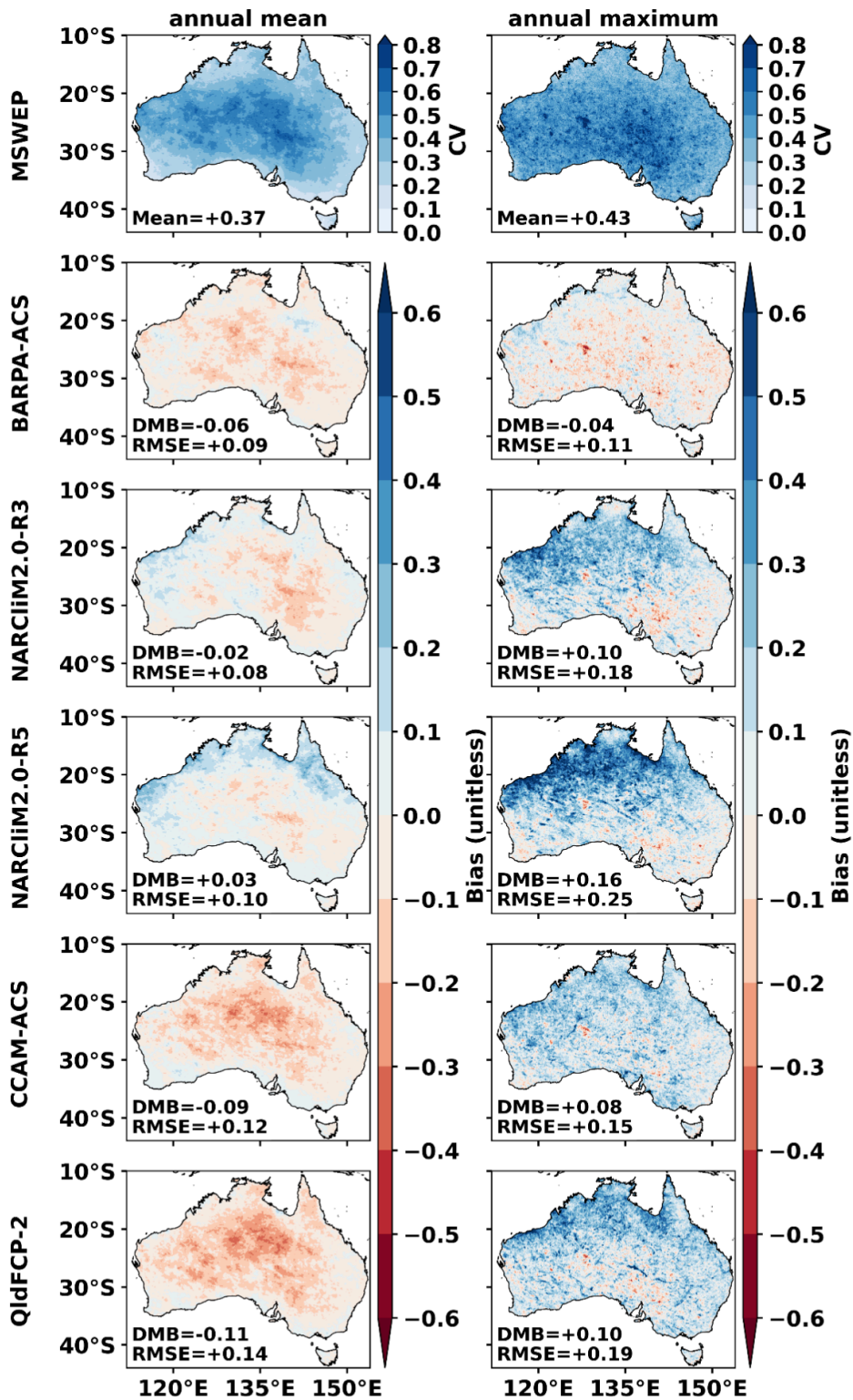


Figure 4

Observed coefficient of variation (CV) for annual mean and annual maximum prhmax and biases in them for five simulations; DMB – domain mean bias and RMSE - Root mean square error.

