Australian Government
Bureau of Meteorology

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Australian Climate Service

Climate Hazard Information developed for use in Climate Risk Assessment

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Bureau Research Report - 116

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1. Working with customers to frame the need for the research
2. Securing financial support for the research
3. Conceptualization and research design
4. Undertaking scientific research and analysis
5. Supervision of the research
6. Software development
7. Supply of unpublished datasets
8. Drafting text
9. Tailoring to customer requirements

Affiliation

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We thank Kathleen Beyer (University of Tasmania) and Darren Ray (South Australian Department for Environment and Water) for their review comments which significantly improved the clarity of this report.

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Acronyms

ACS – *Australian Climate Service*, see Section 1.1

AEP – *Annual Exceedance Probability*. The probability that a threshold (e.g. rainfall total, flood extent) will be exceeded in any one year. For example, a 1% AEP event has a 1% chance of happening in any one year. See Section 5.3 and 5.4

AGCD – *Australian Gridded Climate Data*. The Bureau of Meteorology's official dataset for spatial climate analyses across Australia. See Section 3

ANCHORS – *Australian National Collection of Homogenised Observations of Relative Sea Level*. See Section 3.2.9 and 5.4

BARRA2 – Second version of the Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia. Reanalyses are widely used for climate monitoring and studying climate change as they provide long-term spatially complete records of the atmosphere. BARRA-R2 has a gridded resolution of approximately 12 km. See section 3.2

CMIP – *Coupled Model Intercomparison Project*. CMIP is a project of the World Climate Research Programme (WCRP) providing climate projections to understand past, present and future climate changes. The *CMIP6* ensemble of model simulations was produced in 2015-2021 and was a key input to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report. It involves many models contributed from numerous countries around the world. See Section 3.

CORDEX – Coordinated Regional Downscaling Experiment. CORDEX is a global initiative focused on advancing and coordinating the science and application of regional climate downscaling. See Section 3.1

GCM – A Global Climate Model (GCM) is a complex mathematical representation of the major climate system components (atmosphere, land surface, ocean, and sea ice), and their interactions. They typically have a horizontal resolution of around 100 km. See Section 2.4

GWL – *Global Warming Level*. The increase in the global average surface temperature relative to pre-industrial levels. See Section 2.3

LGA – *Local Government Area*. See Section 2.2

IPCC – *Intergovernmental Panel on Climate Change*. The IPCC was created to provide policymakers with regular scientific assessments on climate change, its implications and potential future risks, as well as to put forward adaptation and mitigation options. Through its assessments, the IPCC determines the state of knowledge on climate change. It identifies where there is agreement in the scientific community on topics related to climate change, and where further research is needed. The Sixth Assessment Report (AR6) was published in stages, between August 2021 and September 2022. See Section 2.4 and 2.7

MRNBC - Multivariate recursive nested bias correction. A multivariate bias correction that is an extension of quantile matching (see QME below) to include inter-variable correlations and in addition corrects across multiple timescales. See Section 3.2.4

NCRA – National Climate Risk Assessment. See Section 1.2

QME – Quantile Matching for Extremes. The QME method is a univariate bias adjustment with special focus on extreme events. See Section 3.2.4.

RCM – Regional Climate Model. RCM can simulate climate and weather at higher resolution than Global Climate Models, typically 10 km. RCMs are a tool to dynamically downscale GCM outputs. See Section 2.5

SLR – *Sea Level Rise*. See Section 2.7 and 3.2.9

SSP – *Shared Socio-economic Pathways*. SSPs are used to explore the consequences of greenhouse gases accumulating in the atmosphere. Each SSP outlines ways the world might change in the future, including different types of energy generation, rates of population growth, economic development and land uses. These lead to different levels of greenhouse gas emissions over time. See Section 2.3

Executive Summary

The Australian Climate Service (ACS) has developed and released climate hazard information. This report describes how this hazard information was produced and provides the rationale behind key decisions. We present information about current and future climate hazards, describe caveats and outline possible further work.

This report is citable and provides technical documentation to underpin a national risk assessment, and sits within a broader suite of papers, fact sheets and reports. The report is aimed at a technical audience. We provide links for readers to access data and scripts, metadata and relevant publications. While activities are ongoing, this report provides a snapshot in time, summarising the development of hazard information for the first (Australian) National Climate Risk Assessment (NCRA) to end of December 2024.

The standard methodology makes use of the latest downscaled climate model projections (CMIP6) developed in partnership between the Bureau of Meteorology and CSIRO. Hazard information is developed based on a 13-member model ensemble for two shared socioeconomic pathways (SSP).

Climate projections have been regridded to a common 5-km resolution and calibrated against observations using univariate and multivariate calibration techniques. We briefly describe the model projections, bias adjustment methods and evaluation of model performance.

Where possible, information on future hazards is provided for four Global Warming Levels (GWL): 1.2, 1.5, 2 and 3 °C against pre-industrial global climate. Coastal hazards are an exception, using sea level rise increments instead noting that global sea level is dependent on both temperature and time.

We have developed information on how key climate variables and ten priority hazards are likely to change under climate change. Key climate variables, sometimes referred to as essential climate variables, include variables such as rainfall and temperature. Section 2 summarises key decisions and definitions.

A companion report (CSIRO 2025) describes the underpinning climate projections. They are based on the latest international climate modelling and have a strong focus on climate extremes, supported by a multi-model Regional Climate Model (RCM) ensemble following the `Coordinated Regional Climate Downscaling Experiment (CORDEX) guidelines, supplemented by insights from Global Climate Models (GCMs) from the Coupled Model Intercomparison Project phase 6 (CMIP6), including large ensembles (many runs of the same model).

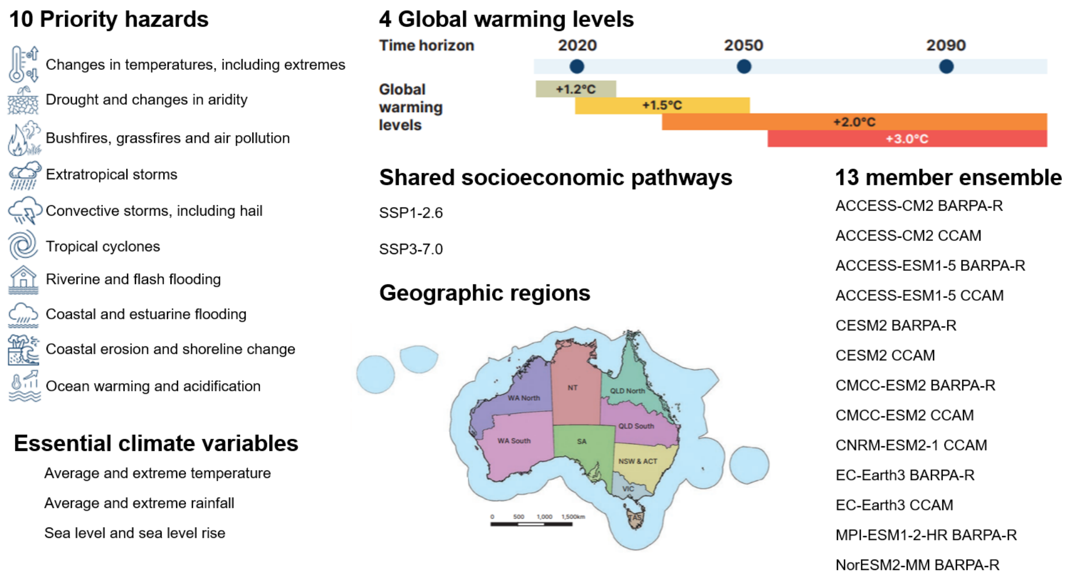


Figure 1: Key decisions and definitions.

The report is structured as follows:

Section 1 provides context, introducing the ACS and the NCRA.

Section 2 provides detail on key decisions and definitions, such as the set of priority hazards, geographical regions, Global Warming Levels, and choice of Shared Economic Pathways. It also provides a detailed description of the workflow developed to regional statistics for key hazard indices.

Section 3 provides detail on the historical and projections information underpinning the information for each of the hazards, the choice of indices and links to data and supporting documentation. This section also provided details on the 13-member ensemble of downscaled climate projections and bias adjustment techniques.

Section 4 describes how the Hazard Teams were structured, how they interacted with their counterparts (Risk Leads) to support developing the risk assessment. This section also documents important learnings such as product planning in the absence of clear requirements.

Section 5 provides detailed information on the priority hazards and key climate variables, including a definition of the hazard, indices used and relevant references. Key findings are presented together with caveats and options for future work.

Section 6 provides information on how to access the hazard information and underpinning climate projections data. This section also has links to Metadata information and supporting documentation, including relevant Python scripts.

References

CSIRO (2025) Australian Climate Service CMIP6-Next Generation downscaled climate change projections: approach and summary. Hobart, Australia: CSIRO & Bureau of Meteorology. csiro:EP2025-1632. https://doi.org/10.25919/9bde-a338

1. Introduction

The Australian Climate Service (ACS) has developed and released climate hazard information, initially for use in the first National Climate Risk Assessment (NCRA). This report describes how this hazard information was produced and provides the rationale behind key decisions. We present information about current and future climate hazards, describe caveats and outline further work.

As such this report is citable and provides technical documentation to underpin NCRA reports, and sits within a broader suite of papers, fact sheets and reports. This report is aimed at a technical audience, with more general information available through fact sheets etc. We provide links for readers to access data and scripts, metadata and relevant publications.

1.1. The Australian Climate Service

Over recent decades, Australia has seen multiple record-breaking events, such as the Millenium Drought (1996-2009), Black Saturday (2009), the Victorian and Queensland floods (2010-11), the Tasmanian Fires (October 2015) followed by Tasmanian floods (June 2016), the South Australian Energy System Blackout (September 2016), the Victorian and NSW Black Summer (2019-20) and the Queensland and NSW floods (2022). These events affected the lives and livelihoods of Australians.

The Royal Commission into National Natural Disaster Arrangements was established on 20 February 2020 in response to the extreme bushfire season of 2019-20 (Black Summer). In October 2020, the Royal Commission set out a number of recommendations, including those listed below, that laid the foundation for the ACS:

- **Recommendation 4.5 - National climate projections** Australian, State and Territory governments should produce downscaled climate projections
- **Recommendation 4.3 - Implementation of the National Disaster Risk Information Services Capability** Australian, State and Territory governments should support the implementation of the National Disaster Risk Information Services Capability and aligned climate adaptation initiatives
- **Recommendation 4.4 - Features of the National Disaster Risk Information Services Capability** The National Disaster Risk Information Services Capability should include tools and systems to support operational and strategic decision making, including integrated climate and disaster risk scenarios tailored to various needs of relevant industry sectors and end users

The ACS came into being with the vision to advance information and knowledge that is used to enable a safer, adaptive and prosperous Australia, resilient and prepared for climate change and natural hazards. The ACS is delivering on this vision by building and enhancing Australia's climate and weather hazard intelligence capability, and improving access to integrated authoritative data, information and expert advice.

The ACS consists of four partner organisations: the Bureau of Meteorology, CSIRO, the Australian Bureau of Statistics (ABS) and Geoscience Australia (GA). Key customers are the Department of Climate Change, Energy, Environment and Water (DCCEEW), the National Emergency Management Agency (NEMA), Australian Prudential Regulation Authority (APRA), Treasury and others. The ACS provided guidance to APRA how climate perils are likely to change under an approximate 2.5 ˚C increase in global mean temperature by 2050. This advice is documented in Black et al. 2024.

The ACS is now integral to the Australian climate risk landscape, e.g. through collaborating with initiatives like the National Partnership for Climate Projections (NPCP) led out of DCCEEW, giving a voice to communities of existing users, especially States/Territories, the National Environmental Science Program (NESP), the Natural Hazards Research Australia (NHRA), state-based initiatives, such as the Victorian Water and Climate Initiative (VicWaCI) and internationally through such contributions to CORDEX efforts.

While the ACS is developing its own purpose-built platform, this is in the context of existing information and portals such as *Climate Change in Australia* (CCiA), the *National Hydrological Projections* (NHP), *My Climate View* (climate information for agriculture), *Canute* (Sea level information) and *Coastal Risk Australia*, and portals developed by States and Territories, e.g. *Queensland Future Climate.* A review of existing portals is provided in Jakob et al 2023.

1.2. The National Climate Risk Assessment (NCRA)

The motivation behind the first NCRA is that climate change is a serious risk to the safety and prosperity of Australians, and the need for a national focus for resilience and disaster risk reduction. The vision for the NCRA was to provide a clear and consistent process for identifying and prioritising climate risks, provide a framework for ongoing monitoring of national priority climate risks, inform the National Adaptation Plan to minimise future adverse impacts from climate change and allow for the evaluation of the effectiveness of adaptation policies and actions. It was anticipated that the ACS would provide the hazard information required for assessing risks, with exposure and vulnerability information coming through the ACS as well as other providers. The first pass risk assessment developed methodologies and the structure for undertaking NCRA activities. The second pass risk assessment is focused on key systems and risks identified through the earlier activities. The work is nearing completion, and has used the hazard information to support quantitative analysis, where possible.

While ACS activities formally commenced in July 2021, the NCRA commenced in January 2023. As such there was a need for the ACS to balance the delivery of longer-term strategic activities against delivering against short timelines for input into the NCRA. For the first pass risk assessment an overview of observed and projected trends in hazards was produced based on a literature review (Figure 2).

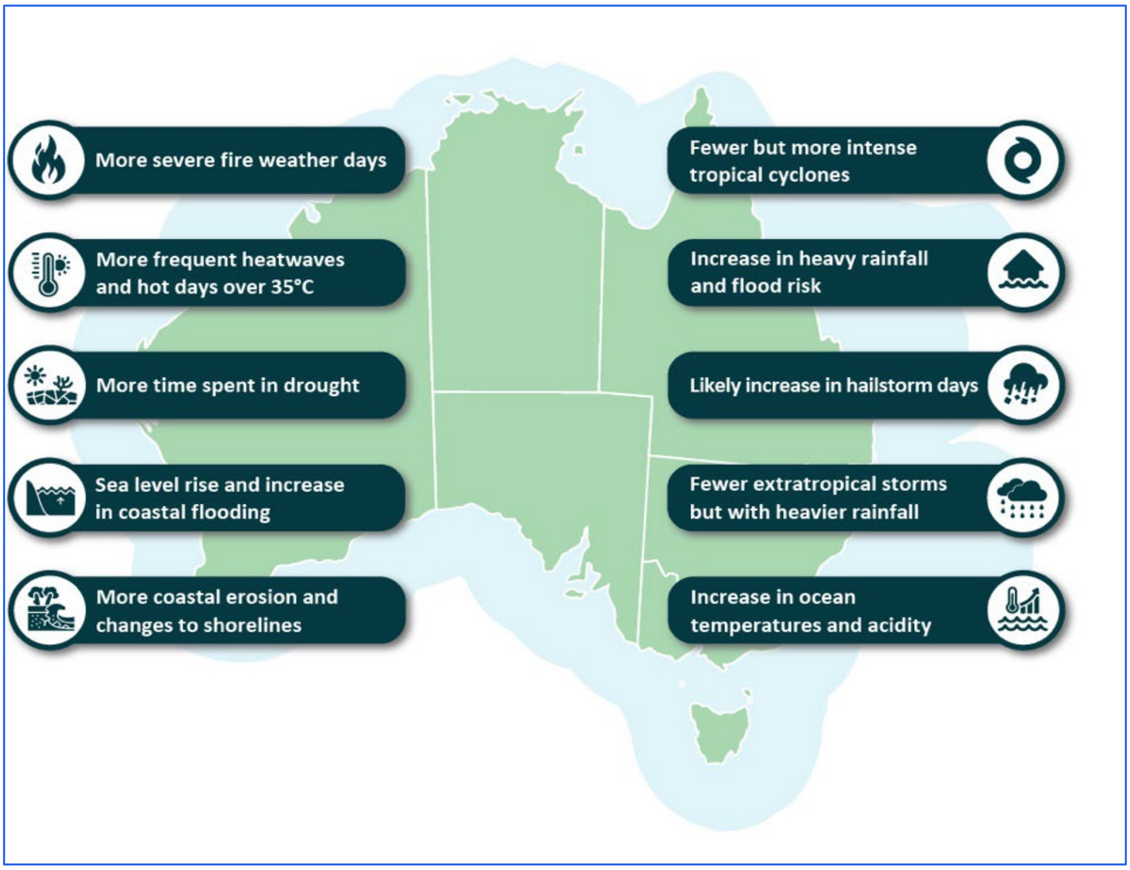


Figure 2: Overview of observed and projected trends in Australia's climate hazard. Source: National Climate Risk Assessment First Pass Assessment Report.

References:

Black M, Jakob D, Jones D, Matear R, Ramsay H, Pepler A, Benger N, Bettio L, Braganza K, Landsberg J, Maguire S, Grose M, Dowdy A (2024) Acute hazards in a future climate: guidance provided to the Australian Prudential Regulation Authority, *Bureau Research Report 96*

Jakob D, Black M, Benger N, Grose M, Hague B, Peter J, Pepler A (2024) A review of existing climate portals, *Bureau Research Report 73*

2. Decisions made

In this section we describe decisions and key definitions that were developed following a literature review, workshops and consultation with stakeholders and scientists. These provide the framework in which climate hazard information was developed and analysed.

2.1. Priority hazards and key climate variables

The priority hazards for the NCRA were defined in an options paper 'NCRA Priority Hazards' (April 2023) and tested with the NCRA Expert Advisory Committee, the National Partnership for Climate Projections (NPCP) and other experts. They were then published in the NCRA Methodology.

These are (in alphabetical order):

- Bushfires, grassfires and air pollution
- Changes in temperature including extremes
- Coastal and estuarine flooding
- Coastal erosion and shoreline change
- Convective storms including hail
- Drought and changes in aridity
- Extratropical storms
- Ocean warming and acidification
- Riverine and flash flooding
- Tropical cyclones

In addition to the above, changes in the key climate variables were also provided for the NCRA:

- Average and extreme temperature (maximum and minimum)
- Average and extreme rainfall
- Sea level and sea level rise

2.2. Regions

Hazard Information was developed and provided nationally and for ten NCRA regions (excluding the Antarctic) (Figure 3). A marine region was included to provide information for risk assessments for marine ecosystems, fisheries, tourism etc.

The State and Territory based regions, including coastal waters, reflect the spatial scale of decisions being made by those making adaptation plans at both state and federal government levels, including departments and nationally focused organisations. This contrasts with Natural Resource Management (NRM) regions which have been used in previous Australian climate assessments and included in some IPCC reports. While NRM regions better align with the Australian climate and previous climate change assessments, they do not necessarily reflect the regions by which climate risk is assessed and adaptation measures employed. Hence, these regions were defined considering requirements of decision-makers and climatic conditions.

More granular information is highly desirable for many stakeholders, such as at Local Governance Areas (LGA) and future assessments may provide information for additional regions. We note that the base data described here largely sits on a 0.05 degree grid over land (with various resolutions over the ocean) supporting a range of spatial scales for analysis.

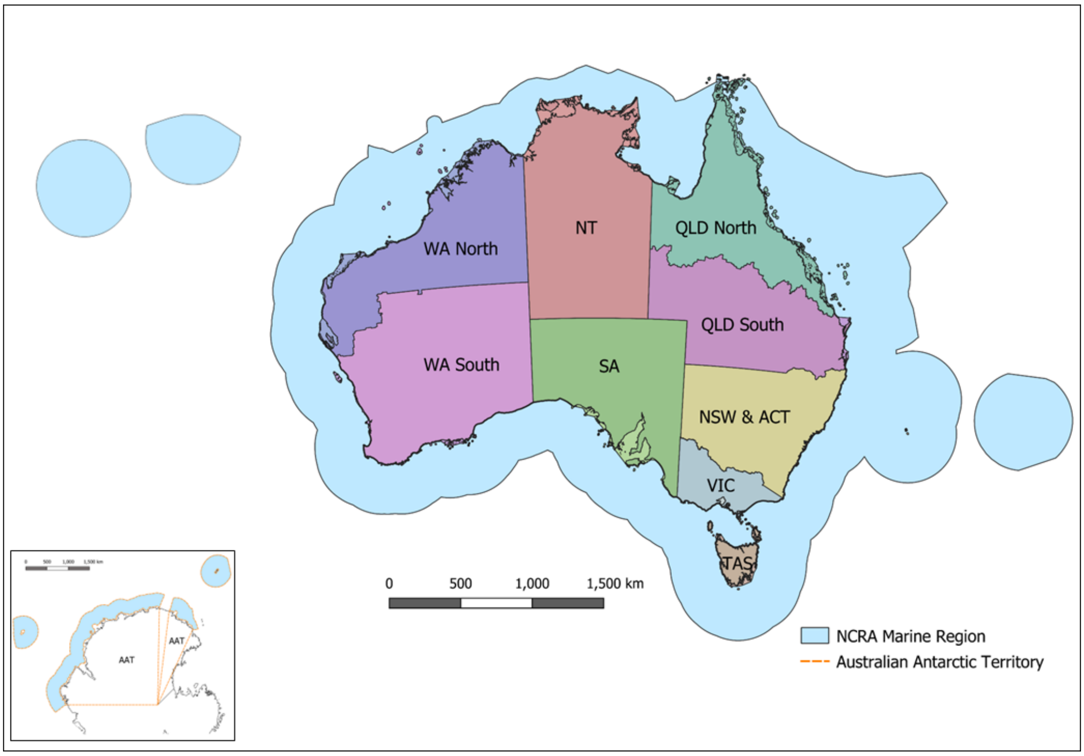


Figure 3: Regions defined by the National Climate Risk Assessment Methodology (DCCEEW 2023).

2.3. Global Warming Levels

Projections are traditionally reported for scenarios to explore emissions and their impact through time. Here we draw on projections for two scenarios, SSP1-2.6 and SSP3-7.0, chosen to "bracket" or "bookend" a range of plausible and policy-relevant SSPs and resulting climate change response (CSIRO 2025). Downscaling climate models, post-processing and storing their data is computationally expensive. Subsampling the full range of emission scenarios is simply pragmatic.