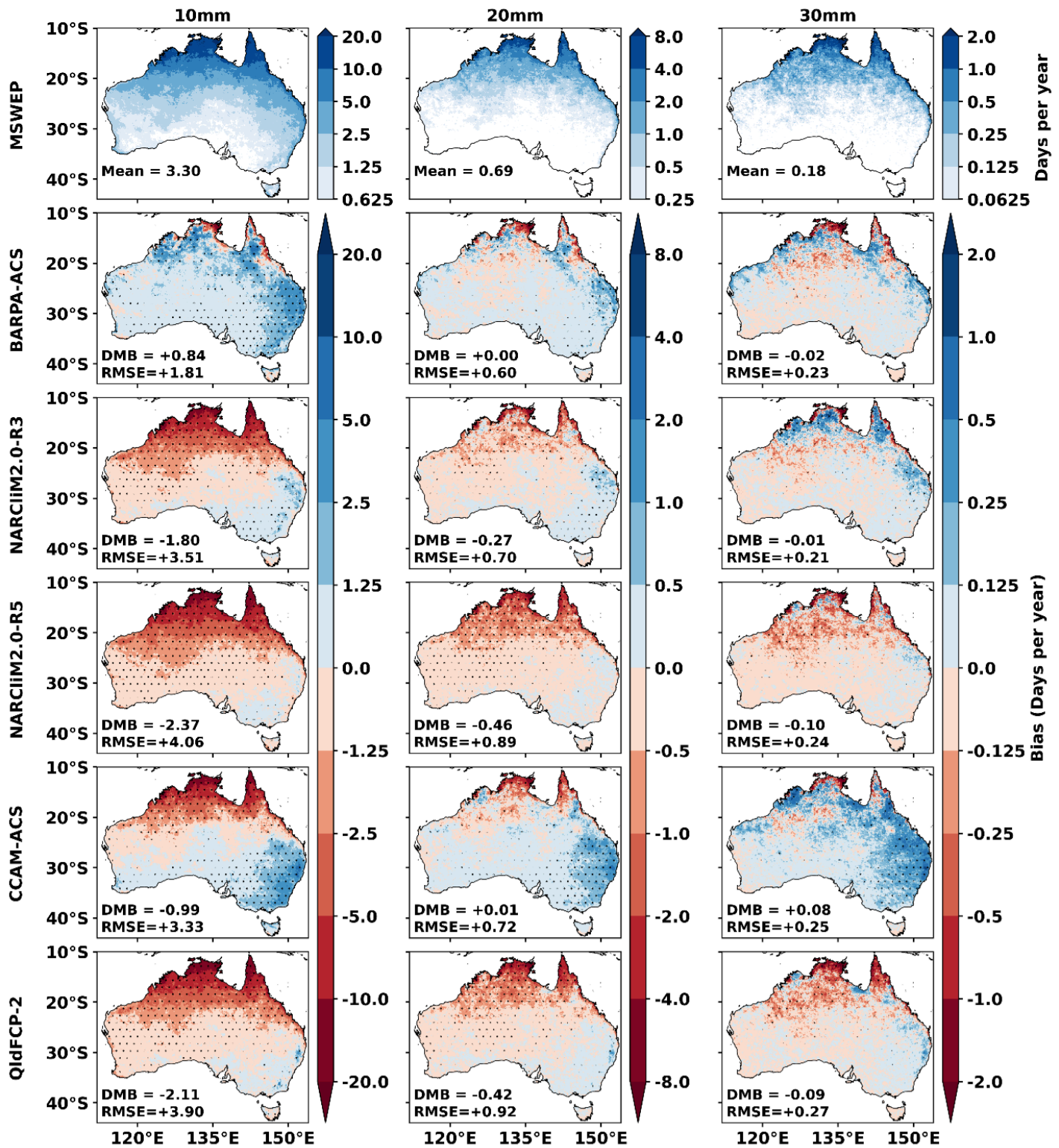


Figure 5

The number of days in a year with prhmax exceeding 10, 20, and 30 mm hr^{-1} in observation and biases in them for five simulations. Stippled areas indicate locations where an RCM shows statistically significant bias ($P < 0.05$).