The relationship between GWLs and the two projection scenarios is illustrated in Figure 4. GWLs are used in climate projections to describe the expected climate and weather changes that Australia will experience when global average temperatures reach particular degrees of warming compared to the pre-industrial era. Depending on emissions levels (SSPs), these levels of warming will be reached at different time periods. Advantages of using the GWLs are that they are informative and easy to understand, are recognised internationally (e.g. Paris Agreement goals) and are highly policy relevant. GWLs also have the advantage of standardising across different contexts, so results presented for GWLs are comparable when using different future pathways (e.g., SSP and RCP) or models (e.g., CMIP5 and CMIP6). The policy relevance and simpler interpretation are key reasons for their choice here. Alternatively, information can be provided according to time and emissions, which might be preferable for some applications. Hazard information is provided for Global Warming Levels (GWLs) of 1.2 ˚C, 1.5 ˚C, 2 ˚C and 3 ˚C. Time periods for which 1.2 ˚C, 1.5 ˚C, 2 ˚C and 3 ˚C GWLs are reached (with respect to the period chosen to be representative of the pre-industrial 1850-1900 mean value) are computed from global climate models using a 20-year moving window, https://github.com/AusClimateService/gwls.

The GWL relates to the global average over land and ocean, global land-only averages are higher because land areas are warming faster than oceans which have greater thermal capacity and hence warm slower.

Global Warming Levels and time periods:

- **1.2 °C** - This is the current level of global warming for the 20-year period centred around 2020 (i.e., 2011 to 2030). Analysing this level allows us to compare future warming scenarios with our current climate. Note that this period is not purely historical as it will include some future years.

- **1.5 °C** - Will be reached in the near-term period under all emissions scenarios. Global average temperatures will only stabilise around 1.5 °C under extremely low emissions scenarios (SSP1-1.9) and with some 'overshoot' likely.

- **2 °C** - Will be reached around mid-century under moderate, high or very high emissions scenarios. Under low emissions, global average temperatures are likely to stabilise at or just under 2 °C. Under extremely low emissions scenarios (SSP1-1.9), this level could be avoided altogether.

- **2.7 °C** - Under current policy (and without further concerted action), 2.7 °C will be reached at the end of the century. Please note, this level will not be assessed on the Hazard Maps and is included only for context as an indication of our current trajectory.

- **3 °C** - It is possible that global average temperatures will reach 3 °C after 2050 under moderate emissions scenarios. It is very likely that this level will be reached after 2050 under high to very high emissions scenarios.

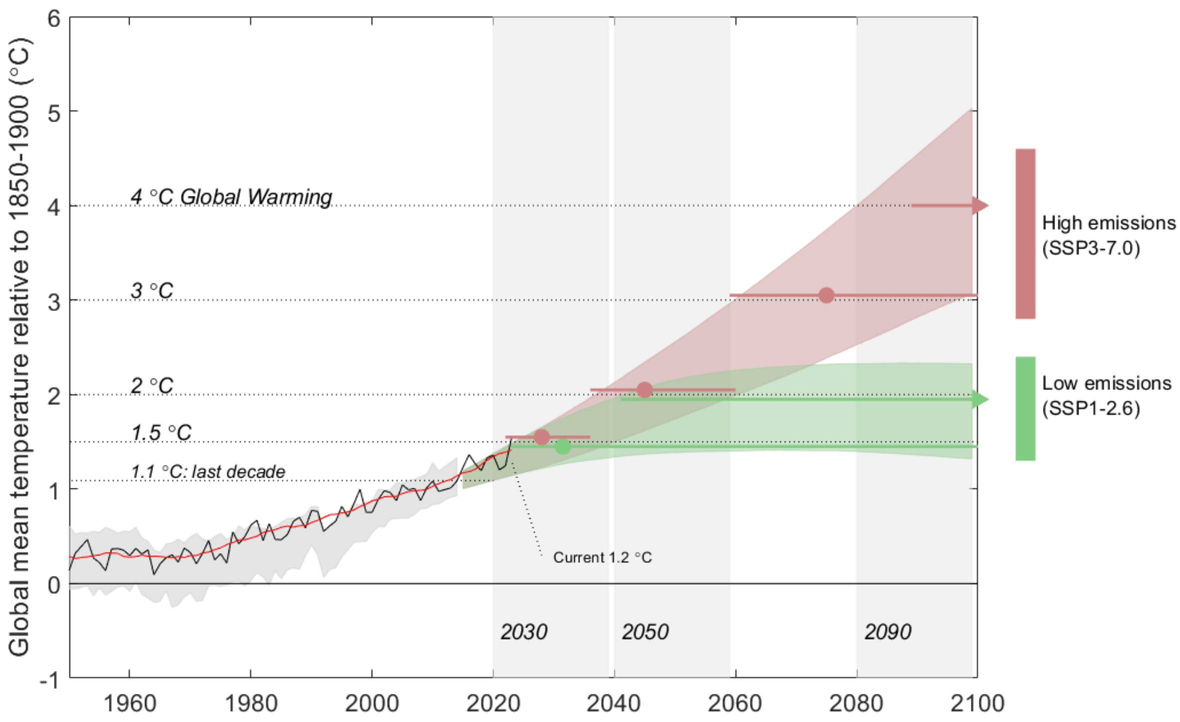


Figure 4: Global warming thresholds of 1.1, 1.2, 1.5, 2, 3 and 4°C (horizontal dotted lines) periods when they are reached under a low emission scenario SSP1-2.6 (green lines and shading) and under a high emission scenario SSP3-7.0. Commonly used 20-year periods (grey shading) are the 2030s (2020 to 2040), the 2050s (2040 to 2060) and the 2090 (2080 to 2100) [adapted from IPCC 2021 Summary for Policymakers].

2.4. Characterising uncertainty and confidence

Projection uncertainty has various causes. Hawkins and Sutton (2009) characterise uncertainty into:

- Internal variability
- Scenario differences
- Model-to-model differences in forced response

For temperature, scenario differences become increasingly important over time with a fairly tight relationship between greenhouse gas concentrations and warming.

For rainfall, internal variability and GCM model-to-model differences in forced response dominate the uncertainty.

RCM model-to-model differences do matter at this regional scale but are generally a smaller factor. More information on the projection uncertainty of the ACS CMIP6-based Next Generation of Projections can be found in an accompanying report (CSIRO 2025).

To assess and report confidence in the projected changes shown here, we use the IPCC system of considering uncertainty, including confidence and likelihood ratings (see

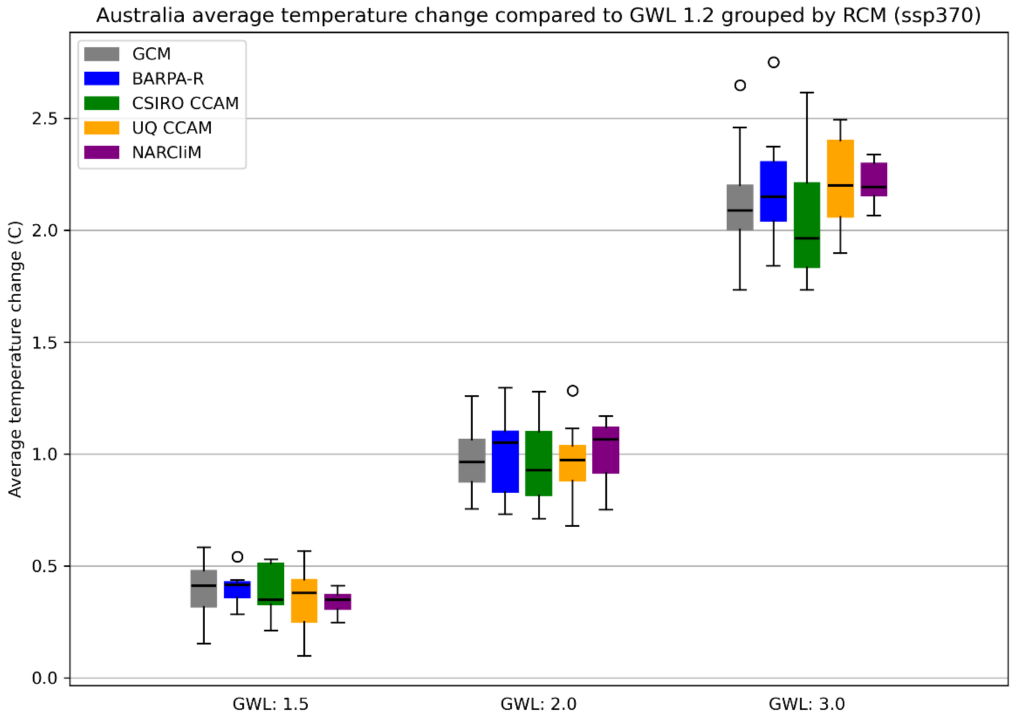
Mastrandrea et al. 2010). This system considers the type, amount, quality and consistency of evidence, and the agreement of that evidence. This assessment is used to derive a qualitative expression of the validity of a finding, such as the direction of change or a range of outcomes, from *low confidence* to *very high confidence*. If confidence is high, an expression of likelihood may also be given, from *exceptionally unlikely* to *virtually certain*, with an additional description of *fact* for things that are not in any doubt.

2.5. Model ensemble

In general, RCMs follow the global driving GCM signal. However, RCMs can modify the regional climate significantly, particularly for rainfall. Some of this may be a modification of "forced signal", some of it may be chaotic internal variability. Currently, it is unclear whether one RCM is better than another. The differences in projections from different RCM provide an estimate of uncertainty due to the choice of RCMs. There are subjective methodological choices conducted in each RCM exercise. Until proven otherwise we must assume that they are all equally valid. For details on the models selected for developing hazard information refer to Section 3.2 Bias adjustment.

For regional temperature change all RCM ensembles project a similar range as seen in the GCM ensemble, since GCM were selected to representatively sample warming (Figure 5, top panel).

RCM ensembles vary widely in their projections of regional rainfall change with global warming (Figure 5 bottom panel). Even though the GCMs were selected to be representative of future rainfall changes, some RCM simulations do alter the GCM signal substantially. Using only one RCM ensemble may bias the projection range significantly, noting the significant variability that can occur.



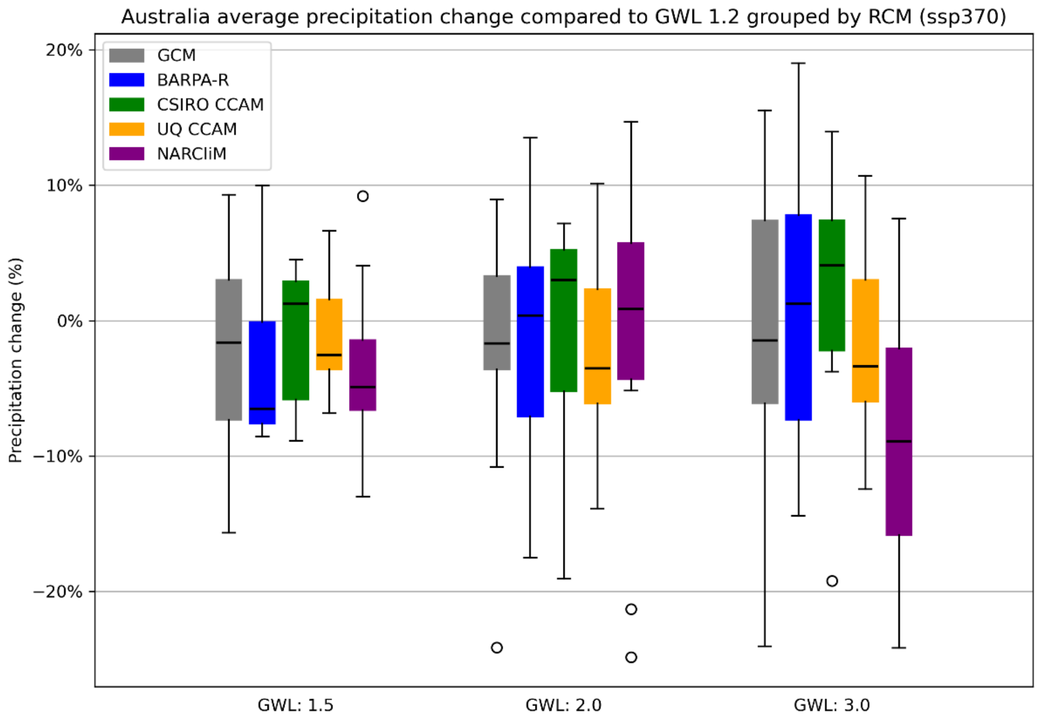


Figure 5: Projected changes for each of the CORDEX-Australasia RCM ensembles as well as the CMIP6 GCM ensemble, for Australian average temperature (top) and rainfall (bottom) at global warming levels 1.5, 2 and 3 °C, relative to the current (1.2C) global warming level. GWL calculations are described in Section 2.6.

2.6. Calculation of regional statistics

Decision-makers typically require summary information at a regional scale, such as those defined in Section 2.2. Accordingly, regional statistics were developed for each of the key hazard indices to characterise:

1. Average conditions, based on the multi-model ensemble median, and
2. the spread of conditions – represented by either the ensemble minimum/maximum or the ensemble 10^{th}/90^{th} percentiles, as deemed most appropriate for the given hazard index.

The workflow for calculating regional statistics required data aggregation across time, space and ensemble members. The specific order of operations is detailed in Technical Box 1.

Technical Box 1. Calculating regional statistics for Global Warming Levels

Regional statistics were calculated for each of the four Global Warming Levels (GWL 1.2, 1.5, 2.0 and 3.0 °C). Understanding how the regional statistics were calculated will help you understand how to interpret these values.

The regional statistics may be summarised using heat maps (see bottom of Figure T1.1. for an example). A heatmap is a two-dimensional graphical representation of data that uses a system of colour coding to represent different values.

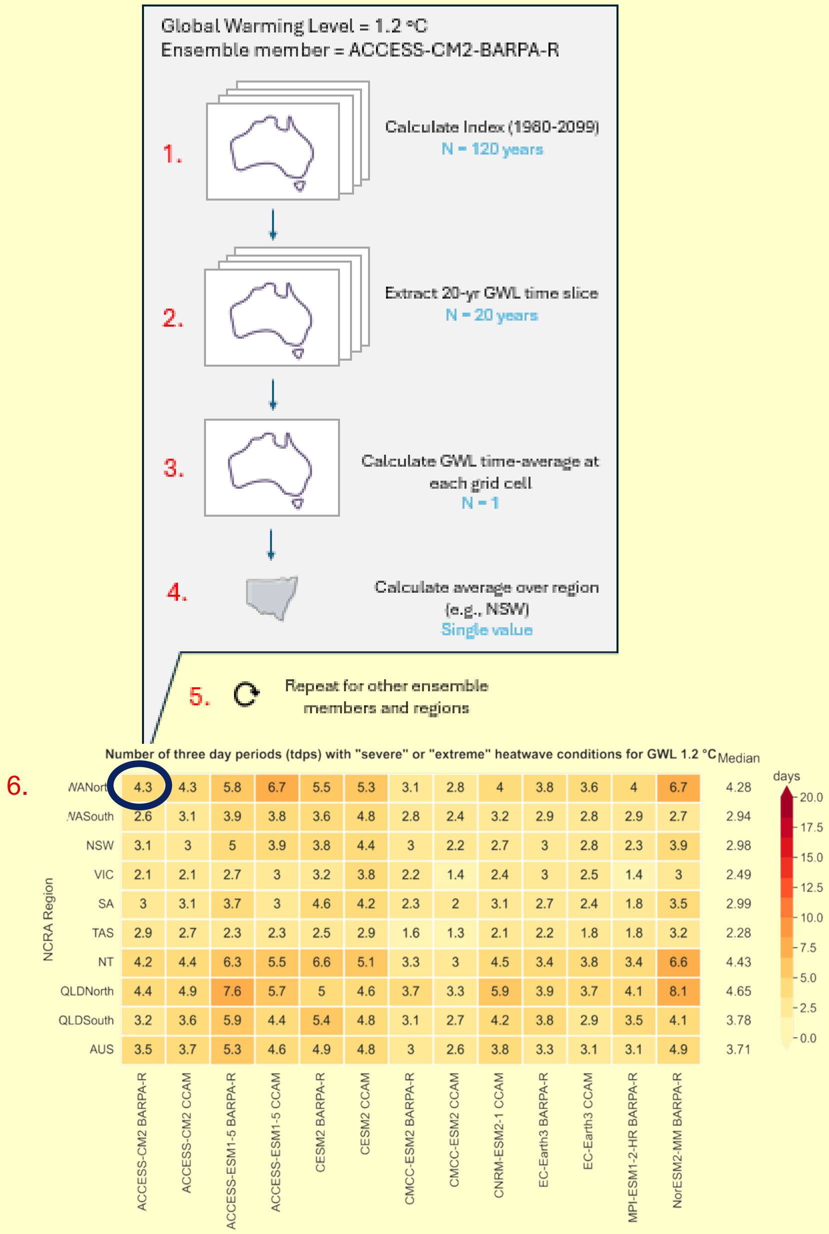


Figure T1.1: Visualisation of the workflow for creating regional statistics of hazard indices for a specified Global Warming Level. The callout box in the upper part of the figure (grey) shows the typical order of operations for calculating regional statistics (shown here for a specific ensemble member and target region). Steps 1 – 4 are repeated for each of the nine study regions and 13 ensemble members; the results are then summarised in the form of a heat map (ensemble members along x-axis and regions along y-axis).

Annotation for the workflow presented in Figure T1.1:

1. Hazard indices are calculated from the climate model simulations at each model grid cell (for the period 1980 – 2099).
2. A 20-year time slice is extracted to represent the desired GWL. The timing of each GWL is identified as the first 20-year period during which the average

global surface temperature change exceeds the specified GWL relative to the 1850 – 1900 base period. The timing of reaching global warming levels is expected to be different under different emissions pathways; it may even differ between climate models run under the same emissions pathway (see Section 2.3 for details).

3. At each model grid cell, the hazard index is averaged over the 20-year GWL time slice, to provide an average value for the specified GWL.
4. Spatial averages for a desired region (e.g. New South Wales) are calculated by averaging all of the model grid cells that fall within that region. The output of Step 4 is a single value that represents the temporal- and spatial-average for that GWL/region combination.
5. Steps 1 – 4 are repeated for each of the study regions (excluding the Antarctic and marine region) and 13 climate model ensemble members.
6. The results are presented in the form of a heat map. The ensemble members are separated along the x-axis and the regions along the y-axis. To calculate a central measure and a measure of spread for a given study region, the ensemble values (represented by the heat map columns) are ranked in increasing order. The value ranked 7th is the median (50th percentile). An approximate value for the 10th and 90th percentile can be found in the same way using the second lowest and second highest value.

Regional statistics for GWL 1.5, 2.0 and 3.0 °C were also presented as changes relative to the GWL 1.2 °C baseline (e.g., see Figure 13). This was achieved using the above workflow, with the addition of Step 3a (whereby, for example, the output of Step 3 was separately calculated for GWL 1.2 and 3.0 °C, the difference computed, and the resulting difference field then used in subsequent Steps 4-6).

For smaller regions (Local Government Area LGA, Statistical Area Level 2 SA2) the spatial averages would be based on a small number of grid points. Averaging over these smaller regions requires further evaluation and these values were not provided with the exception of coastal hazard information (Section 5.4).

2.7. Sea level rise increments

A global warmings levels (GWL) approach was adopted for Australia's first National Climate Risk Assessment (Section 2.3). An important feature of GWLs is an assumption that all climate variables respond proportionately to changes in temperature. In other words, it doesn't matter if a GWL of 2 °C occurs in 2050 or 2070, the expected consequences on other climate variables are the same. This time-independence is broadly true for most terrestrial climate variables (Intergovernmental Panel on Climate Change (IPCC) 2018). However, it is not true for sea level, where the long response time to warming means that sea level continues to rise long after warming has stabilised at a specific GWL (e.g., Figure 6). There isn't a simple mapping between the concept of a "2 °C world" without considering in which year 2 °C is reached and the change in coastal hazards this implies. For example, the IPCC AR6 (Fox-Kemper et al. 2021; their Table 9.10) presents sea-level rise amounts that correspond to given warming levels, contingent on a scenario (e.g., SSP3-7.0) and a year (e.g., 2100) being pre-specified. In other words, some time-dependence is required to ensure the problem remains tractable.

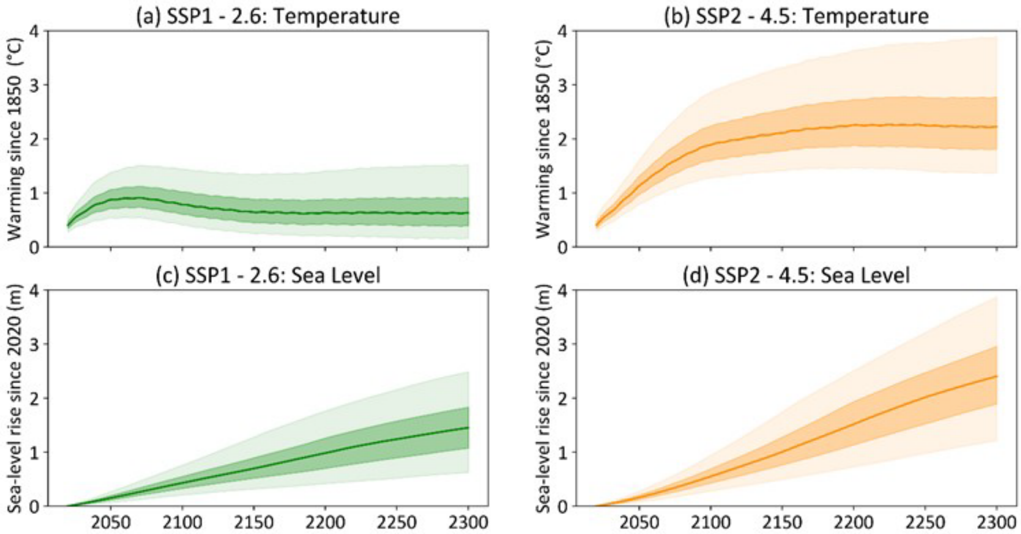


Figure 6: Increase in global temperature (top) and sea level rise (bottom) for two scenarios (left: SSP1-2.6, right: SSP2-4.5). Pale shading indicates the 90% confidence range, while the darker shading indicates the 50% confidence range.

To decouple the time dependence between increases in temperature and increases in sea level with climate change, changes in coastal hazards are presented as a function of a set increment of sea-level rise. Sea-level rise increments are used in coastal research, and coastal adaptation policies and the scientific reports underpinning these (Hague et al. 2023b; Hanslow et al. 2018; McInnes et al. 2022; Dedekorkut-Howes et al. 2021). Sea-level rise increments are conceptually equivalent to GWLs in that they are time-independent bases for the development of climate hazard studies. When viewed on plot of sea-level rise vs time, increments represent a plausible range of values on the horizontal axis as a function of time, whereas projections represent a plausible range of values in the vertical axis as a function of sea level rise. In other words, increments (and GWLs) cast uncertainty of future hazards in terms of 'when' rather than 'how much' (Hague et al. 2023b; Ghanbari et al. 2019). Instead of presenting hazard maps conditional on a chosen year and emission scenarios, maps are provided conditional on an amount of sea-level rise. Sea-level rise projections can then be used to provide estimates of when these hazard levels are expected.

The methodology for Australia's first NCRA used the policy-relevant Global Warming Levels framework to inform adaptation (Department of Climate Change Energy Environment and Water 2023). The NCRA has used a range of warmings projected for plausible emission scenarios, ignoring very small and very large warmings (Table 1). These have been approximated in the NCRA as GWL 1.2, 1.5, 2.0 and 3.0 °C.

Temporally, for 2030 GWL 1.5 °C is most relevant, at 2050 GWL 1.5 and 2.0 °C are most relevant, while for 2090 GWL 1.5, 2.0 and 3.0 °C are all relevant. In this section we describe comparable SLR increments, and how existing information can be presented in terms of them.

For the 2024 NCRA SLR increments, relative to the IPCC AR6 baseline of 1995 – 2014 mean sea level, of 0.0, 0.1, 0.2, 0.38, 0.6 and 1.0 m were used. It is not possible to exactly match the 20-year window used for the GWLs. SLR increments were mostly based on Table 11.3a in the Australasian chapter of the IPCC's 6th Assessment Report from Working Group 2 (Lawrence et al., 2022).

- 0.1 m SLR was chosen as it was representative of minimum SLR expected by 2030 for Australia (regardless of warming level)
- 0.2 m SLR was chosen as it was representative of minimum SLR expected by 2050 for Australia (regardless of warming level)
- 0.38 m SLR was chosen as it was representative of the SLR expected for Australia by 2090 in a 2 °C world.
- 0.6 m SLR was chosen as it was representative of the SLR expected for Australia by 2090 in a 3 °C world.
- 1.0 m SLR was chosen as it is representative of the legislated SLR benchmarks being used in some state jurisdictions (Dedekorkut-Howes et al. 2021). Decision-makers have chosen a risk-averse approach and set SLR benchmarks that have lower probability but higher consequence (van de Wal et al. 2022).

A SLR increment of 0.06 m was also used as the 'present-day' baseline for the period 2010 – 2029, with differences to this level also reported on (e.g., 0.32 m as the difference between 0.38 m and 0.06 m), meaning increments of 0.14 m, 0.32 m, 0.54 m and 0.94 m also appear in the NCRA and this report.

Going forward, we propose a simpler approach that better recognises the independence between future SLR and future GWLs. This is to provide hazard information for all SLR increments between 0.0 m and 2.0 m in 0.1 m increments. This will ensure that policy-relevant information can be obtained from the projection information, regardless of the legislated jurisdictional sea-level rise benchmark and locally relevant adaptation triggers, which are typically expressed as a sea-level rise increment above a mean value over some baseline (Hague et al. 2024a; Dedekorkut-Howes et al. 2021).

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3. Description of input data

In this section, we provide a summary of the modelling chain and bias adjustment methods used to develop the hazard information. A companion report (CSIRO 2025) describes the choices, development, production and evaluation of GCM and RCM data used to derive the hazard information. At the time the analysis was undertaken, a total of 8 GCMs dynamically downscaled using the Bureau of Meteorology's BARPA and CSIRO CCAM RCMs were available (Table 2). GCMs were carefully selected to meet evaluation tests, meet a threshold of independence from each other, and to representatively sample the range of change from the CMIP6 ensemble as a whole (Grose et al. 2023).

Two shared socioeconomic pathways were used for the GCM projections (SSP1-26 and SSP3-70). Two bias adjustment methods were subsequently applied to the dynamically downscaled data; the univariate Quantile Matching for Extremes (QME) method and the Multivariate recursive nested (MRNBC). See section 3.2 for details.

In addition, two 'target' or reference datasets were used to adjust or calibrate the model data to match; Australian Gridded Climate Data (AGCD) and Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia version 2 (BARRA-R2). When using AGCD the variables daily gridded precipitation, maximum temperature and minimum temperature only were bias adjusted while when using BARRA-R2 as reference, maximum surface windspeed, downwelling shortwave solar radiation, maximum surface relative humidity and minimum surface relative humidity were also included. See Figure 7 for a flow diagram of the modelling chain. We elaborate on this in the following sections. Refer to Table 1 for the model data that was used to develop hazard information. Note that while 8 GCM were used, not all were available for both RCMs.

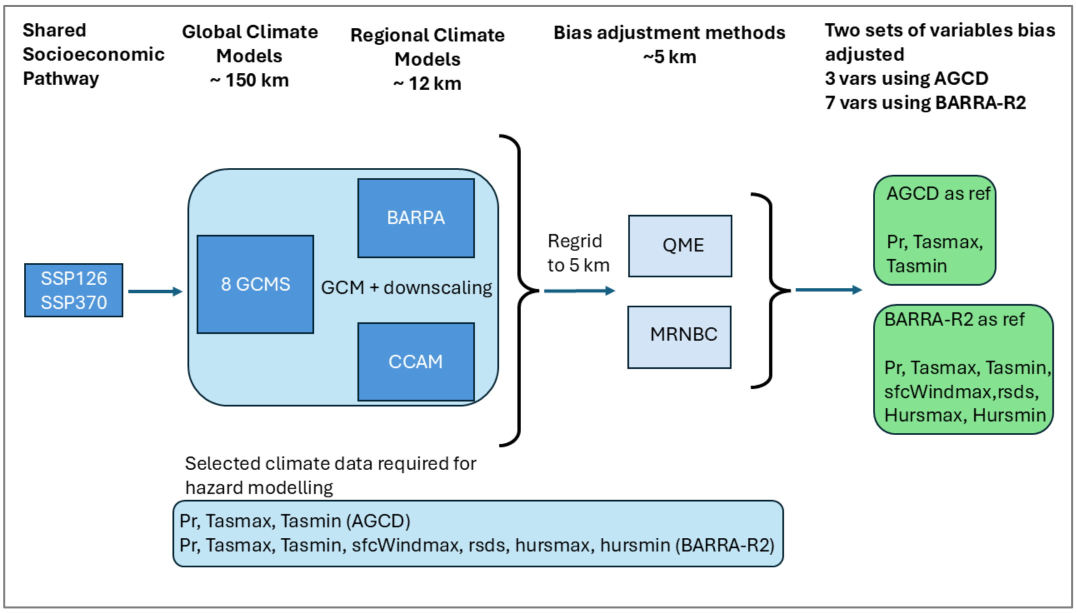


Figure 7: Flow diagram of the sequence used to produce bias-adjusted data.

Table 1: Projections data used in developing hazard information, including links to relevant sections of this report.

Hazard/Essential climate variable	Projections information	Bias adjustment	Location on NCI	Additional documentation on GitHub
Extreme temperatures and heatwaves (5.1.1)	CMIP6 13-member ensemble GWL 1.2, 1.5, 2.0, 3.0	QME against AGCD	/g/data/ia39/ncra/heat/	https://github.com/AusClimateService/hazards-heat
Drought and changes in aridity (5.1.2)	**SPI and 15th percentile rainfall** CMIP6 13-member ensemble **Aridity index** CMIP5 (NHP)	QME against AGCD	/g/data/ia39/ncra/drought_aridity	https://github.com/AusClimateService/hazards-drought
Bushfire (5.1.3)	**Fire climate classes** CMIP6 13-member ensemble **FFDI** CMIP6 13-member ensemble	MRNBC against BARRA-R2	/g/data/ia39/ncra/bushfire/	https://github.com/AusClimateService/fire_climate_classes https://github.com/AusClimateService/hazard_fire
Extratropical cyclones (5.2.1)	CMIP6 13-member ensemble SSP3- 7.0 GWL 1.2, 1.5, 2.0, 3.0	Mean sea level pressure not bias corrected	/g/data/ia39/ncra/extratropical_storms	https://github.com/AusClimateService/NCRA_ExtratropicalHazardTeam
Tropical cyclones (5.2.2)	CMIP5 9-member ensemble RCP 8.5		/g/data/ia39/ncra/tropical_cyclones	https://github.com/AusClimateService/hazards-TC
Convective storms including hail (5.2.3)	Only qualitative assessment of future changes provided Changes in CAPE and CIN based on BARRA-R2 (1995-2014)		/g/data/ia39/ncra/convective	N/A
Extreme rainfall (5.3.1) and	**RX1D, RX5D, RX1H** CMIP6 13-member ensemble (SSP3 -7.0)	QME against AGCD Hourly rainfall is not	/g/data/ia39/ncra/extratropical_storms	N/A

Hazard/Essential climate variable	Projections information	Bias adjustment	Location on NCI	Additional documentation on GitHub
Average rainfall (5.3.2)		bias adjusted just scaled		
Riverine and flash flooding (5.3.3)	**Rainfall** CMIP6 8-member ensemble downscaled using BARPA for SSP5-8.5 **Soil saturation and runoff** CMIP5 ensemble developed for NHP (RCP 4.5 and RCP 8.5 which is equivalent to SSP5-8.5)		/g/data/ia39/ncra/flood	https://github.com/AusClimateService/hazard-flood
Coastal hazards (0)	Based on IPCC AR6 projected future changes in mean sea levels		g/data/ia39/ncra/coastal	https://github.com/AusClimateService/hazards-coastal
Marine extremes (5.5)	**Ocean warming and acidification** CMIP5 multi-model mean projections for RCP8.5 used to drive eddy-resolving model (OFAM3)			https://github.com/AusClimateService/hazard_ocean

3.1. Model selection

A total of eight GCMs were selected for producing new Regional Climate Model (RCM) projections from CSIRO and BoM (listed in Table 2). They were chosen to span a range of hot/cool and wet/dry models with a range of climate sensitivities, and a consideration of changes in important features of atmospheric circulation (e.g. subtropical ridge and monsoonal shear line).

The simulations we have produced are compliant with the Coordinated Regional Downscaling Experiment (CORDEX) protocols, and there are two other contributors to CORDEX Australasia, the NARCLIM2.0 program and the Queensland Future Climate Program v2 (see Grose et al. (2023) for more details). Each group selected their own set of models to form a ‘sparse matrix’ of GCM-RCM combinations (see Table 2 for details).

The models are designed to span the host CMIP6 model ensemble as much as possible, so that statistics such as ensemble mean should replicate the ensemble of host CMIP6

GCMs reasonably well. Projections from the 14 simulations from these two RCMs are also broadly representative of the 39 simulations from four models in the entire CORDEX Australasia ensemble in terms of projected change in mean temperature and rainfall (CSIRO 2025).

Where hazard information developed for NCRA made use of these simulations, they were based on a 13-member ensemble (labelled from 1 through to 13 in Table 2) because one of the 14 simulations was not available at the time (NorESM2-MM downscaled using CCAM-ACS).

For some purposes, users may wish to explore the set of ACS RCMs along with the entire CORDEX ensemble. Also, given that there is still a relatively small sample size of modelling, rather than use traditional statistics of ensemble mean and range, it can be useful to take a storyline or "representative climate futures" approach (CSIRO and Bureau of Meteorology 2025). This could take the form of investigating a drier (e.g. ACCESS-ESM1.5), hotter (e.g. ACCESS-CM2) or wetter (e.g. EC-Earth3) future determined by a host GCM and exploring all the RCM downscaled experiments, to fully explore these plausible future climates. For this purpose, the EC-Earth3 and EC-Earth3-Veg models were selected as a wetter representative climate future, so can be considered together.

Table 2: The CMIP6 GCMs downscaled with four different RCM configurations (top row), including the seven downscaled by the Bureau of Meteorology Atmospheric Regional Projections for Australia (BARPA) and the CSIRO CCAM model using spectral nudging. The 39 ensemble members are sequentially numbered.

	BARPA-R	CCAM-ACS	QldFCP-2	NARCLIM2.0
ACCESS-CM2	1	8	15	
ACCESS-ESM1-5	2	9	16-18	30, 31
CESM2	3	10		
CMCC-ESM2	4	11	19	
CNRM-CM6-1-HR			20, 21	
CNRM-ESM2-1		12		
EC-Earth3	5	13	22	
EC-Earth3-Veg				32, 33
FGOALS-g3			23	
GFDL-ESM4			24	
GISS-E2-1-G			25	
MPI-ESM1-2-HR	6			34, 35
MPI-ESM1-2-LR			26	
MRI-ESM2-0			27	
NorESM2-MM	7	14	28, 29	36, 37
UKESM1-0-LL				38, 39

3.2. Bias adjustment

3.2.1. The need for bias adjustment

Climate projections are initially produced from output from relatively coarse resolution Global Climate Model (GCM) simulations (~100–300 km). Regional Climate Models (RCM) use the output of GCMs as the boundary conditions to provide much higher resolution simulations (~10 km) that include increased topographic information. This helps resolve local -scale processes such as coastal circulations and uplift over topography (Giorgi and Gutowski 2015; Jones et al. 2011; Giorgi et al. 2009). This modelling is the primary source of information to assess future climate change and variability, and the impact of extremes at both the global and regional scale. However, the modelling process still produces inherent biases, seen in comparison of GCM and RCM output with observations. These persistent differences from observed datasets makes their direct use unsuitable for decision-making processes at a local scale (Gebrechorkos et al. 2023). In addition, running high-resolution dynamical models is computationally intensive making them difficult to run at the resolution required for local-scale information (Maraun 2013).

Therefore, to produce ‘application-ready, locally relevant’ datasets suitable for applied analysis, we need to perform further downscaling and calibration to a reference dataset. A practical method to produce these datasets is scaling or the ‘delta method,' which means applying change factors from a model to an observed dataset, often using quantiles. Statistical downscaling methods and bias adjustment are relatively cheap to run and remove the biases inherent in the GCM/RCM simulations (Maraun 2013). Note that in the literature, these techniques are often described as ‘bias correction’. Because we adjust for biases by calibrating model data against observations we prefer ‘bias adjustment’ or ‘calibration’.

Bias adjustment can take many forms, however, most modern techniques use a form of quantile matching, whereby the quantiles of the modelled data are matched to those of the historical data over a defined period. These quantile differences are then applied to the future climate model output for that parameter (Maraun and Widmann 2018; Maraun et al. 2010). Bias adjustment assumes that the statistical relationships that exist in the historical period apply in the future period (i.e. the relationships are stationary), which may not be a valid assumption (Maraun 2016, 2013). However, the application of bias adjustment and their relative simplicity makes it suitable for understanding hydro-climate extremes and use in impact assessment studies and hazard projections at a local scale in many sectors (Peter et al. 2024; Shrestha et al. 2014; Vogel et al. 2023; Wasko et al. 2021; Wilson et al. 2022).

3.2.2. Reference data sets

The bias adjustment requires reference data sets to calibrate the output of the RCM. These can take the form of gridded data of point observations or a reanalysis product. We used the Australian Gridded Climate Data (AGCD) gridded observations and the Bureau of Meteorology (Bureau) Atmospheric high-resolution Regional Reanalysis for Australia version 2 (BARRA-R2) reanalysis to provide the reference data.

The AGCD provides daily gridded precipitation (pr) and maximum and minimum temperature (tasmax/tasmin) at 0.05° resolution. BARRA-R2 has a more extensive range of variables and so the above three variables were supplemented by maximum surface wind speed (sfcWindmax), downwelling shortwave solar radiation (rsds) and maximum and minimum surface relative humidity (hursmax/hursmin). The BARRA-R2 data is at 0.11° (~12 km) resolution. In the future it will be possible to add additional variables to the bias adjusted outputs.

3.2.3. Preprocessing

Before the bias adjustment is implemented, all data sets must be interpolated to a common grid. This was chosen to be that of the AGCD 0.05° grid (~ 5 km) over the same

Australian domain as AGCD. This required the BARRA-R2 reference data and the RCM data to be interpolated to the AGCD grid which was achieved using bilinear interpolation (https://github.com/AusClimateService/bias-correction-data-release) . This approach can be expected to work best where topographical variations are less, and for data on a finer input grid.

When using the BARRA-R reference data set it contains some physically *unrealistic* relative humidity values (hursmin and hursmax) of greater than 100%. For this reason, values above 100% in the BARRA-R data are truncated to 100% before applying the bias adjustment. Quality check thresholds for each variable are listed in Table 3. No preprocessing is applied to the other variables.

Table 3: Minimum and maximum thresholds used in pre-processing. Bias-corrected values equal to the lower and upper threshold for tasmin and tasmax and the upper threshold for other variables should be treated with caution.

Variable	**Min threshold**	**Max threshold**
Precipitation (pr)	0 mm/day	1000 mm/day
Min. temperature (tasmin)	–20 °C	65 °C
Max. Temperature (tasmax)	–20 °C	65 °C
Max. surface wind speed (sfcWindmax)	0 m/s	300 m/s
Downwelling shortwave solar radiation (rsds)	0 W/m^2	500 W/m^2
Min. relative humidity (hursmin)	0%	100%
Max. relative humidity (hursmax)	0%	100%

3.2.4. The bias adjustment methods

One scaling method and two bias adjustment methods were applied for the ACS. The scaling approach was not considered in developing hazard information:

- Quantile Delta Change (QDC; univariate) - scaling of observations using GCM change signals
- Quantile Matching for Extremes (QME) - adjustment/calibration of RCM data and,
- Multivariate Recursive Nested Bias Correction (MRNBC) - adjustment of RCM data.

The first two are univariate methods and the last is a multivariate method. The QDC method uses the Equidistant Cumulative Distribution Function quantile matching method (ECDFm; Li et al. 2010). It is the simplest quantile-based bias adjustment method available. The quantile differences between future and historical model simulations are calculated and then applied to observations to produce a future timeseries. It has the big advantages of having realistic variability at all timescales and a realistic sequence of events, as well as the observed correlation between variables. It has the disadvantage of the future time series simply following the same sequence of events as the observations, meaning that any projected changes in typical sequencing are not expressed in the calibrated data. The QDC cannot produce a continuous time series of projections. In addition, it was applied to the raw GCM data and not the dynamically downscaled RCM projections for each model, providing a GCM based benchmark dataset. It was developed as a suitable dataset for many applications, and while it provides a useful benchmark for the QME and MRNBC methods to be compared against, it is not used in the hazard analysis in this report. The QDC technique had been used to develop ‘application-ready’ data which is available through the ‘Climate Change in Australia’ webpage (https://www.climatechangeinaustralia.gov.au/en/). For details refer to Irving & Macadam (2024).

The QME method is a bias adjustment applied to the model data, and has a special focus on extreme events. It involves scaling the data before matching the model and observations by quantile (Dowdy et al. 2019; Dowdy 2023). Rather than using uniform quantiles, the QME method applies a logarithmic transformation so that there is higher resolution in the quantile bins in the upper and lower ranges. This means that quantiles in the upper and lower tails (extremes) can be assigned without resorting to interpolation. Before removing the quantile biases from the model data of interest, the bias adjustment factors at the extreme ends of the distribution are also modified in an attempt to avoid potential overfitting or an excessive influence of very rare events.

The MRNBC is an extension of quantile matching to include inter-variable correlations and in addition corrects across multiple timescales in an attempt to capture low-frequency variability present in the simulations (Johnson and Sharma 2012; Mehrotra and Sharma 2012, 2015, 2016). It does this by correcting the mean and standard deviation of the distribution as well as the persistence (lag 1 autocorrelation) at monthly, seasonal and annual timescales using an autoregressive lag 1 model (Srikanthan and Pegram 2009). This imparts observed distributional and persistence properties of the input fields. The multivariate aspect of the MRNBC may better capture the joint dependence among input variables and hence be more effective in capturing natural processes that contribute to the variability of a field, especially a complex one such as precipitation. In addition, since the MRNBC corrects across multiple timescales it may provide a better representation of long-term variability. This is of particular importance for hydrological applications where the representation of variability and persistence of precipitation is important for the simulation of extreme events such as floods and drought (Peter et al. 2024; Vogel et al. 2023). Note that only the QME and MRNBC methods were used for the hazards evaluation.

Key points

Both the univariate QME and the multivariate MRNBC technique were applied to regridded (i.e. preprocessed) RCM data.

The QME method is constructed to optimally adjust very low and very high values in an attempt to better capture the extreme values (greater than 99th percentile and less than 1st percentile) of each field.

MRNBC corrects across multiple timescales and may provide a better representation of long-term variability. In addition, it adjusts all variables to preserve intervariable correlations.

3.2.5. Bias adjustment for hazard information

The use of AGCD and BARRA-R2 data sets as reference data across the complete suite of CORDEX RCMs (see Table 2) results in two corresponding bias-adjusted data sets; those using AGCD as reference data for which only the variables precipitation (pr), maximum temperature (tasmax) and minimum temperature (tasmin) were adjusted and those using BARRA-R2 for which the seven variables listed in Table 3 were adjusted. In addition, for each reference data set, there are three data sets available corresponding to the three bias adjustment techniques detailed in Section 3.2.4. This is summarised in Table 4.

Table 4: Availability of bias-adjusted variables using the two reference data sets (AGCD and BARRA-R2) and the three bias adjustment techniques used (QDC, QME and MRNBC).

Dataset specifications	
Timescale	daily
Variables	tasmax, tasmin, pr, rsds, hursmax, hursmin, sfcWindmax
Observations	AGCD (tasmax, tasmin, pr), BARRA-R2 (all seven variables)
Models	All RCM/GCM combinations from BoM, CSIRO
Time range	1960-2099 (for SSP1-2.6 and SSP3-7.0)
Spatial grid	AUST-05i
Bias adjustment	QDC, QME, MRNBC
Documentation	https://dx.doi.org/10.25914/xeca-pw53
Location	NCI: /g/data/kj66

The bias-adjusted data sets are essential for initialising impact models and also for the production of hazard indices projections. It is, however, noted that the choice of variables that were bias-adjusted (see Table 3) determines that not all hazards can be evaluated with the available data. For instance, a hazard using potential evapotranspiration which requires the variable Mean Sea Level Pressure (mslp) as an input could not be evaluated with the available data sets. Nevertheless, the available bias-adjusted data are suitable for a large range of hazard indices. For a hazard index that requires any combination of only the variables precipitation (pr), maximum temperature (tasmax) and minimum temperature (tasmin), then a choice needs to be made as to whether the bias-adjusted data using AGCD or BARRA-R2 should be used. Alternatively, it allows a comparison between the two reference data sets to be made. If any other variable from Table 3 is required then only the data using BARRA-R2 as reference is suitable.