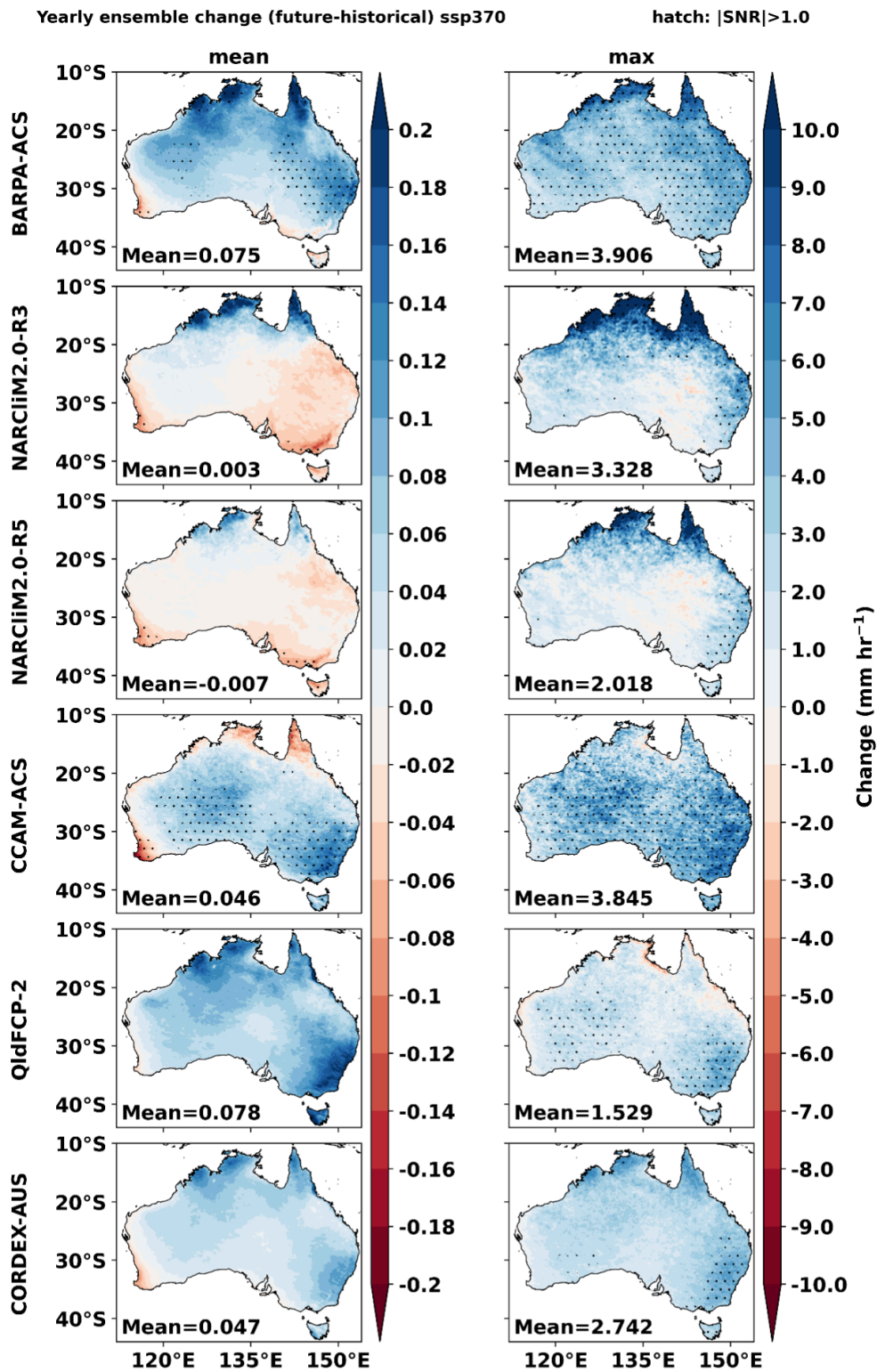


Figure 6

future projection of annual mean and annual maximum prhmax for ssp370. Stippled areas indicate locations where the signal-to-noise ratio is greater than 1.