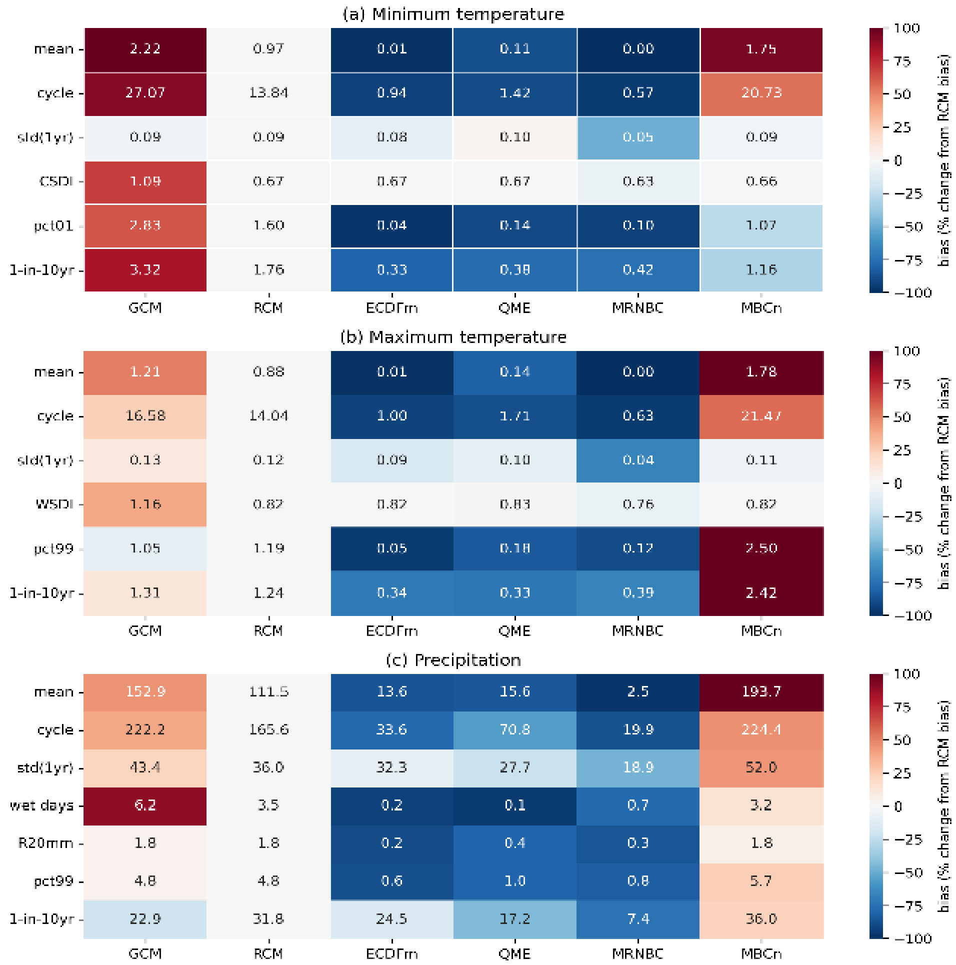
The availability of the QME and MRNBC bias adjustment techniques enables comparisons of how each bias adjustment method affects the RCM output. This is particularly important when evaluating hazard metrics, which often rely on several variables. For instance, Qiu et al. (2023) examined two heat stress indicators, wet bulb globe temperature (WBGT) and apparent temperature (AT), both of which have dependencies on temperature (T) and relative humidity (RH), however with differing T-RH dependencies; WBGT varies more strongly with both RH and T while AT varies mostly with T. They demonstrated that using a multivariate bias adjustment method (MBCn; Cannon 2018) improved the inter-variable dependence, resulting in better outcomes, especially for WBGT which depends more equally on the T-RH interdependence. This was demonstrated for the "indirect" correction, where each variable was corrected prior to the calculation of the hazard metric. When using "direct" correction (i.e. the derived indicators were bias corrected rather than their components), then the univariate quantile delta matching (QDM) performed similarly to the multivariate method. The intercomparison of the univariate (QDC/QME) and multivariate (MRNBC) is crucial for the evaluation of how the methods influence the hazard metrics and is required for guiding their use for the end-user community.

ACS activities have leveraged existing expertise in bias adjustment of climate projections such as for Climate Change in Australia (https://www.climatechangeinaustralia.gov.au/en/) where a Quantile Delta Change (QDC) method was applied and the National Hydrological Projections https://awo.bom.gov.au) which for example made use of the Multivariate Recursive Nesting Bias Correction (MRNBC).

3.2.6. NPCP bias adjustment intercomparison

Several bias adjustment methods were implemented for ACS, however the QME and MRNBC were chosen for the hazard information. This was motivated by an NPCP evaluation which showed that the ECDFm and QME performed similarly. In this manner, univariate and multivariate methods were able to be compared for subsequent evaluation of multivariate hazard indices. For further details see AusClimateService/npcp and Irving et al (2025).

To assess the performance of bias adjustment methods, comparisons were undertaken for the calibration and cross-validation tasks. Figure 8 summarises the assessment for three variables: minimum temperature, maximum temperature and precipitation. The evaluation was undertaken for the annual mean, the seasonal cycle, interannual variability, cold spell duration, warm spell duration, 1st percentile, 99th percentile, 1-in-10 year event, wet day frequency and annual number of very heavy precipitation.



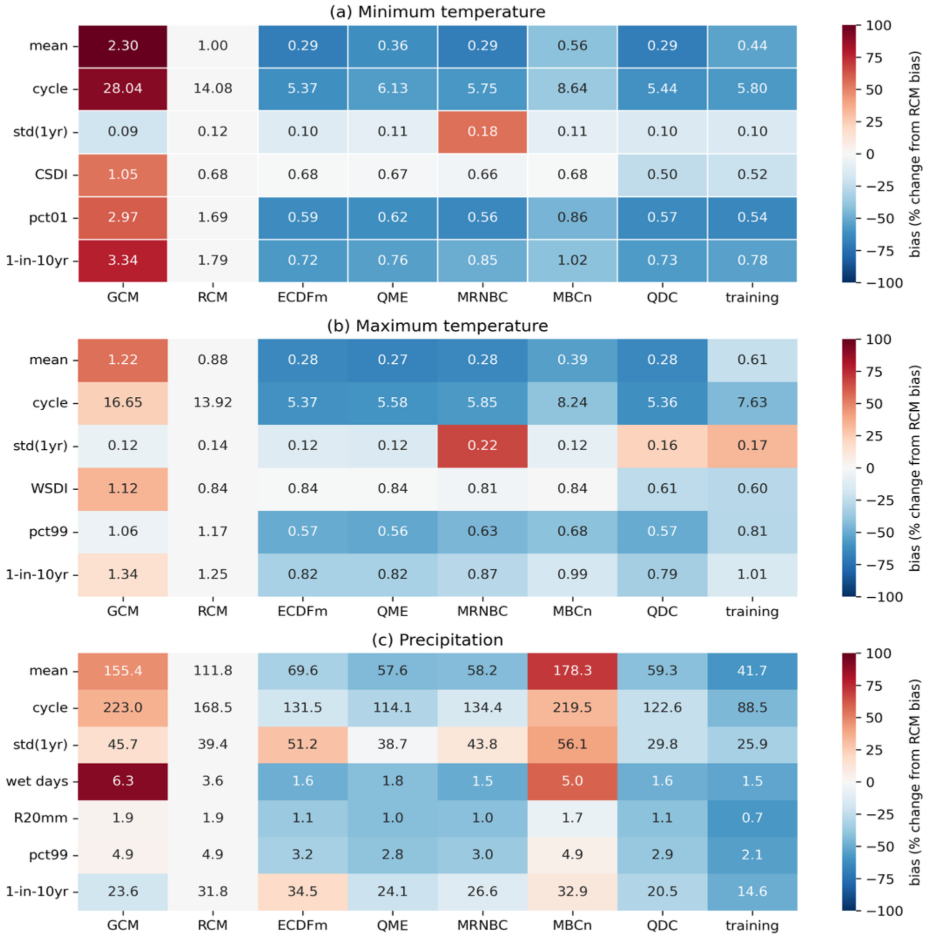


Figure 8: Mean absolute error/bias across all grid points and all CMIP6 GCM/RCM combinations for the calibration assessment task (top) and based on cross-validation (bottom). The number in each cell corresponds to the mean absolute error/bias (with units of degrees Celsius, millimetres or days depending on the metric), while the colour is that bias value expressed as a percentage change relative to the RCM value.

3.2.7. Bias adjustment next steps

The bias adjustment intercomparisons described in Section 3.2.6 have been undertaken for three climate variables. This type of comparison should be expanded to hazards, especially multivariate hazards. This would enable performance-based guidance on choice of bias adjustment method.

Bias adjustment techniques presented here are applied at the daily time steps although for some hazards higher temporal resolutions are required. We will therefore explore bias adjustment at subdaily (likely hourly) timesteps, building on work undertaken by NPCP partners and as part of the National Bushfire Intelligence Capability (NBIC). Hourly timestep calibration will require greater use of reanalyses or similar data, and will grealy increase data volumes.

For many univariate hazards, there are applications that require information at the subdaily timescale. A useful example are rainfall extremes, where subdaily data would enable us to both analyse hourly rainfall extremes and include information about the diurnal cycle in rainfall extremes.

For multivariate hazards such as fire weather risk, subdaily data are required to study current and future hazards. This would allow the inclusion of information on the diurnal cycle of variables and also the co-occurrence of extremes. A notable example is bushfire danger indices, where the subdaily timescale is critical, such as the classic setup of prefrontal winds followed by a cool change. Indices such as FFDI based on daily data are insufficient, as the maximum temperature, maximum windspeed and minimum humidity may not be aligned in time, meaning the index can be misleading.

Another example is on renewable energy in this Electricity Sector Climate Information (ESCI) Case Study, where wind farm output is affected by changes in wind through the day but also through extreme heat shutting down operation (Figure 9).

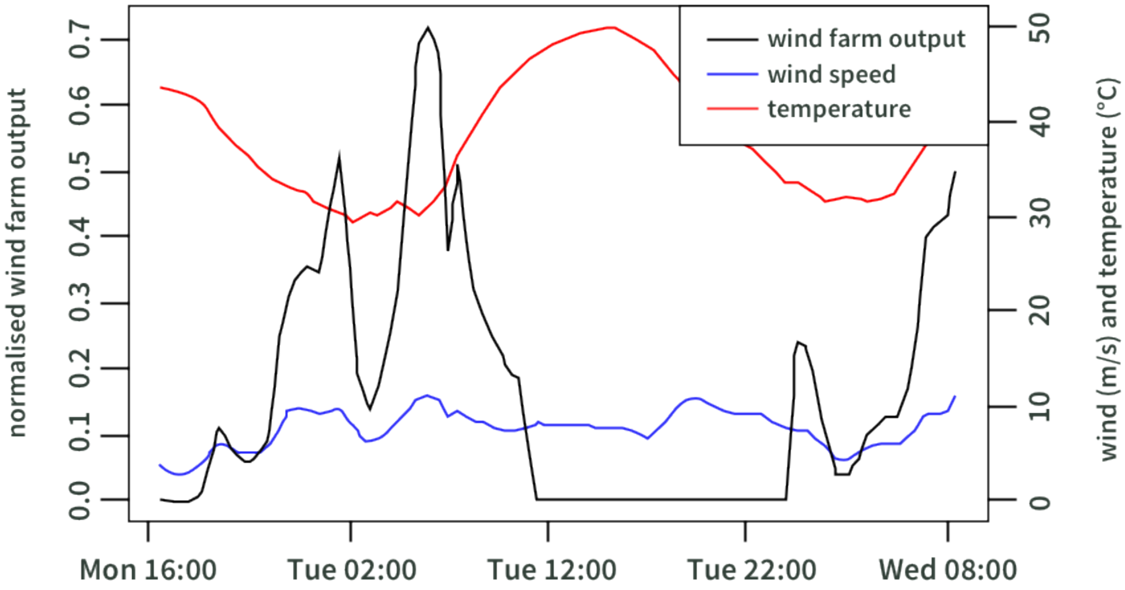


Figure 9: Thirty-minute simulation of wind farm output (black line) for varying temperature (red line) and wind speed (blue line) in Western Victoria.

Source: https://www.climatechangeinaustralia.gov.au/en/projects/esci/esci-case-studies/case-study-heat/.

Especially for multivariate bias adjustment techniques applied at subdaily timesteps which are computationally expensive, machine learning approaches would be an attractive alternative.

3.2.8. Choice of bias adjusted datasets

The effect of the choice of model dataset and choice of bias adjustment is illustrated in Figure 10. This figure shows the average number of severe and extreme heatwave days for Northern Australia under GWL 3.0 based on SSP3-7.0 for 17 realisations.

- The first panel (ACS QME) indicates the dataset used as basis for developing hazard information provided for the NCRA.

- The next two panels indicate ACS-CORDEX runs, downscaled using BARPA (blue shading) and CCAM (green shading). The spread is shown for the raw model output and three bias corrected datasets.
- The fourth panel (magenta shade) and the fifth panel (orange) show the same information for ensembles used by NPCP partners (NSW and Queensland).
- The last boxplot shows results based on application ready data where a delta scaling approach was applied directly to GCM data.

In this example:

- Bias adjustment typically leads to an increase in the number of extreme heatwave days.
- Results are similar for the two RCMs used in ACS and comparable to estimates using the NSW dataset but use of UQ would lead to lower frequency estimates.
- ‘Application ready’ data show very little spread compared to other datasets.

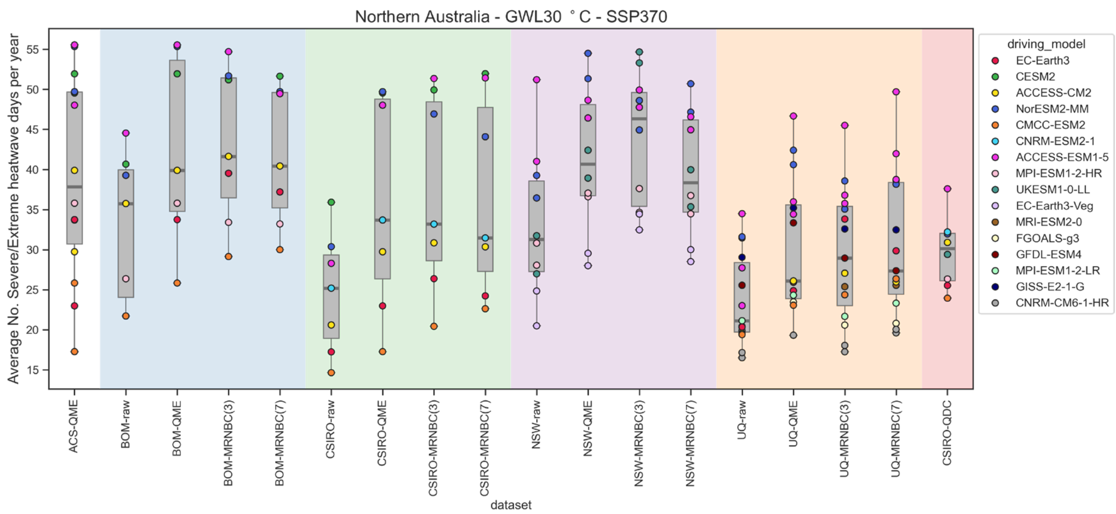


Figure 10: Average number of severe and extreme heatwave days for Northern Australia under GWL 3.0 based on SSP3-7.0. The colour of dots indicates the driving GCM (as per legend).

Key points

- Bias adjustment was applied to downscaled climate projections (RCM). The exception is *QDC scaling* which was applied to GCM data directly. These projections are only available for discrete future time periods resulting in a non-continuous timeseries over the projection period (2015-2100). The sequencing of weather events is determined by those of the observations in the reference period resulting in no change in weather sequencing / variability (from observations). This data is available through Climate Change in Australia.
- *Raw RCM output* has the advantage that it is available for a wider range of variables than the bias adjusted data but it has not been adjusted for biases. For applications where large ensembles are of high value and biases are less critical,

this might be a suitable choice. Not all variables have been calibrated, e.g. for Mean Sea Level Pressure only the raw data are available.

- RCM data that has undergone *bias adjustment* using the (univariate) QME are best suited for applications where single-variable hazards are concerned, e.g. heat, especially where extreme events are important. For such applications they may be superior to data that has been bias corrected using the (multivariate) MRNBC technique.
- Depending on the reference data used, the MRNBC technique has been applied to calibrate 3 variables against AGCD and 6 variables against BARRA-R. The choice here is therefore guided by the set of variables required. Typically, the MRNBC adjusted data are judged best suited for assessing multivariate hazards. However, for hazard specific applications such as flooding or tropical cyclones, which are driven by highly heterogeneous fields such as rainfall and wind, the data used for bias correcting needs to be carefully selected. For example, BARRA-R data may not be suitable for these hazards, given its limitations in reproducing rainfall and wind extremes.
- Initial evaluations indicate that there may also be value in using the MRNBC technique for single variable hazard indices, such as the Standardised Precipitation Index, SPI (see section 5.1.2) which is calculated for 3, 12 and 24-month periods
- For risk assessments that combine information on multiple hazards, the choice of bias adjustment technique may be guided be the desire to use a consistent basis for deriving the hazard information.
- There is merit in combining the insights from analyses of multiple streams of data, i.e. GCM data, raw RCM output and bias adjusted RCM data, potentially in combination with storylines.

3.2.9. Sea-level rise projections

For coastal hazards, projections of sea level rise are required. Sea level rise projections were produced (Zhang and McInnes 2024) for the National Climate Risk Assessment based on IPCC AR6 (Fox-Kemper et al. 2021). Multi-model ensemble median and percentiles projections from IPCC AR6 have been updated for two components to provide estimates of changes in mean sea level, relative to the local land level, under different future emission scenarios.

The first component is the *Vertical Land Motion* (VLM) component. While the fifth assessment report of the IPCC (AR5) and the 'Special Report on the Ocean and Cryosphere under Climate Change' (SROCC) incorporated only the VLM effect due to Glacial Isostatic Adjustment (GIA), the sixth assessment report (AR6) included GIA as well as estimation for local VLM due to other factors such as tectonics and groundwater extraction. However, it is noted that the IPCC states that 'depending on location, there is low to medium confidence' in these GIA and VLM projections and 'In many regions, higher-fidelity projections would require more detailed regional analysis' (Fox-Kemper et al. 2021). For the Australian region notable differences in regional sea-level projections can be found between AR5 and AR6, with the VLM component being a key factor. Regional features of the AR6 VLM component are not supported by (or in direct contradiction with) available VLM observations (Naish et al 2024), including a local uplifting VLM (up to 25 cm by 2100) in the Torres Strait. To address this, VLM from AR5 and SROCC due to GIA only was swapped in.

The second component is *dynamic sea level* (Kopp et al 2014). Dynamic sea level components were derived directly from the ensemble of CMIP6 climate models to better represent coastal sea level around Australia.

Indices

Annual mean sea level rise from present to 2150, relative to 1995 – 2014 baseline period.

Data sources

CSIRO data portal (DOI https://doi.org/10.25919/rwma-zw18)

Outputs

netcdf files available on NCI at g/data/ia39/ncra/coastal/MSL:

- Gridded (1x1 deg) sea level projections for Australian region ('yearly_final' files) and at points along the Australian coastline ('continentborder' files) for SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5
- Annual mean sea level for SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 at ANCHORS tide gauges ('anchors' files)
- Gridded difference between chosen sea-level increments representing global warming levels (refer **Section 2.7**) for Australian region at 1x1 degree and at points along the Australian coastline.

3.2.10. Developing climate projections data for hazard information

The outputs provided for NCRA were computed on a 13-member downscaled and bias-adjusted ensemble (Table 2). As ACS activities progress further and ensembles are expanded upon, the NCRA indices will be recomputed on the larger ensemble and with multi-variate bias adjustment.

Convection permitting models are crucial for the accurate representation of hazards such as flash flooding, damaging wind, and extreme rainfall (Wasko et al 2024). Examples of where the use of convection permitting models could add value include: improvements in modelling extreme hourly rain rates, and sea level pressure and wind speeds for tropical cyclones.

The development, evaluation runs and testing of models has been completed. Prototype datasets are currently being produced so that once downscaled CMIP7 projections become available, hazard indices could potentially be based on convection permitting models.

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4. Hazard Teams

For each of the priority hazards, a Hazard Team was formed with a Team Lead, an Alternate Lead, and Hazard Team members. While these were ACS staff, we also included subject matter experts in the field (including experts from academia) without an ACS allocation to act in an advisory capacity.

There were twelve Risk Teams that required input from the Hazard Teams. These twelve risks were organised into Risk Clusters of two or three risks, e.g. Primary Industries, Natural Environment, Water security, etc. Risk Liaisons were identified for each risk cluster.

To streamline the interactions between Hazard Teams and Risk Clusters, Hazard Knowledge Brokers were identified on the hazard side (Figure 11). There was a designated coordinator to facilitate interactions but typically communications occurred directly between Hazard Brokers and Risk Liaisons. This setup was largely successful in enabling the teams to deliver on time, critical to that success were existing strong relationships between Hazard Knowledge Brokers and Risk Liaisons.

4.1. Product planning

In the absence of clear requirements, Hazard teams developed a summary and options for hazard indices/metrics that they could develop and deliver. This information was put together to facilitate discussions with Risk Teams, many of which were new to the tasks and did not have specifications on the information that they required for their risk assessments.

These plans included information on:

- team responsible for providing the information
- proposed indices and metrics (with precedence for use)
- proposed input data (e.g. AGCD, BARRA, CMIP6)
- spatial and temporal resolution and domain for which hazard information would be developed
- analysis form (e.g. map, time series, summary statistics)
- location where hazard information was to be made available

The Risk Teams then identified and prioritised their requirements against the proposed set of outputs.

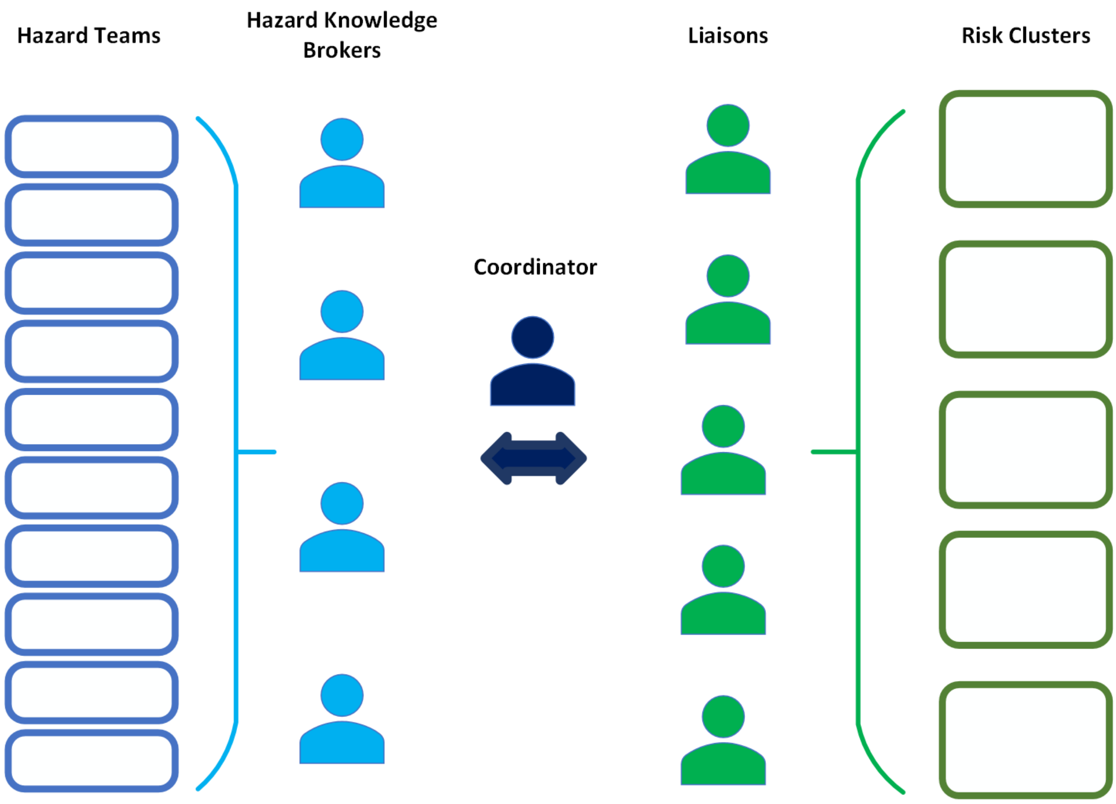

Figure 11: Schematics illustrating the structure for interactions between Hazard Teams and Risk Teams.

4.2. Challenges navigated & learnings

A debrief of staff involved found that pressures to deliver early without a clear roadmap and requests for additional hazard metrics at short notice, as well as unclear decision-making roles, responsibilities and boundaries contributed to communication delays from the Risk Teams and burnout within the Hazard Knowledge Brokers and the Hazard Teams.

Future NCRAs should create a clear roadmap, allocate sufficient time for tasks to be completed, have well-defined roles and responsibilities to support decision-making processes, as well as a single source of truth to facilitate communication. Along with a staged delivery approach, this would support a more seamless knowledge brokering process, overall. The requirements that the NCRA set fell ahead of the initial ACS delivery which put additional pressure on all teams.

5. By Hazard

This section provides detailed information about key climate variables (temperature, rainfall and sea level) and priority hazards. While activities are ongoing, this report provides a snapshot in time, summarising the development of hazard information for the first National Climate Risk Assessment.

Where feasible, each section provides a definition of the hazard. We provide definitions of indices used, including equations and relevant citations, and provide caveats and discuss options for additional indices for future work. Current maturity (and gaps) are discussed alongside the use of hazard information for risk assessments. Where available, we include heatmaps to summarise changes in an index (e.g. the hottest day of the year, Figure 13) relative to GWL 1.2. Heatmaps illustrate these changes for each NCRA region (and Australia as a whole) and for each of the 13 ensemble members, giving an indication of the spatial variability and the spread across models.

Table 1 lists the hazards included in this section together with relevant projections information, information on bias adjustment applied, location of data on NCI and links to supporting documentation on GitHub.

5.1. Hot extremes

5.1.1. Extreme temperatures and heatwaves

Contributors

Mitchell Black (Lead), Cassandra Rogers

Indices

Extreme temperatures in Australia pose a threat to health, infrastructure, agriculture, and the natural environment. Heatwaves, characterised as extreme heat that lasts for three or more days, cause more loss of life in Australia than any other extreme weather hazard (Handmer et al. 2018).

A range of indices were calculated for the NCRA to quantify changes in extreme temperatures and heatwaves, as summarised in Table 5.

Table 5: Description of the various indices calculated for the NCRA to define heatwaves and extreme temperatures.

Index		Description	Temporal resolution	Reference
Heatwaves	HWF	Heatwave frequency – number of days per year experiencing heatwave conditions	annual	Nairn and Fawcett 2015
	HWD	Heatwave duration – length of the longest heatwave	annual	Nairn and Fawcett 2015
	HWN	Heatwave number – number of separate heatwave events in a given year	annual	Nairn and Fawcett 2015
	HWAtx	Heatwave peak temperature – hottest day of the hottest heatwave	annual	Nairn and Fawcett 2015
Extreme temperature	TXm	Annual mean daily maximum temperature	annual	ETCCDI Climate Change Indices
	TXx	Annual maximum daily maximum temperature	annual	ETCCDI Climate Change Indices
	TXge35	Days above 35 °C	annual	ETCCDI Climate Change Indices
	TXge40	Days above 40 °C	annual	ETCCDI Climate Change Indices
	TXge45	Days above 45 °C	annual	ETCCDI Climate Change Indices
	TNle02	Days below 2 °C	annual	ETCCDI Climate Change Indices

In Australia, heatwaves are monitored and forecast by the Bureau of Meteorology using the Excess Heat Factor (EHF), which was designed to identify heatwaves based on the potential impact on human health (Nairn and Fawcett 2015). The EHF is calculated from the mean daily temperature, calculated as the average of the daily minimum and maximum temperatures. This incorporates both how high temperatures reach during the day, as well as how low night-time temperatures drop, allowing the body to cool off overnight. A three-day average of mean daily temperature is used to calculate the EHF, as prolonged exposure to heat exacerbates the impact on human health.

The EHF is calculated based on the difference between the three-day average daily mean temperature and the 95th percentile of daily mean temperature calculated over the period 1985–2014. A three-day average above the 95^{th} percentile indicates that temperatures are unusually hot relative to the reference period. This temperature anomaly is then multiplied by a factor related to the difference between the three-day mean temperature and the previous thirty days. This enhances the EHF in cases where the preceding period has been relatively cool, as an abrupt increase in temperature can have a larger impact on health than where bodies are more acclimatised to high temperatures. Periods of consecutive days with EHF > 0 are combined into heatwave events.

The Bureau of Meteorology further classifies heatwaves into three severity levels — *low-intensity*, *severe* and *extreme* (Table 6) — based on how the EHF values compare against the severity threshold EHF_{85} (which is the 85th percentile of all the positive EHF values within the climatology period 1985–2014):

$$EHF_{sev} = EHF / EHF_{85}$$

Further details on how the EHF is calculated is provided in Nairn and Fawcett (2015). A description of heatwave severity ratings is summarised in Table 6 and details can be found at http://www.bom.gov.au/australia/heatwave/knowledge-centre/understanding.shtml.

Table 6: Description of the heatwave severity ratings used by the Bureau of Meteorology (BoM 2024).

Heatwave classification	EHF_{sev} threshold	Description
Low-intensity	$0 < EHF_{sev} < 1$	Low-intensity heatwaves are frequent during summer. Most people can cope during these heatwaves. Heatwave warnings are not issued for low-intensity heatwaves.
Severe	$1 \leq EHF_{sev} < 3$	Severe heatwaves are less frequent. They are likely to be more challenging for vulnerable people. This can include older people, particularly those with medical conditions.
Extreme	$3 \leq EHF_{sev}$	Extreme heatwaves are rare. They are a problem for people who don't take precautions to keep cool – even for healthy people. Anyone who works or exercises outdoors can be at risk.

Datasets

All of the indices identified in Table 5 were calculated for each of the 13-member ensemble of regional climate model (RCM) simulations that were available at the time of analysis. These RCM datasets were bias adjusted using the Quantile Matching for

Extremes technique (Section 3.2.4) and provided daily temperature fields at ~5 km resolution across Australia. Accordingly, the NCRA was provided with the following:

1. Daily/annual timeseries of each hazard index on the 5 km model grid, spanning 1980–2100, for each input RCM dataset.
2. Hazard index datasets were further aggregated per Global Warming Level (1.2, 1.5, 2.0 and 3.0 °C) using [bespoke python code](#).
3. Ensemble maps and regional statistics — expressed as absolute values and changes relative to GWL1.2 °C (e.g., Figure 12 and Figure 13) — were computed per the methodology outlined in Technical Box 1.

All data were made available to the NCRA via the National Computational Infrastructure (NCI) (hosted at: */g/data/ia39/ncra/hazards/heat/<data/figures>/*) and the supporting code is documented on the [ACS heat team's GitHub page](#).

Results

A significant amount of data and synthesis was created for each of the extreme temperature and heatwave indices identified in Table 5. Accordingly, only two indices are highlighted here — the 'hottest day of the year' and the 'number of heatwave days per year' — as these were the two indices most commonly utilised across the NCRA projects.

Hottest day of the year

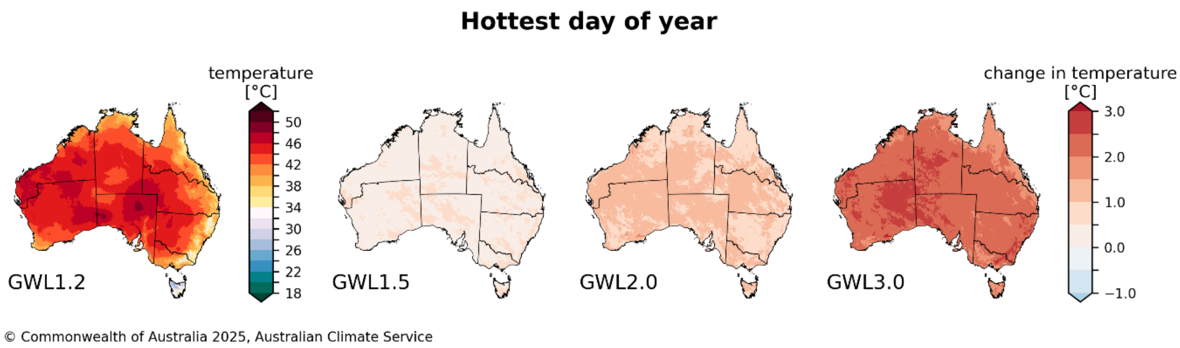

Figure 12: Change in the hottest day of the year.

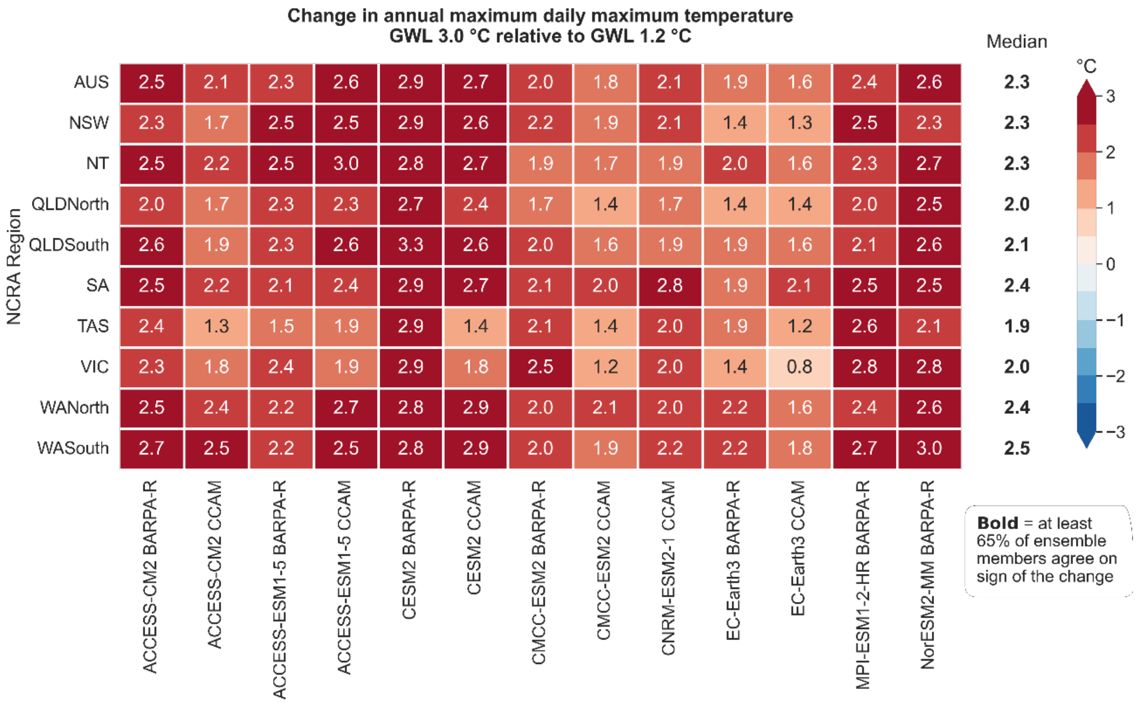

Figure 13: Sample heatmap showing TXx (hottest day of the year) for GWL 3.0 °C relative to GWL 1.2 °C, averaged across the different NCRA study regions. Here, results are presented for each of the 13 ACS regional climate model simulations, as well as the ensemble median.

Key finding: the hottest day of the year is projected to increase across Australia (very high confidence).

Number of heatwave days per year

After consultation with the NCRA, the index representing the 'number of heatwave days per year' was further refined to only include heatwave days classified as *severe* or *extreme* (i.e., does not include low-intensity heatwave days) (Figure 14 and Figure 15). This aligned the index with the Bureau's operational heatwave service, which only provides public warnings for severe or extreme heatwaves.

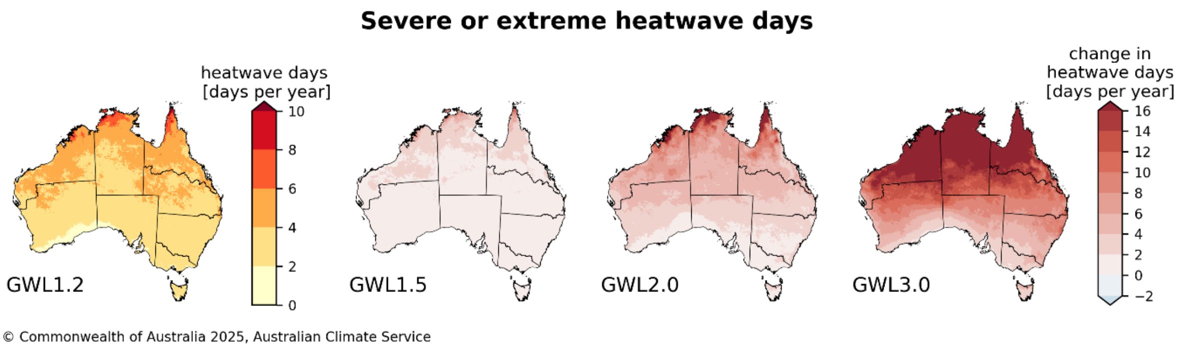

Figure 14: Change in the number of days experiencing severe or extreme heatwave conditions.

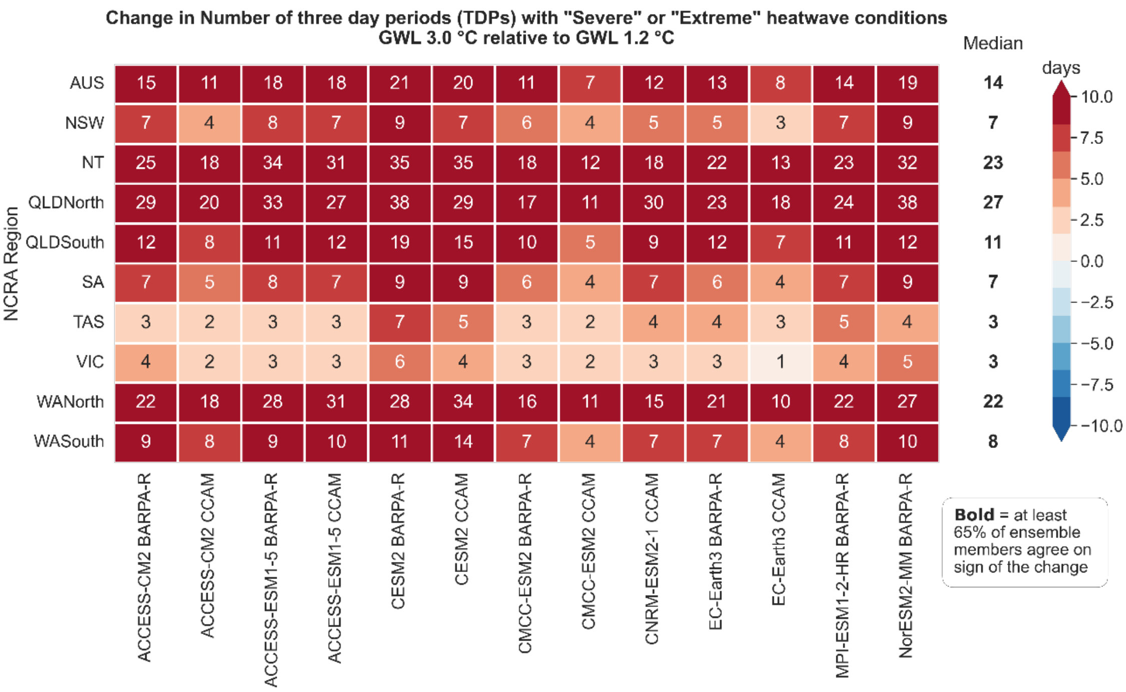

Figure 15: Sample heatmap showing the average number of days per year experiencing *severe* or *extreme* heatwave conditions, averaged across the different NCRA study regions and expressed as the change between GWL3.0 °C and GWL 1.2 °C. Here, results are presented for each of the 13 ACS regional climate model simulations, as well as the ensemble median.

Key finding: the number of days experiencing *severe* or *extreme* heatwave conditions is projected to increase across Australia (very high confidence). The projected increases are greatest in northern parts of Australia.

Limitations and proposed future work

The heatwave and extreme temperature indices provided to the NCRA are based on dry-bulb temperature only; they do not account for the additional health impact when heatwaves coincide with high humidity, which decreases the ability of humans to lose heat by sweating and increases overall health impacts. The indices also assume a static temperature threshold for identifying heatwaves based on the distribution of temperature in the recent past (1985–2014). When considering health impacts, these thresholds may not be appropriate in a significantly warmer climate as they do not account for potential acclimatisation to heat.

There is ongoing work within the ACS heat hazard team to 1. extend the above analysis to include additional ACS and non-ACS RCMs, 2. develop wet-bulb temperature datasets (historical and future projections), and 3. investigate the suitability of heatwave definitions under a changing climate.

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5.1.2. Drought and changes in aridity

Contributors

David Hoffmann (Lead), Jess Bhardwaj, Tess Parker

Drought is a recurring natural phenomenon characterised by a prolonged period of abnormally dry conditions, where the amount of available water is insufficient to meet normal needs. Drought can have profound impacts on Australian communities and ecosystems with far-reaching consequences on agricultural, water management, economic and public health sectors (Van Dijk et al. 2013). For example, the 2017-2019 Tinderbox Drought left an indelible mark, with an estimated economic cost of $53 billion (Wittwer and Waschik 2021), positioning Australia as the fifth most drought-affected country globally (González Tánago et al. 2016). Beyond its immediate effects, drought acts as a catalyst for heatwaves and severe fire seasons (Ruthrof et al. 2016). The complex and multifaceted impacts of drought make it difficult to derive a universal definition that can be applied consistently for many purposes. Instead, drought is often categorised by impacts and propagation through the hydrological cycle and timescales beginning with meteorological drought (rainfall deficiency), agricultural drought (impacted vegetation/crop yields), hydrological drought (reduced streamflow/ groundwater storages) and ending with socio-economic drought (declining socio-economic wellbeing), (McKee et al. 1993; Wilhite and Glantz 1985).

While droughts are synoptically driven phase shifts in water availability, aridity is a more defining and sustained feature of a region's climate related to the long-term ratio between moisture availability and supply. Shifts in a region's aridity can be indicative of long-term declines in rainfall or increases in evaporative demand or both. Such shifts can have impacts on a region's water availability, soil quality, biodiversity, fire risk and agricultural efficiency (Greve et al. 2019).

Due to the far-reaching consequences of drought and the potential for changing aridity in certain parts of Australia, the ACS recognises these as priority hazards. A range of relevant indices and analyses were computed for Australia's first NCRA.

Indices

Standardised Precipitation Index (SPI)

The Standardised Precipitation Index (SPI) is a widely used index that measures the amount of precipitation over a specific period relative to the long-term average for that period. It is typically used to identify and quantify the severity of droughts making it a valuable index in water resource management, agriculture, and climate studies for its simplicity and effectiveness in drought monitoring (McKee et al. 1993). Strictly speaking the SPI is a meteorological drought measure.

The SPI uses a historical base period of rainfall to derive a probability distribution that observed rainfall can be fitted to and transformed into a normal distribution such that SPI values are denoted by z-scores that indicate the number of standard deviations rainfall is above or below a long-term median. This approach makes it possible to compare rainfall between different locations and time scales. Positive SPI values indicate wetter-than-average conditions, while negative values indicate drier-than-average conditions.

In delivering for the NCRA, the drought and aridity team analysed 3-month SPI (calculated on the basis of rainfall aggregated over rolling 3-month windows) by evaluating changes in the proportion of time spent below a commonly accepted drought threshold of SPI3 ≤ -1 for GWLs 1.5, 2.0 and 3.0 relative to GWL1.2. This metric was calculated using the ACS CMIP6 downscaled and AGCD-QME bias-adjusted suite of ensemble members.

Rainfall Percentiles

Rainfall percentiles indicate the value below which a certain percentage of observed rainfall amounts fall, based on a historical reference period. A z-score/SPI threshold of -1 corresponds to the point in a standard normal distribution where 15.87% of values fall below it. Thus, evaluating the 15th percentile threshold is an effective way to investigate threshold changes between GWLs. The 15th rainfall percentile was computed on 3-month timescales similar to SPI and is an absolute value index (mm). Shifts in this threshold highlight changes in the lower tail of the precipitation distribution and, combined with the percent time of SPI3 ≤ -1, provide insight into both threshold shifts and time spent below the threshold across different GWLs. This metric was calculated using the ACS CMIP6 downscaled and AGCD-QME bias-adjusted suite of ensemble members.

Aridity Index (AI)

The Aridity Index (AI) is a numerical indicator used to quantify the dryness of a region. The atmospheric equation of AI was used to calculate the ratio of annual precipitation to potential evapotranspiration (PET). Lower values of AI indicate more arid conditions, while higher values suggest more humid conditions. The AI is commonly used in climatology, agriculture, and environmental studies to classify climates, assess water availability, and manage land and water resources (UNEP 1992).