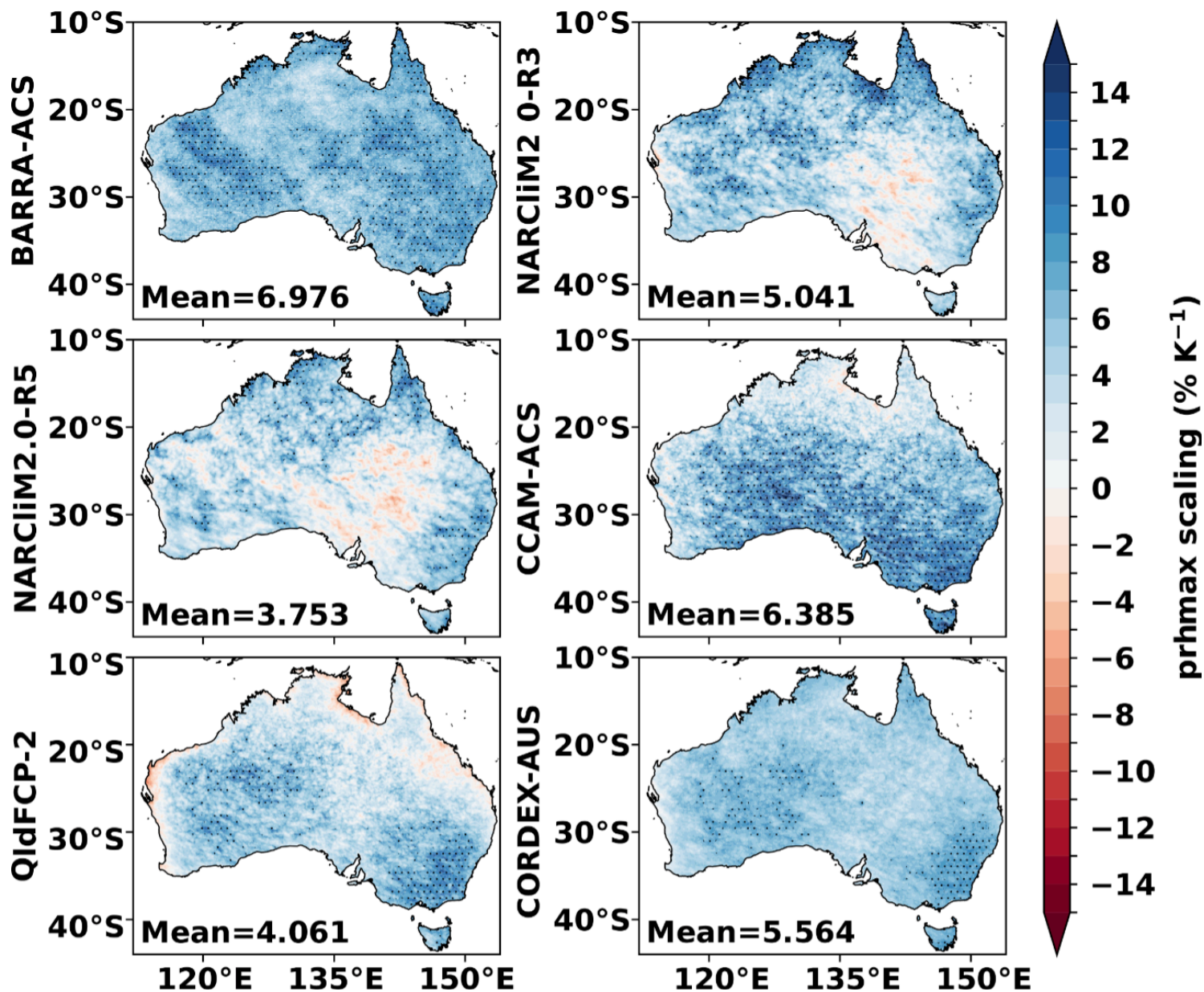


Figure 7

Relative change of annual maximum prhmax per degree global warming (prhmax scaling) for five simulations and their ensemble (CORDEX-AUS). The Stippled areas indicate the scaling is above 7% per degree global warming