In delivering for the NCRA, the drought and aridity team analysed absolute changes in AI values as well as changes across categories (Hyper-Arid, Arid, Semi-Arid, Dry, Sub-Humid, Humid) for GWLs 1.5, 2.0 and 3.0 relative to GWL1.2. Since PET is not yet a bias-adjusted output from the ACS CMIP6 downscaled suite, this metric was calculated using the National Hydrological Projections (NHP1) CMIP5 downscaled and hydrological impact modelling outputs (Srikanthan et al. 2022).

The calculation, relevant scripting and ensemble members of these indices are summarised in Table 7. After deriving each index, the shared GWL function, developed for inter-hazard team use, is applied to slice indices to the relevant GWL for each driving model. Plotting and regional statistical analysis is also computed using shared functions described in section 2.6.

Table 7: Drought and aridity indices, calculation, relevant scripts and ensemble members.

Index with link to relevant scripting	Calculation	Ensemble members
Standardised Precipitation Index *3-month aggregation*	This approach utilises the gamma distribution as originally proposed by McKee et al., (1993), where additional methological details can also be found. • Historical rainfall from a base period of 1965-2014 is used to estimate gamma distribution fit parameters (using the maximum likelihood approach). • A cumulative gamma probability distribution is derived with a necessary extension for zero value observations. • Cumulative probabilities are converted to a z-score (SPI value) using inverse normal approximation.	ACS CMIP6 downscaled and AGCD-QME bias-adjusted outputs
15th percentile threshold *3-month aggregation*	• Relevant base period or GWL over which to derive 15th percentile is selected. • Rainfall is ranked and the amount which corresponds to 15% of observations falling below it in the rainfall period is calculated.	
Aridity Index *Atmospheric-based*	• Rainfall and PET is aggregated to annual totals. • Ratio of annual rainfall to PET is derived and 20-year averages calculated. • Repeated for different bias-adjusment methods in NHP1 CMIP5 suite.	NHP1 CMIP5 downscaled and hydrological impact modelling outputs

Due to the historical paucity of observations in central interior Australia, all our final outputs apply the standard AGCD quality mask which limits the contribution of spurious values to regional averages and as non-plausible spatial features. A list of further Frequently Asked Questions (FAQs) relevant to this analysis have been summarised in the FAQ section of the drought and aridity github.

Results

Spatial change plots, regional statistics and bespoke analyses were passed forward to the NCRA team, some of which are visualised below. Figure 16 and Figure 18 summarise spatial changes in SPI and AI outputs. Figure 17 summarises regional statistics for changes in SPI for GWL 3.0. The 10th and 90th ensemble members (second driest/wettest, marked by red/blue annotations) were used to provide plausible ranges of change beyond the median. Regions where more than 66% of all our ensemble members agree on the sign of the projected change are indicated in bold (Mastrandrea et al. 2011). Additionally, external users in the NCRA risk teams could scrutinise the regional summaries provided in this format to select regionally relevant ensemble members for storylining.

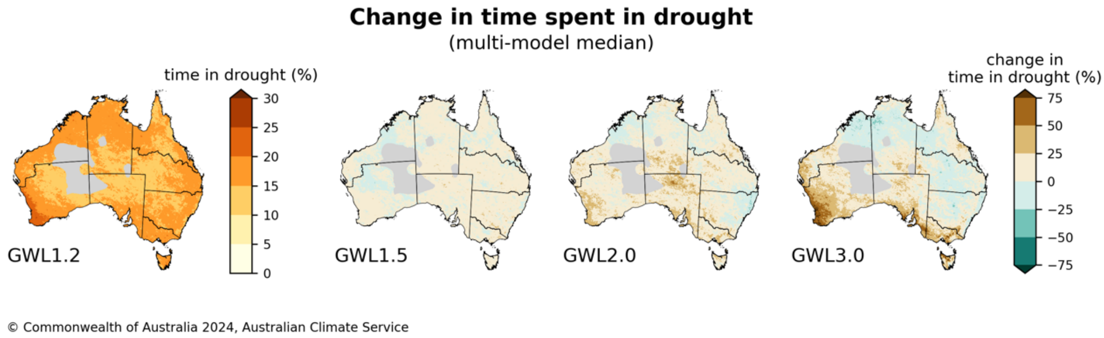
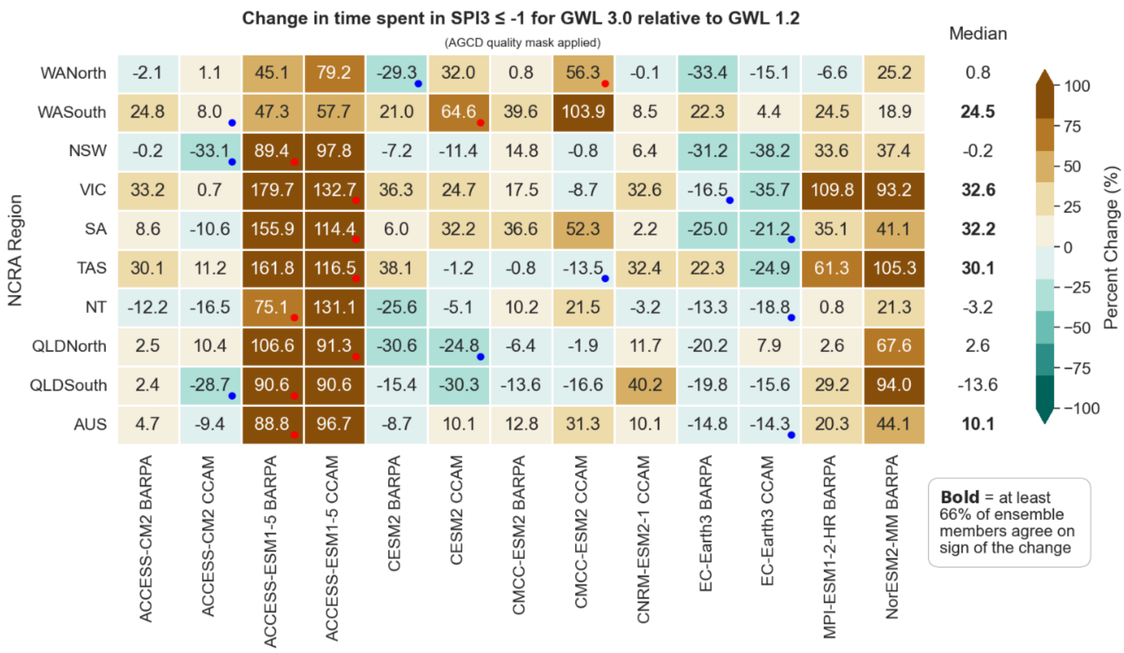


Figure 16: Change in time spent in drought relative to GWL 1.2, from left to right: the proportion of months below SPI -1 for GWL1.2 followed by relative percent changes in this time for GWL1.5, 2.0 and 3.0.



NCRA Region	ACCESS-CM2 BARPA	ACCESS-CM2 CCAM	ACCESS-ESM1-5 BARPA	ACCESS-ESM1-5 CCAM	CESM2 BARPA	CESM2 CCAM	CMCC-ESM2 BARPA	CMCC-ESM2 CCAM	CNRM-ESM2-1 CCAM	EC-Earth3 BARPA	EC-Earth3 CCAM	MPI-ESM1-2-HR BARPA	NorESM2-MM BARPA	Median
WANorth	-2.1	1.1	45.1	79.2	-29.3	32.0	0.8	56.3	-0.1	-33.4	-15.1	-6.6	25.2	0.8
WASouth	24.8	8.0	47.3	57.7	21.0	64.6	39.6	103.9	8.5	22.3	4.4	24.5	18.9	**24.5**
NSW	-0.2	-33.1	89.4	97.8	-7.2	-11.4	14.8	-0.8	6.4	-31.2	-38.2	33.6	37.4	-0.2
VIC	33.2	0.7	179.7	132.7	36.3	24.7	17.5	-8.7	32.6	-16.5	-35.7	109.8	93.2	**32.6**
SA	8.6	-10.6	155.9	114.4	6.0	32.2	36.6	52.3	2.2	-25.0	-21.2	35.1	41.1	**32.2**
TAS	30.1	11.2	161.8	116.5	38.1	-1.2	-0.8	-13.5	32.4	22.3	-24.9	61.3	105.3	**30.1**
NT	-12.2	-16.5	75.1	131.1	-25.6	-5.1	10.2	21.5	-3.2	-13.3	-18.8	0.8	21.3	-3.2
QLDNorth	2.5	10.4	106.6	91.3	-30.6	-24.8	-6.4	-1.9	11.7	-20.2	7.9	2.6	67.6	2.6
QLDSouth	2.4	-28.7	90.6	90.6	-15.4	-30.3	-13.6	-16.6	40.2	-19.8	-15.6	29.2	94.0	-13.6
AUS	4.7	-9.4	88.8	96.7	-8.7	10.1	12.8	31.3	10.1	-14.8	-14.3	20.3	44.1	**10.1**

Figure 17: Change in time spent in drought aggregated by region and by ensemble member. Blue/red dot annotations indicate the 10th and 90th percentile ensemble member for each region.

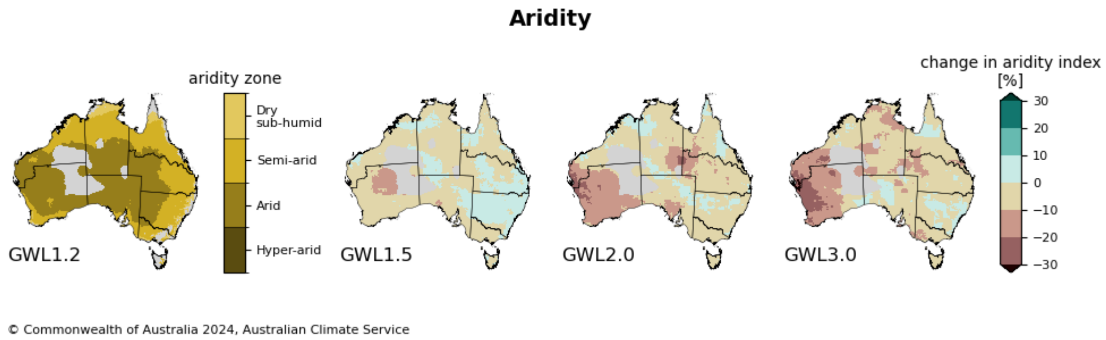


Figure 18: Change in Aridity Index relative to GWL 1.2, from left to right: the AI categories followed by relative percent changes in AI values for GWL1.5, 2.0 and 3.0.

Analysis from our indices and regional statistics were combined with other lines of evidence that analysed changes to drought in a warming world to provide summary statements (Kirono et al. 2020; Ukkola et al. 2020; IPCC 2023, 2021; Earth Systems and Climate Change Hub 2020; CSIRO and BoM 2015). Some of these key findings are detailed below.

Key findings

- Nationally, there is low to medium confidence in overall increased time spent in drought for GWL2.0 and 3.0 with considerable regional differences.
- There is moderate to high ensemble agreement in overall increased time spent in drought for southern parts of SA, VIC and south-west regions of WA South consistent with observed drying trends over recent decades.
- There is little ensemble agreement in the sign and magnitude of change in time spent in drought for regions of the tropical North and inland NSW.
- Aridity analysis indicates that an increased time spent in drought for south-west regions of WA South is likely to be accompanied by longer term shifts towards a more arid climate, which are more pronounced under GWL 2.0 and 3.0.

Limitations and proposed future work

The drought and aridity analysis conducted for NCRA focusses solely on meteorological drought and only on one metric which is the proportion of time below a threshold. Considering the multi-faceted impacts of drought, future indices for exploration are the Standardised Precipitation and Evapotranspiration Index (SPEI), Standardised Soil Moisture index (SSMI), Standardised Runoff Index (SRI), Evaporative Demand Drought index (EDDI) and the Evaporative Stress Index (ESI). The analysis of these indices can further be expanded upon by considering metrics beyond proportion of time alone, such as shifts in intensity, frequency and duration.

The drought and aridity team is also interested in investigating flash drought. While prolonged droughts garner attention, flash droughts, rapidly intensifying dry spells, also pose significant challenges. Under conducive synoptic conditions, agricultural regions can transition from average conditions to severe drought within weeks (Parker et al. 2021). These abrupt shifts combined with a warming climate demand adaptive strategies to mitigate their impact on crops, livestock, and water availability. Future analysis of flash drought will involve investigating the variability of evapotranspiration through a first-order second moment decomposition of four major driving variables as per the approach of Hobbins et al., (2012) and Hobbins (2016).

Additionally, given the cascading nature of drought, there is also significant scope for inter-hazard team collaboration, investigating the interplay of heat, fire and drought-breaking rainfall in historical and future droughts in Australia.

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5.1.3. Bushfire

Contributors

Naomi Benger (Lead), Aurel Griesser, Alex Evans, Richard Matear

The priority hazard of bushfire, grassfire and air pollution is referred to as *bushfire* for brevity. There are currently no projections of fire related air pollution for Australia.

Past bushfire risk assessments and climate hazard summaries, such as those provided in (CSIRO and BoM, 2015; Lawrence, et al., 2022), have focussed mainly on the fire weather aspect of bushfire risk, generally measured using the Forest Fire Danger Index (FFDI) for Australia (BoM, CSIRO, Dept Ag, Water, and Environment, 2021; BoM, CSIRO, AEMO, 2021a). While these assessments clearly state that FFDI is only a partial indicator of risk, it was recognised that this approach alone would not suffice for the NCRA.

For a holistic bushfire hazard assessment, we consider the four necessary elements: sufficient biomass, its availability to burn, fire weather, and ignition, as defined in (Bradstock, 2010). The *fire climate classes* (FCCs), developed for the NCRA (Benger, Griesser, & Evans, A class-y approach to assessing future bushfire risk, 2024), provide a framework to assess the changing bushfire risk incorporating all elements for the first time at this scale. The boundaries of the FCCs are defined using temperature and rainfall which are available from climate models, allowing us to look at the potential future vegetation distribution. Climate and ecology research results characterise the FCCs and describe influences on fire risk.

Using FFDI in isolation has been highlighted as an issue from an ecological perspective (Clarke, et al., 2020), and from fire behaviour and process perspective (Jones & Ricketts, 2024; Peace & McCaw, 2024; Tory, Cruz, Matthews, Kilinc, & McCaw, 2024). Other contributors to bushfire, such as drought and heat, are commonly examined in climate change attribution studies for significant bushfires in Australia and internationally (Kirchmeier-Young, P., Zwiers, Cannon, & S., 2019; van Oldenborgh, et al., 2021) but have until now not been incorporated into bushfire risk assessments.

The approach of using FCCs was developed based on consultation with experts from fire science, ecology, forestry, fire agencies, and climate experts. Given the constraints for delivery and the strong support for a more holistic view of bushfire risk, this was considered a practical and acceptable solution with significant development potential (Benger, Griesser & Evans 2024). Both the FCC design and analysis methodology were informed through expert engagement and feedback, detailed in (Benger, Griesser & Evans 2024) and (Benger et al 2025) respectively.

Application of FCCs for bushfire risk assessment

The FCCs provide an interpretive framework to perform a qualitative hazard assessment (with aspirations to develop indices for quantitative risk assessments). The assessment examines both the projected shifts in FCC boundaries, as shown in Figure 19, and projected changes to the drivers which increase the risk of extreme fires, listed for each of the FCCs in Table 8.

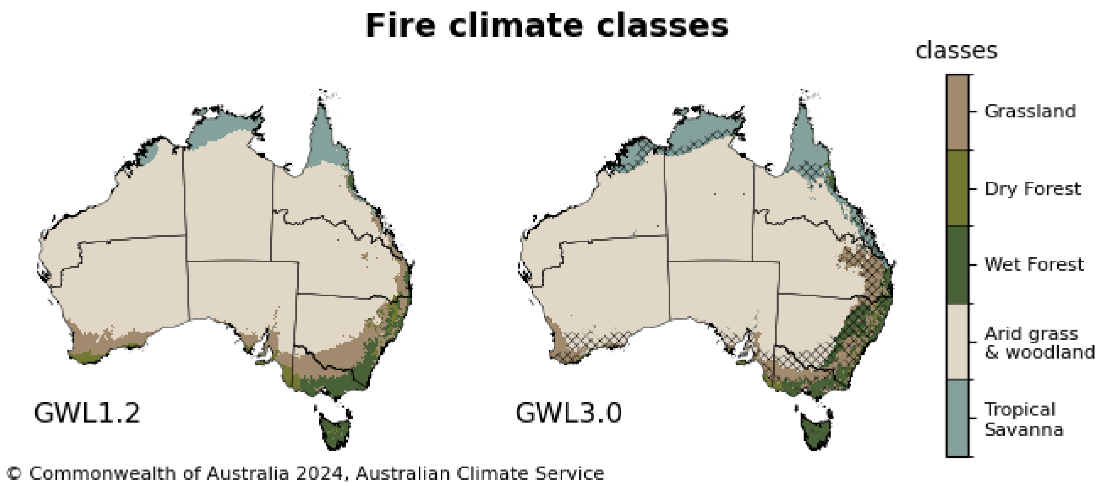

Figure 19: FCCs using MRNBC for GWL1.2 (L) and GWL3.0 (R) with hashing where GWL3.0 differs to GWL1.2.

Details for computing the FCC boundaries shown in Figure 19 are available in Benger (2024).

Table 8: FCC drivers of extreme fires.

Fire climate class	Drivers of extreme fire
Tropical savanna	• Increased rainfall
Arid grass and woodlands	
Grassland	• Increased rainfall followed by drought
Wet forest	Increases to: • fire weather • heatwave • drought
Dry forest	

FCCs hazard assessment summary

The full assessment is available in Benger et al 2024 and Benger et al 2025 with specific regional risk statements, confidence ratings, and references.

Here we will provide a summary of:

- The intermediate assessment based on class shifts (Table 9), drawing on the shifts shown in Figure 19.
- The intermediate assessment based on changes to drivers (Table 10), using the assessments on changes to heatwaves (discussed in Section 5.1.1), drought (discussed in Section 5.1.2), and fire weather (Section 5.1.3)
- Combined overall assessment (Table 11).

Assessment based on class shifts

All evidence for these assessments and confidence levels is provided in Benger et al 2025. The shifts shown in Figure 19 specific to the choice of GCM, other model selections may result in variations to the regions. The table below summarises the shifts by region, and the implications on the risk of extreme fire.

Table 9: Summary of the changes to extreme fire risk based on fire climate class shifts.

Region	Shift	Change	Confidence
South and east	Contraction of regions which promote forest growth, shift to grassland (forest die off possible).	↑ then ↓ (increased fuel availability then overall reduction in biomass)	High
East (but west of the Great Dividing Range)	Expansion of regions which promote forest growth (forest may encroach on grass areas).	↑ (increased biomass)	Moderate
Northern Australia	-	-	High confidence in relationship between rainfall and fire, low confidence in rainfall projections (future FCC boundaries).

Assessment based on driver shifts

For FCCs in the northern parts of Australia, rainfall is the main driver of increases to fire intensity (through the responsive enhanced vegetation growth). Rainfall projections are highly variable, particularly monsoonal regions, and previous research has found that it is likely that interannual and interdecadal variability will continue to play a significant role in fuel loads in future (Beringer, Hutley, Tapper, & Cernusak, 2007; Liedloff & Cook, Modelling the effects of rainfall variability and fire on tree populations in an Australian tropical savanna with the Flames simulation model, 2007; Liedloff & Cook, The interaction of fire and rainfall variability on tree structure and carbon fluxes in savannas: Application of the FLAMES model., 2011). While it is not possible to make an assessment about rainfall changes with any confidence, the relationship between rainfall and vegetation is very well understood, so conditional information can be provided for potential changes to rainfall.

For the forested regions of the south and east, changes to the behaviour of heatwaves, drought, and fire weather will influence the risk of extreme fires. Changes to heatwaves and drought have been discussed in Sections 5.1.1 and 5.1.2 respectively. The number of days in heatwave is projected to increase over all forested areas. The number of days in drought is projected to increase over southern regions, but a mixture of increase and decrease in the east as some regions are projected to have increased rainfall (generally to the west of the Great Dividing Ranges).

Key findings

Multiple contributing factors will change the risk of extreme fires across Australia.

Forest regions will likely see an acute increase in extreme fire risk (more acute than estimated by fire weather alone). Ecosystem prosperity will be hampered by climate change; warmer and dryer conditions for southern Australia will result in a reduction in forest coverage and long-term reduction in fire intensity in some currently forested areas.

In monsoonal and arid regions, rainfall is associated with vegetation growth and precedes extreme fire activity. Better understanding of changes to rainfall patterns is needed to better understand future fire in these regions.

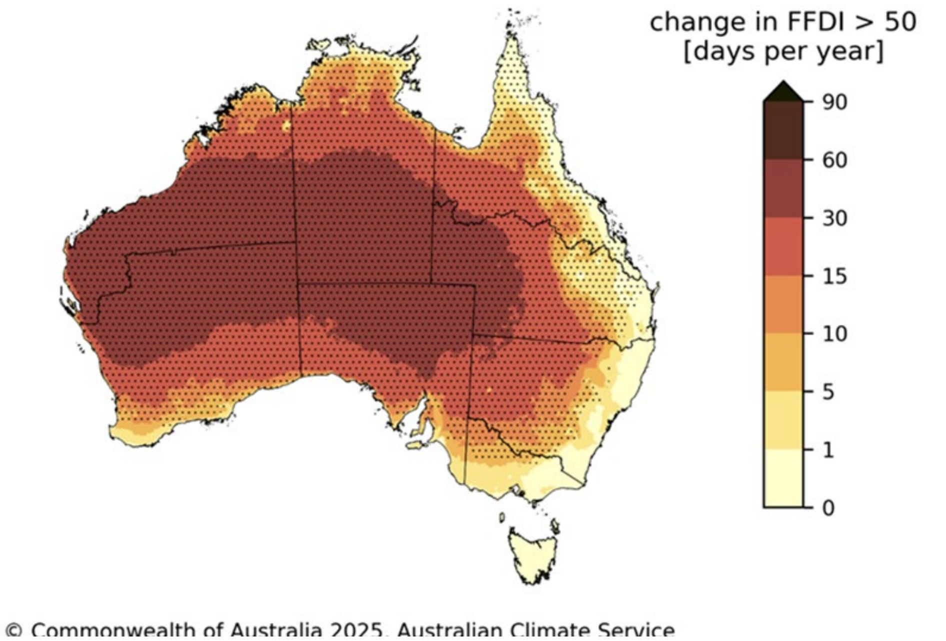

Figure 20: Difference in median number of days of FFDI > 50 from GWL1.2 to GWL3.0.