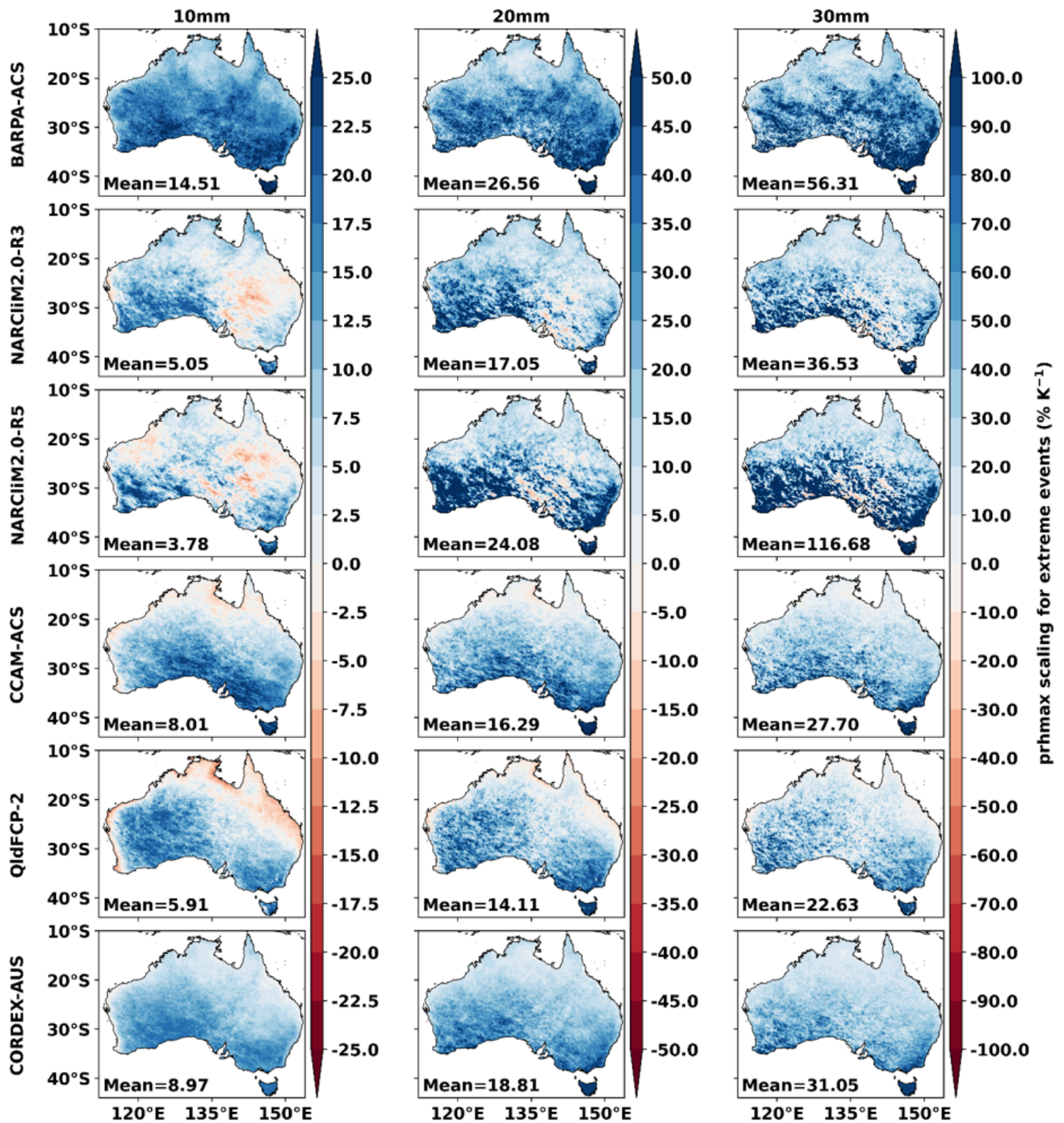


Figure 8

Relative changes in frequency of extreme events exceeding 10, 20 and 30 mm hr⁻¹ per degree global warming for ssp3-7.0.

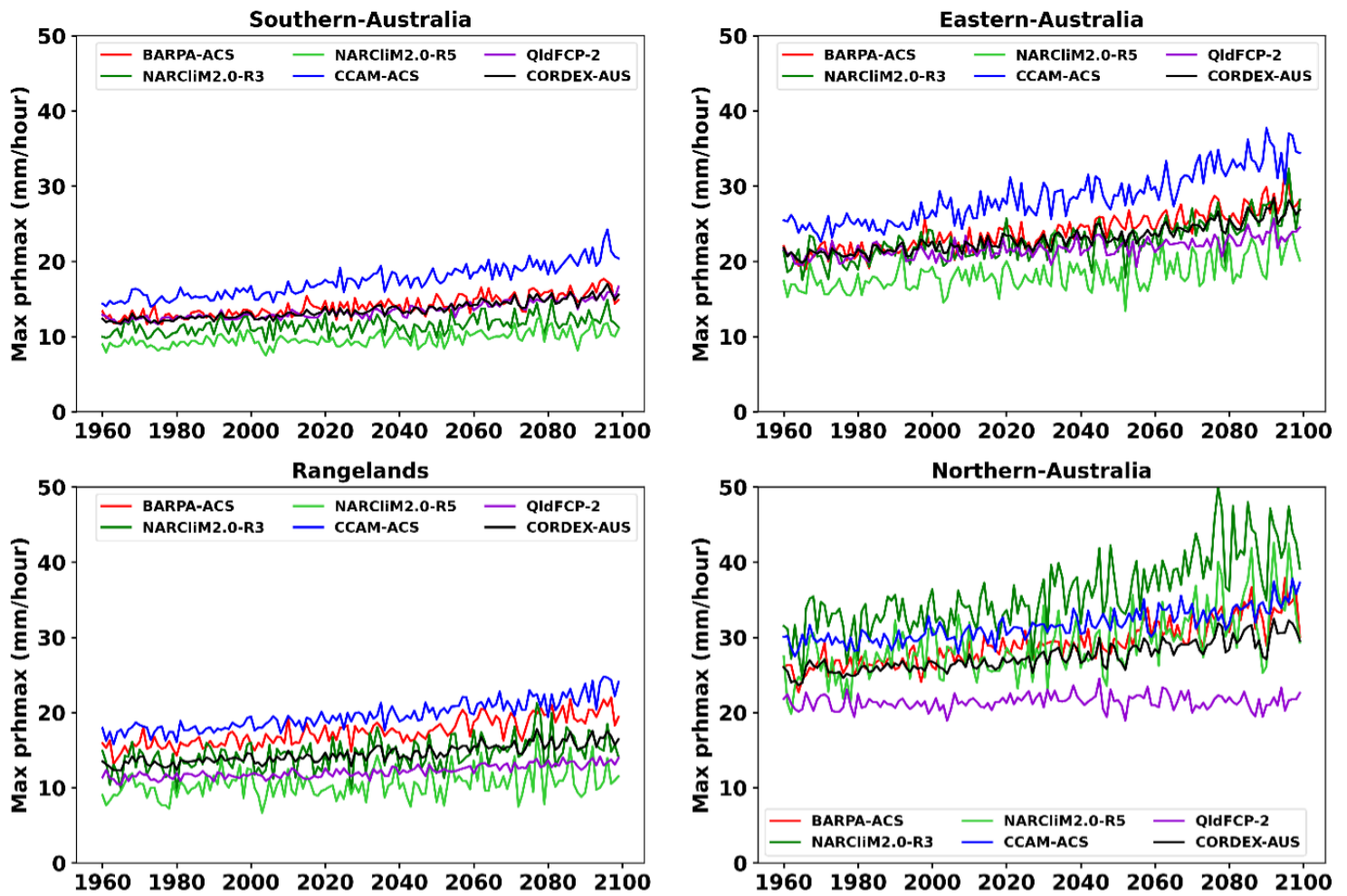


Figure 9

Interannual variation of annual maximum prhmax for five simulations and their ensemble mean over four NRM regions for SSP3-7.0