The frequency and severity of dangerous fire weather conditions (assessed using FFDI) is increasing in forest areas, especially during spring and summer; this is at least partly attributed to climate change (Abram, et al., 2021; Dowdy & Pepler, 2018; Harris & Lucas, 2019).

There is high confidence that future fire weather in southern and eastern Australia will be more extreme (Lawrence, et al., 2022). These results are supported by our analyses, Figure 20 shows that the number of days of severe fire weather (given by FFDI > 50) increase nationally from GWL1.2 to GWL3.0.

The analysis done by van Oldenborgh, et al. (Attribution of the Australian bushfire risk to anthropogenic climate change, 2021) showed that at GWL2.0 the fire weather index observed during Black Summer becomes around 4 times more likely than in the pre-industrial climate.

In Table 10 a summary of the changes to drivers of extreme fire weather for each FCC is provided.

Table 10: Summary of changes to drivers of extreme fire for each of the fire climate classes.

Class	Driver	Change
Tropical savanna	Rainfall (monsoonal)	↑* interannual and interdecadal variation still plays a dominant role, high uncertainty in rainfall projections.
Arid grasses and woodlands	Rainfall (sporadic)	More evidence needed: regionally specific rainfall drivers need to be investigated.
Grassland	Biomass productivity/fuel load	More evidence needed: regionally specific rainfall drivers need to be investigated. Increased drought in the south may decrease productivity. But increasing incidence of high rainfall preceding drought may increase risk of fire.
Wet and Dry Forest	Extreme fire weather	↑
	Heatwave	↑
	Drought	↑ in south mixed in east (areas of ↑ and ↓)

Holistic assessment

Combining the results of the intermediate assessments on FCC shifts and changes to drivers of extreme fire behaviour, our national overview of changes to risk of extreme fire across Australia is provided in Table 11.

Table 11: Regional overview of changes risk of extreme fire.

Region	Change in risk of extreme fire	Confidence
South and east	↑↑ **then** ↓ (A period of increased availability, coupled with increased number of days in heatwave and/or drought leads to increased risk of megafires, followed by a shift in vegetation which results in a reduction in biomass, decreasing fire susceptibility)	**High**
East (but west/inland of the Great Dividing Range)	↑↑ (Increased biomass, increased number of days in heatwave. Mixed signals about changes to drought)	**Moderate**
Northern Australia	**-*** interannual and interdecadal variation still plays a dominant role (knowledge gap in future monsoonal behaviour)	**Low**

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5.2. Wild extremes

5.2.1. Extratropical cyclones

Contributors

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Indices

Low-pressure systems are regions where atmospheric pressure is lower than the surrounds, usually occurring with one or more closed contours of pressure. They are generally detected using automated methods, applied to gridded mean sea-level pressure or geopotential height data. For the purposes of this report the University of Melbourne[1] tracking method (Murray and Simmonds 1991; Simmonds et al. 1999) was used, which has been widely applied in Australia. The results are qualitatively similar to other approaches in the scientific literature, but the magnitude of the projected changes may differ.

In contrast to tropical cyclones, there is no well-established set of criteria for identifying low-pressure systems with significant impacts. Some criteria, and the measures used for this report, are shown in Table 12.

Table 12: Criteria used for identifying lows.

Criteria	Used for this report	Explanation
Intensity	Laplacian >= 0.6 hPa/deg.lat^2, averaged within a 2° radius	The intensity of the low can be defined based on the central pressure, the pressure gradients, or measures of vorticity (such as the Laplacian of pressure). Stricter criteria identify lows with stronger circulation and more intense winds but are less tightly linked to rainfall.

[1] https://cyclonetracker.earthsci.unimelb.edu.au/

		This is a *weak* criterion compared to many other studies, so may identify larger numbers of lows including less impactful systems.
Duration	>=6 hours (2 time steps)	Longer-lasting lows that travel a longer distance can produce larger impacts, and durations >=48 hours are common for Northern Hemisphere studies and regions in the extratropical storm track. Gridded data may spontaneously generate lows at individual time steps due to spatial variability, particularly at high resolutions. In Australia, short-lived lows have been known to develop close to the coast and cause notable impacts, so a short duration threshold is chosen.
Vertical extent	Corresponding low detected at 500 hPa within 500 km at least once	Many studies identify lows at a single atmospheric level, such as the surface or 500 hPa (cut off lows). However, deep lows which extend vertically into the troposphere, such as those associated with a cut-off low, produce heavier rainfall, while lows identified only at the surface over land areas are often heat lows with little impact. This dataset focusses on lows that extend from the surface to 500 hPa (~5 km).
Thermal structure	Not used	Lows can be categorised as having a warm core (e.g. tropical cyclones), a cold core (e.g. extratropical cyclones), or a hybrid core (e.g. many east coast lows). These have different characteristics and may have different future changes. No such criteria is applied here, so the dataset includes tropical lows and depressions in addition to extratropical lows.
Radius of influence		A low-pressure system is considered to influence the region within a 5 degree radius of the low centre, which is approximately the average extent of the outer closed contour. However, the extent of the rain associated with lows is often significantly larger than this, at closer to 10 degrees.

Data sources

Data for extratropical lows is provided using the 13-member ACS regional climate model (RCM) ensemble using SSP3-7.0. Tracking is performed on the raw MSLP and 500 hPa geopotential height data, after regridding to a common polar stereographic grid with an equivalent resolution of ~1.5° at 30°S. This regridding is important to reduce the detection of anomalous small-scale lows, which can lead to large uncertainties in high-resolution datasets (Di Luca et al. 2015).

Limitations

Biases

Global climate models underestimate the frequency of low-pressure systems in the Australian region, particularly at upper levels. While this is partially improved by regional downscaling (Pepler and Dowdy 2022), the datasets continue to underestimate the frequency of lows in the cool season, particularly in southern Australia where the median frequency in the ACS ensemble is 29% lower than in BARRA-R2. At the same time the ACS RCMs overestimate the frequency of warm-season lows in northern Australia. For these reasons, we do not report changes for Australia as a whole, to avoid trends being biased by changes in tropical lows. Instead, we focus on southern Australia (south of 28°S), where extratropical lows are an important source of cool-season rainfall and the projected trends are more consistent.

Other limitations

- Interannual variability in the frequency of low-pressure systems is large and may override anthropogenic changes for some periods, particularly for smaller regions and at lower Global Warming Levels
- Events with larger impacts occur less frequently, are likely to be less well-simulated and may have different changes to those shown here. Notably, changes to rainfall intensity and sea levels may increase the impacts from severe systems.
- Regional means are calculated for each ensemble member from the gridded percentage change. This can give slightly different relative changes to those obtained if the regional mean was calculated for each GWL first.
- GWL1.2 represents the "current climate" of ~2011-2030 – this already represents a decrease in cool season frequency relative to a pre-industrial climate.
- Ensemble medians are provided as "one member – one vote", and some GCMs are therefore included more times than others depending on the number of ways each has been regionally downscaled.
- There is likely to be an increase in shallow (heat) lows over southern Australia during the warm season, which is not captured in this analysis, due to the requirement for lows to be deep.
- The impacts of more distant extratropical storms whose centres are not on the continent are not included here. These lows can create severe impacts by extending strong winds across broad reaches of the continent. The impacts of

these remote lows can also be felt through extended frontal systems and features embedded in the fronts. These impacts are not considered here.

Outputs

- Annual mean frequency of lows (low_freq), shown as the percentage of time with a low centre within a 5-degree radius (Table 13).
- Percent change in frequency relative to GWL1.2 (Figure 21).

Proposed future indices

- Additional detail on impactful lows, e.g. based on strength or movement.
- Data for changes in fronts.

Current maturity

- Current maturity for frequency of lows: Medium.

Use for risk assessments:

- Nationally consistent analysis for Climate Hazard Overview (CHO): frequency of lows (low_freq), restricted to regions south of 28°S

Key findings

Based on multiple lines of evidence, there is **medium confidence** that the frequency of lows will decrease in a warmer climate. This confidence level is given because the number of Australian studies is relatively small and models may not fully represent the underlying processes, leading to uncertainty. However, there is strong model agreement on the sign of the change in frequency of lows (Pepler et al. 2025, Priestley & Catto 2022), which is supported by data on historical trends (Pepler 2024). All regional models project a decrease in the frequency of extratropical lows in southern Australia between GWL1.2 and GWL3, with an ACS ensemble median change of -10% and potentially larger decreases from other RCMs.

There is **low confidence** for changes in the frequency of the most intense lows. Impacts of extratropical lows may increase despite declines in frequency, linked to both increases in rainfall intensity and rising mean sea levels (medium confidence) (Pepler & Dowdy, 2022)

Table 13: Proportion of hours influenced by a low in southern Australia (south of 28 S) for GWL 1.2 and changes for GWL 1.5, GWL 2.0 and GWL 3.0 relative to GWL 1.2.

	Current	**Future Change relative to current**		
Metric	**GWL 1.2**	**GWL 1.5**	**GWL 2.0**	**GWL 3.0**
Proportion of hours influenced by a low in southern Australia (South of 28°S)	**1.0%** [0.8% to 1.2%]	**No detectable change** *Low confidence*	**-10%** [-19% to +8%] *Medium confidence*	**-10%** [-25% to -3%] *Medium confidence*

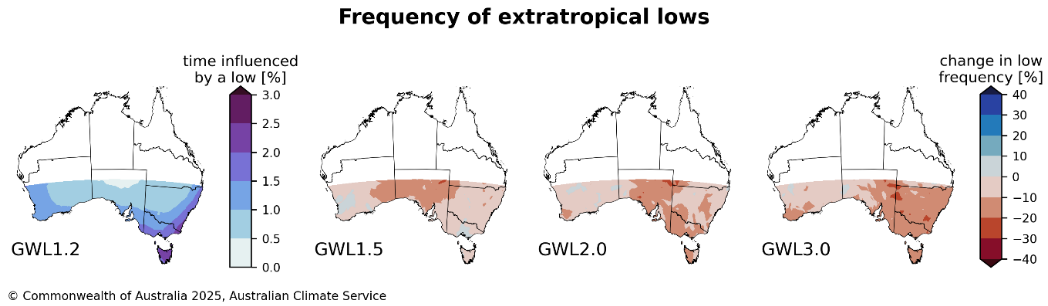

Figure 21: The median (50th percentile) percentage change in extratropical low frequency for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2). Declining trends are visible across much of Australia, particularly in the southeast and at higher global warming levels

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5.2.2. Tropical cyclones

Contributors

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Hazard definition and impacts

Tropical cyclones are intense, low-pressure systems that form over warm tropical oceans and generate gale-force or stronger winds, heavy rainfall and coastal storm surges. The severity of a tropical cyclone is ranked in categories from 1 (with sustained winds above 63 km/h) to 5 (sustained winds above 200 km/h).

Tropical cyclone impacts include loss of life, threats to human health, destruction of property and critical infrastructure such as energy and communication networks, roads and seaports, and substantial damage to the natural environment including polluting waterways and soils, eroding coastlines and threatening ecosystems.

Compound tropical cyclone hazards, such as combined wind and heavy rainfall, can exacerbate impacts. While the most extreme winds tend to be confined to coastal zones, creating very large waves and storm surges, prolonged heavy rain and flooding can impact communities well inland from where landfall occurs. Antecedent wet soils on land can further compound impacts, resulting in major flooding. Cascading impacts include heatwaves and high humidity after an event, which can increase mortality in the event of power loss. If tropical cyclones move southwards in Australia, they will increasingly impact areas where the natural environment and human infrastructure has limited capacity to withstand tropical cyclone conditions.

Key findings

Tropical cyclones are among the costliest natural hazards affecting Australia over the past 60 years and are estimated to be the costliest natural hazard globally (Munich Re, 2025). Coastal and offshore regions of northern Australia are most at risk, but central west Western Australia and southeast Queensland are also at moderate risk.

Overall tropical cyclone frequency has been observed to have decreased in the Australian region by approximately 10% over the past 40 years. A further decrease in frequency is generally projected (medium confidence) although there remains uncertainty around the magnitude (and in some places, the sign) of changes (Table 14). There has been a detected increase in the fraction of high-intensity TCs observed since 1979, both globally and for ocean basins around Australia.

Projections from published studies indicate that globally a greater proportion of tropical cyclones will be of high intensity, with greater rainfall associated with them, and higher storm surges due to rising sea levels (high confidence). There is currently uncertainty as to the extent to which the global projections for intensity and rainfall apply to the Australian region, this being an important gap with work currently underway in ACS, NESP and Australian universities.

There is low confidence in projections of other aspects of TCs, such as poleward movement and changes in absolute number of very intense TCs (as opposed to proportion). Year-to-year variation in number and intensity of tropical cyclones affecting Australia is large and is projected to remain so. There is large uncertainty in projection of TC behaviour because of the relatively poor representation of tropical cyclones in global climate models due to coarse model resolution, and the variation in number of cyclones simulated in different climate models.

Table 14: The change in tropical cyclone parameters for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2) is shown in bold, along with an indication of confidence. The 10th to 90th percentile range is shown in square brackets.

	Current	Future change relative to current		
Metric	**+1.2 °C**	**+1.5 °C**	**+2 °C**	**+3 °C**
Tropical cyclone frequency (all categories)	**10 per year average**	**little change or small decrease** *medium confidence*	**decrease** *medium confidence*	**decrease** *medium confidence*
Tropical cyclone frequency (category 4-5)	**2-3 per year average**	**little change or small increase** *low – medium confidence*	**little change or increase** *low – medium confidence*	**little change or increase** *low – medium confidence*

Past and future hazard changes

Australia currently experiences around 10 tropical cyclones in the Australian region each year, with about four of these crossing the coast. There is large interannual variation in the frequency of TCs, primarily driven by El Niño and La Niña.

For Australia, the frequency of observed tropical cyclones has decreased by around 10% since 1982 (based on IBTrACS from Knapp et al 2010). The trend in TC intensity in the Australian region is harder to quantify compared to frequency, because of uncertainties in estimating the intensity of individual TCs and the relatively small number of intense TCs. This problem is compounded by changing data availability.

The frequency of TCs in the Australian region is projected to further decrease in the future (medium confidence). Figure 22 shows projected decrease in the average annual number of TCs by late 21st century (approximately GWL3) over the southwestern Pacific and southern Indian Ocean (Rafter et al 2019). There remains uncertainty around the magnitude (and in some places, the sign) of changes in frequency. The year-to-year variation in the number and intensity of TCs is projected to remain large.

Projections from published studies indicate that globally a greater proportion of TCs will be of high intensity, with greater rainfall associated with them, and higher storm surges due to rising sea levels (high confidence) (Knutson et al 2020). There is currently uncertainty as to the extent to which the global projections for intensity and rainfall apply to the Australian region, this being an important gap with work currently underway in ACS, NESP and Australian universities.

There is low confidence in projections of other aspects of TCs, such as poleward movement, speed of translation, and changes in the absolute number of very intense TCs (as opposed to proportion). The low confidence in the understanding of potential poleward expansion of the TC risk zones represents another significant gap for Australia, because building codes are at lower standard for moderate risk areas (e.g., southeastern Queensland). Hence buildings are more vulnerable in those regions so under greater risk of impact if the southward range of TCs increases significantly.

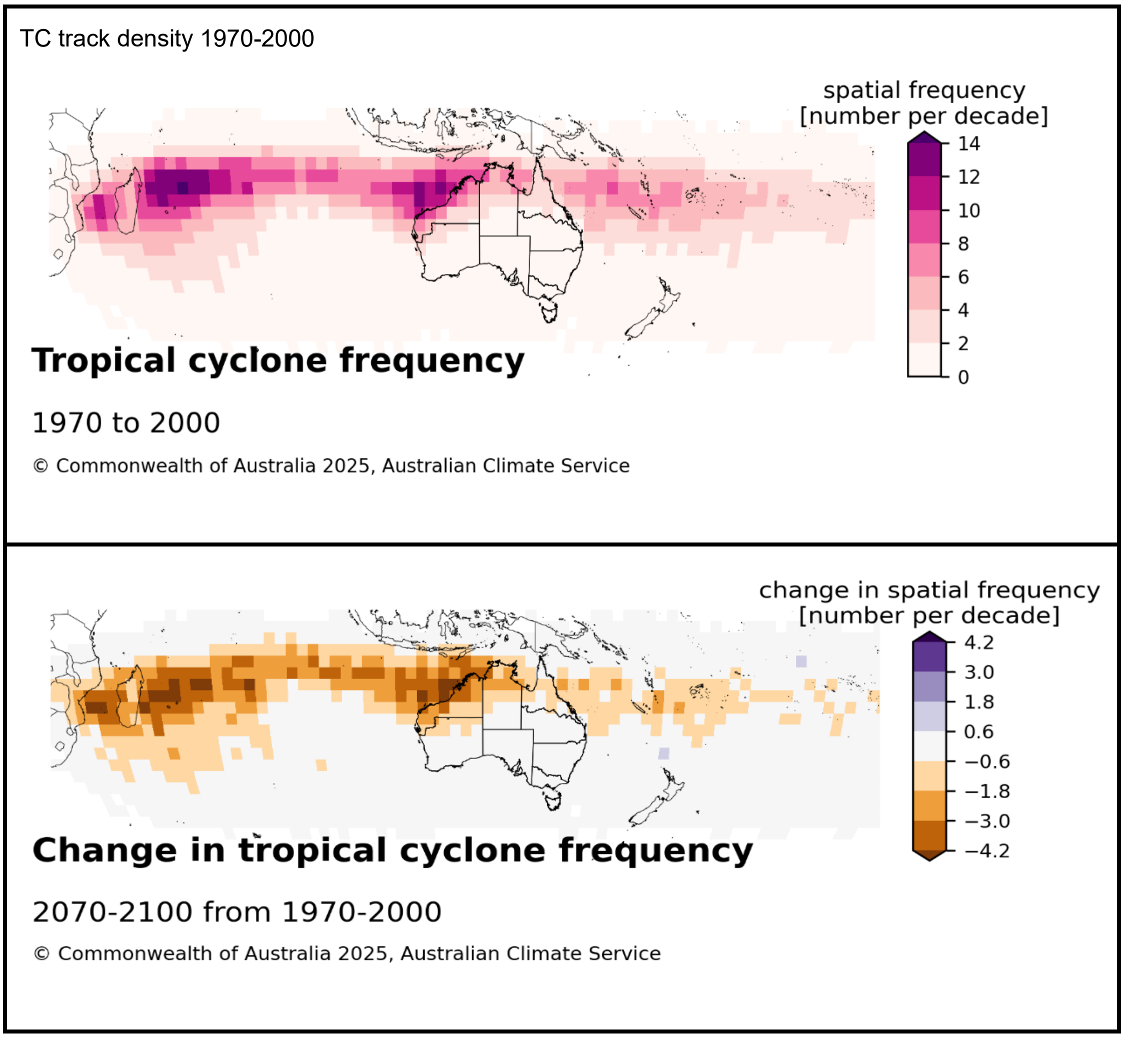

Figure 22: Spatial frequency of tropical cyclones (TCs) simulated by 9 climate models for the period 1970-2000 (upper panel) and the projected change to 2070-2100 for a high emissions scenario (approx. GWL3.0) (lower panel). Based on data from Rafter et al (2019).

Gaps in the current knowledge and next steps

The relatively low confidence in projection of key aspects of tropical behaviour regionally is a result of several factors, including:

- The most intense winds of tropical cyclones are confined to a relatively small region surrounding the centre, which is typically much smaller in size than climate model resolution, meaning estimations of tropical cyclone occurrence and strength are made from large scale conditions. Substantial variations in the number of cyclones simulated in different climate models and using different estimation techniques, and typically peak wind speeds are underestimated
- Uncertainty caused by the dependence of tropical cyclone frequency on sea surface temperature patterns (i.e., projected changes in El Niño-Southern Oscillation and the state of the Pacific Ocean by climate models which currently have significant uncertainties).
- Discrepancies in the projected trends of large-scale tropical cyclone formation indices (which mostly increase with warming) and the explicit number of detected tropical cyclones in climate models (which mostly decrease with warming).

Impact studies need projections of recurrence rates for a range of intensities, rainfall totals and storm surge for particular regions. Such quantitative projections require thousands of tropical cyclone cases to define recurrence rates of the rare extreme events of highest impact, which cannot be done by direct climate model simulation due to the computational expense.

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5.2.3. Convective storms including hail

Contributors

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Convective hazards like thunderstorms are not directly simulated in our climate and weather models. Instead, we use large scale indicators including Convective Available Potential Energy (CAPE) and Convective Inhibition (CIN) as measures of the environmental conditions that encourage or inhibit the formation of thunderstorms. CAPE measures the integral of the upward buoyancy on an air parcel rising through the atmosphere. A larger value of CAPE suggests that thunderstorms are more likely to form. CIN is a measure of the potential energy that would prevent an air parcel from rising. A more negative value of CIN would inhibit the formation of thunderstorms. In situations where both CAPE and CIN have a large magnitude, then we may expect more severe thunderstorms if thunderstorms develop.

The climatology of CAPE and CIN is calculated from Bureau's Atmospheric high-resolution Regional Reanalysis for Australia version 2 (BARRA2) at 12 km resolution, developed by the Bureau of Meteorology (Su et al. 2022). Following the method of Chen et al. 2020, we have calculated the climatology of CAPE and CIN by averaging hourly values but ignoring values of zero CAPE or CIN. The climatology is calculated from 1995–2014. Projections for convective storms using these and other convective indices were not produced for the NCRA, but will be produced for future assessments (see Next Steps).

Key findings

Changes in hail events remain intractable. While hail is expected to be affected by climate change there is high uncertainty on how changes will manifest and geographical differences in observed and modelled trends (Table 15). An overall reduction in hail frequency is likely but with an increase in large hail occurrence.

Next steps

To assess the changes in risks from Convective storms, we need to understand changes in frequency and intensity of these events. Conducive environments for convective storms can be characterised by high moisture, steep lapse rate and some lifting mechanism. This implies that changes in frequency and intensity might be affected in different ways for different storm types. An initial next step is establishing a comprehensive list of storm relevant indices (currently underway) to support a multiple lines of evidence approach to past change and future projections.

Changes in impacts will come about through changes in damaging winds, rain, hail and flash flooding associated with these events. From a risk perspective, convective storms could therefore be considered compound events which means this work should be linked into studies of synoptic drivers for other climate hazards, including heat, drought and fire.