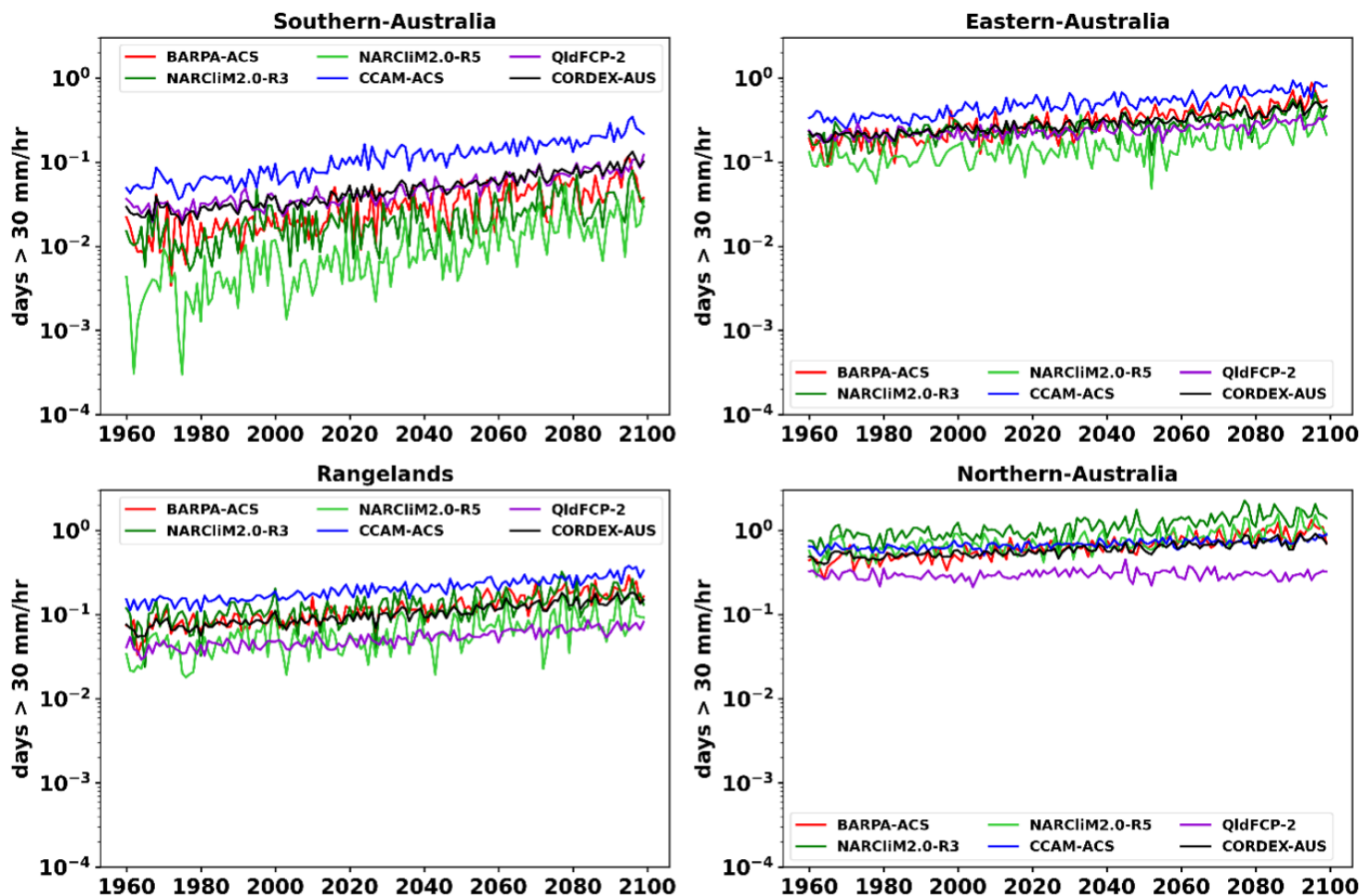


Figure 10

Interannual variation of days with prhmax exceeding 30 mm hr^{-1} for five simulations and their ensemble mean over four NRM regions for SSP3-7.0

Supplementary Files

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