Existing thunderstorm observational datasets are largely insufficient due to their limited length (typically less than 30 years), low spatial density of observing networks (e.g. lightning and severe storm archive) and not all relevant variables are observed. The best source currently are radar data which does not exist nationally. Suitable datasets and opportunities to improve them (e.g. homogenise/extend) should be identified (e.g. extending existing lightning datasets).

Changes in frequency and intensity of convective events may require different indices. Consideration needs to be given to how well indices link to relevant processes (especially processes we expect to change under climate change). The objective choice of indices needs to be guided by observations and model data (including reanalysis) as it is possible that model data do not fully resolve all relevant physical processes.

Given that many aspects of changes in convective storms are currently intractable, a meta study of existing literature could result in practical guidelines and recommendations based on the current state of science.

Table 15: The change in median annual frequency of large hailstorms (hail> 2.5 cm) for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2) is shown in bold, along with an indication of confidence.

	Current	Future change relative to current		
	+1.2 °C	+1.5 °C	+2.0 °C	+3.0 °C
Annual frequency of large hailstorms (hail> 2.5 cm)	~ **5-10** events in eastern regions and ~ **0-5** hail events elsewhere	insufficient data	**little change**, but potential increase in east and spread further south *low confidence*	insufficient data

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5.3. Wet extremes

5.3.1. Extreme rainfall

Contributors

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Indices

The extratropical storm team currently provides projections for three indices of extreme rain:

- Highest annual 24-hour total (RX1D) - this is the highest daily rainfall falling at each grid point in a year,
- Highest annual 5-day total (RX5D) - this is the highest five-day rainfall total falling at each grid point in a year, and
- Highest annual hourly total (RX1H) - this is the highest rainfall falling over one hour at each grid point in a year.

RX1D and RX5D are very widely used indices, which were defined as part of the key indices by the World Climate Research Program's Expert Team on Climate Change Detection and Indices[2]. They are commonly used when assessing future intensification of extreme rainfall, for example as part of the IPCC reports and the Interactive Atlas[3]. They are also the key datasets needed to generate and understand extreme value distributions for calculating the intensity of rarer events such as rainfall with a 10% Average Exceedance Probability (AEP). They can be calculated from any dataset using standard tools such as *cdo*, as documented in the hazard team github[4].
While the ETCCDI indices were designed for application to daily data, RX1H can be calculated by applying the same methods to hourly rainfall. Very heavy short-duration rainfall is important for understanding future changes in flash flooding, particularly in urban areas. Hourly rainfall is linked to convection and thunderstorm activity, which can be poorly simulated even at the spatial scales of regional climate models, but observational evidence indicates that hourly rainfall is intensifying at a higher rate than for daily rainfall extremes (Wasko et al. 2024).

Data sources

Data for these extreme rainfall indices is provided using the 13 member ACS regional climate model (RCM) ensemble using SSP3-7.0, which has been downscaled and bias adjusted to the 5 km AGCD grid using the Quantile Matching for Extremes approach. This corrects for a tendency of the raw RCM data to overestimate heavy rain but has created data gaps in inland regions where observations are sparse and which need to

[2] https://www.wcrp-climate.org/etccdi

[3] https://interactive-atlas.ipcc.ch

[4] https://github.com/AusClimateService/NCRA_ExtratropicalHazardTeam

be masked before calculating regional means. The projected change in the raw and bias adjusted datasets are very similar.

Hourly rainfall is not bias adjusted due to a lack of sub-daily observational data. However, a partially bias adjusted dataset was created by multiplying the bias adjusted daily rainfall with the proportion of rainfall that fell during the wettest hour of the day in the raw RCM output. This method assumes that RCMs can replicate the temporal distribution of rainfall but may underestimate the intensity of very high hourly rainfall given the poor simulation of thunderstorms.

Confidence is assessed based on both model agreement and other lines of evidence, including other regionally downscaled models and the scientific literature, particularly the recent review paper of Wasko et al. (2024) in support of the updated Australian Rainfall and Runoff Guidelines.

Limitations

- These indices represent how extreme rainfall is at a given location, but do not directly translate into flood risk, which is influenced by a range of factors including:
  - whether the soils are wet or dry and river levels are high or low: wetter soils increase flood risk;
  - whether rainfall is widespread or localised: this influences how much of a catchment received rainfall, and the total water volume in a river; and
  - the period over which the rain fell: a daily total of 25 mm could fall in a single hour or be spread over 24 hours, with very different flash flood potential.
- Interannual variability in extreme rainfall is large and may override anthropogenic changes for some periods, particularly for smaller regions and at lower Global Warming Levels (medium confidence).
- Many of the key weather systems that generate heavy rainfall are poorly simulated by models, particularly thunderstorms, but biases also exist for both tropical and extratropical lows. This means there may be key processes missing that would affect projected changes. This is particularly important for RX1H.
- Rare events, such as those that occur once per decade or less frequently, have larger impacts and are expected to have stronger increases in intensity, but data for these are not currently presented.

Considerations for appropriate use of downscaled climate projections

- Regional means are calculated for each ensemble member from the gridded percentage change. This can give slightly different relative changes to those obtained if the regional mean was calculated for each GWL first.
- GWL1.2 represents the "current climate" of ~2011-2030 – already a significant increase in both temperature and rainfall hazards relative to both a pre-industrial climate, or the ~1961-1990 period used for defining current flood risk.

- Ensemble medians are provided as "one member – one vote", so some GCMs are included more times than others depending on the number of ways each has been regionally downscaled.

Outputs

- Annual mean RX1D, RX5D and RX1H for each GWL.
- Percent change in each index relative to GWL1.2.

Proposed future indices

- Days above specified thresholds, if thresholds are identified by users through co-design
- Rarer events using Generalised Extreme Value analysis, e.g. rainfall extremes with an Annual Exceedance Probability of 10%, 5% or 1%

Current maturity

- Current maturity: Medium for daily indices, low for RX1H due to lower confidence in regional model capacity to simulate sub-daily processes e.g. thunderstorms.

Use for risk assessments:

- Nationally consistent analysis for CHO: RX1D, RX5D, RX1H

Key findings

For the highest annual 24-hour rainfall total (RX1D) and the highest annual 5-day total (RX5D), data is extracted from the 13-member bias-adjusted ACS model ensemble (Table 16). There is an Australian mean change in RX1D of +12% between GWL1.2 and GWL3, close to the thermodynamic expectation of a ~7% increase per degree of global warming, with 85% of models agreeing on the sign of the trend. Both model agreement (75%) and the magnitude of the projected change (+9%) are smaller for RX5D, consistent with previous studies (e.g. Wasko et al. 2024).

There is medium confidence in an increasing trend in both RX1D and RX5D, based on both process-understanding of thermodynamic changes, moderate model agreement on the sign of the change, and consistency of the change with observed changes and other lines of evidence. However, there is lower confidence in the magnitude of the change, due to large interannual variability, uncertainty around future changes in key drivers such as ENSO, and uncertainty around key processes such as weather system movement and blocking, as well as smaller projected changes in other CORDEX-CMIP6 simulations for Australia.

Projected changes are heterogenous around Australia, and these spatial patterns vary between models (Figure 23). This gives low confidence in estimating regionally varying projected changes for rainfall intensity, consistent with Wasko et al. (2024).

For the highest annual hourly total (RX1H), there is very high model agreement on an increase between GWL1.2 and GWL3 (92% agreement), with an ensemble median increase of 13%. This is lower than the best estimate of change from multiple lines of evidence of +15% per degree of global warming (Wasko et al. 2024) and likely indicates deficiencies in RCM simulation of the processes influencing extreme sub-daily rainfall.

Table 16: Extreme rainfall metrics for GWL 1.2 and changes for GWL 1.5, GWL 2.0 and GWL 3.0 relative to GWL 1.2.

	Current	**Future**		
Metric	**GWL 1.2**	**GWL 1.5**	**GWL 2.0**	**GWL 3.0**
Highest 1-hour total (RX1H)	**18 mm** [17, 19]	**no detectable change** *low confidence*	**+12%** [+6, +22] *high confidence*	**+29%** [+13, +50] *high confidence*
Highest 24-hour total (RX1D)	**59 mm** [55, 62]	**no detectable change** *very low confidence*	**+6%** [-4, +14] *medium confidence*	**+12%** [-2, +27] *high confidence*
Highest 5-day total (RX5D)	**100 mm** [95, 107]	**no detectable change** *very low confidence*	**+5%** [-7, +12] *low confidence*	**+9%** [-6, +27] *medium confidence*

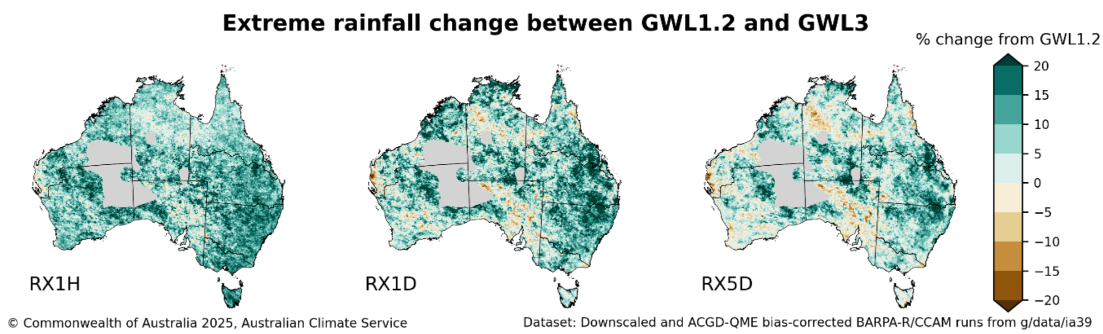

Figure 23: Multi-model median percentage change between GWL1.2 and GWL3 using the ACS QME ensemble for a) RX1H, b) RX1D and c) RX5D.

References

Wasko C and Coauthors (2024) A systematic review of climate change science relevant to Australian design flood estimation. *Hydrology and Earth System Sciences* 28:1251–1285. https://doi.org/10.5194/hess-28-1251-2024

5.3.2. Average rainfall

Contributors

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Daily bias-corrected (QME) rainfall was converted into monthly totals, which were used to derive annual and seasonal means. On an annual basis, no NCRA region had a robust change signal across the ACS ensemble, although consistent changes were identified in some small sub-regions including in the southwest of western Australia. Consequently, total rainfall analysis was separated into two seasons:

- April-October, representing the southern wet season
- November-March, representing the northern wet season

During April-October (Figure 24), the overall pattern favours a decrease in Australian rainfall at all GWLs, but with relatively little model agreement. At GWL3, the median change in Australian mean rainfall is -2%, but with a 10^{th}-90^{th} percentile range between -27% and +18%. There is stronger model agreement on a decline in April-October rainfall in southwestern Western Australia, with a median decline of -10% at GWL3 [-17% to -7%]. There are also areas of model agreement on declines on the order of -5% in parts of southeastern Australia (Figure 24). However, these changes do not map neatly onto NCRA regions, and no NCRA region has more than 80% agreement on the sign of the change between GWL1.2 and GWL3.

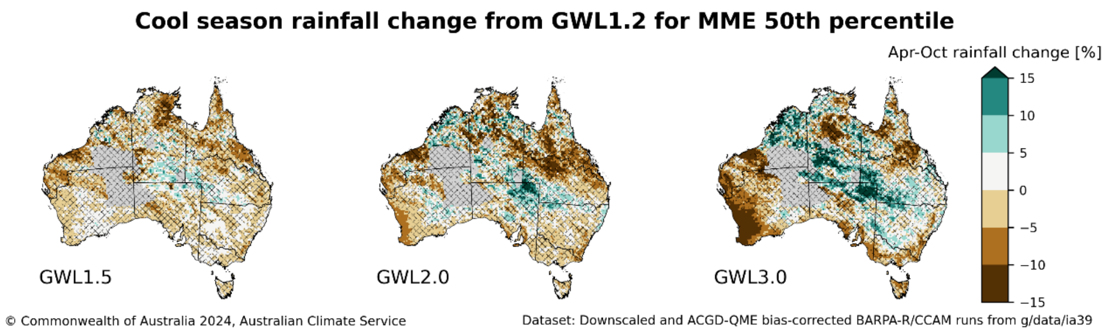

Figure 24: Ensemble median change in total April-October precipitation at each GWL, as a percentage change relative to GWL1.2. Hashes indicate where less than 80% of ensemble members agree on the sign of the change.

During November-March the median change in Australia at GWL3 is an increase of +1%, with a large range (-11% to +16%). While there are some small areas of model agreement on increasing trends in inland eastern Australia (Figure 25), resulting in a median projected change of +7% for NSW [-4%,+24%] no NCRA region has at least 80% agreement on the sign of the change. The range of potential change is very large in some regions, including a range from -20% to +25% in SA imply very low confidence in future changes.

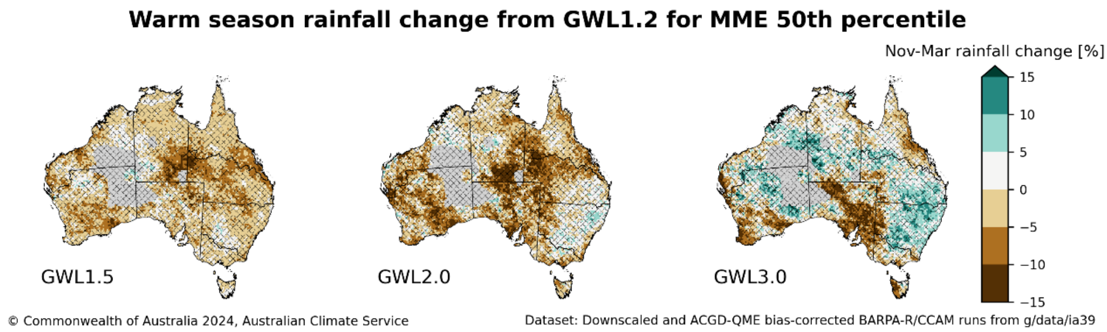

Figure 25: Ensemble median change in total November-March precipitation at each GWL, as a percentage change relative to GWL1.2. Hashes indicate where less than 80% of ensemble members agree on the sign of the change.

Projected rainfall changes in the 13-member ACS ensemble (numbered 1 to 13 in Table 2) are broadly within the broader CMIP6 ensemble range (CSIRO 2025), although there are regional and seasonal variations.

References

CSIRO (2025) Australian Climate Service CMIP6-Next Generation downscaled climate change projections: approach and summary. Hobart, Australia: CSIRO & Bureau of Meteorology. csiro: EP2025-1632. https://doi.org/10.25919/9bde-a338

5.3.3. Riverine and flash flooding

Contributors

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Overview

In support of the Hazard Insurance Partnership (HIP), the Australian Climate Service (ACS) has developed new flood indicators to enable greater understanding of Australia's future flood risk. The flood indicators, made available in a series of spatial and regional maps, consider the main factors causing floods including rainfall, and runoff intensity as flood drivers and landscape antecedent conditions as flood preconditioners.

Key findings

The findings show an increase in future flood risk nationally, particularly along the east coast and the northern tropics. Key regions, such as the Northern Rivers region and parts of the Murray-Darling basin, could expect to see more intense rainfall and river flow under future global warming. Whereas areas in the northwest, including regions around Fitzroy Crossing, are projected to see more intense flood preconditioning under future global warming levels.

Our results can be used to undertake a preliminary assessment of future flood risk, where flood indicators are chosen based on the best available science and an extensive literature review.

While confidence ratings vary (see more in 'confidence' section) the direction of these changes are consistent with trends outlined in the State of the Climate (2020-24).

Data Sources

This information has been developed using rainfall data from the ACS QME ensemble developed for the ACS based on the BARPA modelling approach using CMIP6 GCM data (Su et al. 2022) to calculate the rainfall indicators for selected global warming levels. The ACS National Projections comprise an ensemble of 8 GCM models at 0.2° × 0.2° spatial resolution for the period 1960-2100 and 3 socio-economic pathways (SSP 585 was used in this study).

Soil saturation and runoff data from National Hydrological Projections (NHP, Wilson et al., 2022) are used to calculate the flood indicators for selected global warming levels. The NHP comprise an ensemble of 32 CMIP5 bias-corrected climate model data and derived hydrological projections (including runoff projections) at daily temporal and 0.05° × 0.05° spatial resolution for the period 1976–2100 and two emission scenarios (RCP 4.5 and RCP 8.5, where RCP 8.5 is equivalent to SSP 585). Rainfall and runoff are measured in millimetres per day, and soil saturation is measured in fraction fullness, where 1.0 is completely saturated.

The information has been developed at a national scale to provide a national picture of riverine and flash flooding for medium to long-term planning.

Definitions of Riverine Flooding Indicators

Riverine flood maxima can be summarised by both rainfall and runoff indicators, where heavy rainfall can generate excess runoff whereby rivers exceed their capacity and runoff into surrounding low-lying regions. The Max1-Day Rainfall variable values indicate the meteorological drivers for a flooding hazard, and the Max1-Day Runoff variable and 90th percentile values indicate the severity of the flood.

Riverine flooding is dependent on antecedent conditions, with saturated soils acting to increase runoff for a given amount of rain. Thus, it is important to consider projected changes in extreme soil saturation, or something called Max-monthly soil saturation when considering changes in flood maxima.

Max1-Day Rainfall: The maximum 1-day rainfall indicator was derived by analysing 21-year periods centered on the above selected GWLs across the ACS QME ensemble for SSP585 (RCP 8.5). For each period, the annual maximum daily rainfall was extracted for each year within the period. The median value of the daily maximum runoff was calculated for each GWL. This indicator represents the intensity of rainfall. For consistency in notation, we are referring in this section to Max1-Day rainfall and Max1-Day Runoff. Note that section 5.3.1 (extreme rainfall) uses the notation RX1D to indicate the highest annual 24-hour rainfall total.

Max1-Day Runoff: The maximum 1-day runoff indicator was derived by analysing 21-year periods centered on the above selected GWLs across the NHP ensemble for RCP 8.5. For each period, the annual maximum daily runoff was extracted for each year within the period. The median value of the daily maximum runoff was calculated for each GWL. This indicator represents the intensity of flow.

Annual Total 90th Percentile Runoff: The 90th percentile of annual runoff was computed for selected GWLs using each NHP ensemble for RCP 8.5. For each GWL, the percentile runoff data from a 20-year period was used to calculate where the 90th percentiles were chosen to represent the distribution of projected runoff under future climate scenarios. This indicator represents the high flow volume.

Max-monthly soil saturation: The maximum monthly mean soil saturation indicator was derived by analysing 20-year periods centered on the above selected GWLs across the NHP ensemble for RCP 8.5. For each period, the annual maximum monthly rootzone soil saturation was extracted for each year within the period. The median value of the monthly maximum rootzone soil saturation was calculated for each GWL. This indicator represents potential flood impact where very saturated soil could lead to severe flooding, and dry soil could lead to moderate flooding.

National Picture

Current trends

A current wetting trend was found across most regions, where the rainfall and flow intensity has increased, along with the increase in flood impact potential. This trend is particularly noticeable along the coastline in the eastern and northern parts of Australia, consistent with the recent State of the Climate reports, which may have exacerbated flooding across the country in the short term.

Future trends

Rainfall intensity will increase across most parts of Australia in the far future (GWL 3.0) warming) and there is a slight wetting trend from current conditions across most regions in the near future (GWL 1.5 and 2.0) for flood impact potential, which could exacerbate flooding. There is a consistent decrease in flow intensity the southern parts of the country which could mean that the flood risk in those areas is reduced. High volume flows in general are projected to decrease, with implications for recharging groundwater stores.

Description

Flood indicators are defined as either flood drivers such as rainfall and flow intensity, and flood preconditioners such as soil saturation.

The changes in flood indicators across identified global warming levels are detailed both spatially in the form of maps of ensemble medians and in the form of a spatial average. The raw data is available for use on the National Computational Infrastructure (NCI).

Summary of future flooding indicator changes – National

Future changes in four flood indicators are summarized in Table 17 and Figure 26, Figure 27, Figure 28 and Figure 29.

Table 17: National picture of changes in flooding indicators at each global warming level; spatially averaged with median and 10th – 90th percentile ranges.

Nationally	Current	Future		
Indicator	**GWL 1.2**	**GWL 1.5**	**GWL 2.0**	**GWL 3.0**
Rainfall intensity RX1D (ACS CMIP6)	**59 mm** [55, 62]	**no detectable change** *very low confidence*	**+6%** [-4, +14] *medium confidence*	**+12%** [-2, +27] *high confidence*
Flow intensity Max1-Day Runoff (NHP CMIP5)	**2.6 mm** [1.6 – 4.3 mm]	**-3.8 %** [-39 to 47%] *Low confidence*	**-10 %** [-53 to 58%] *Low confidence*	**- 12 %** [-57 to 59%] *Low confidence*
High flow volume Annual Total 90th Percentile Runoff (NHP CMIP 5)	**108 mm** [74 – 166 mm]	**- 0.13 %** [-0.3 to 0.07%] *Low confidence*	**- 0.22 %** [-0.4 to 0.1%] *Low confidence*	**-0.22 %** [-0.4 to 0.1%] *Low confidence*
Flood impact preconditioner Max monthly soil saturation (NHP CMIP5)	**57%** [49 – 66 %]	**-1.2%** [-15 to 12%] *Low confidence*	**-1.5%** [-19 to 22%] *Low confidence*	**-1.3%** [-19 to 24%] *Low confidence*

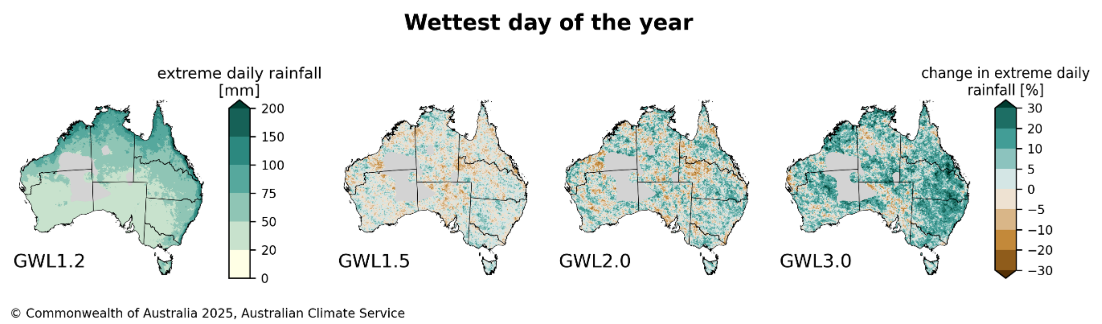

Figure 26: The median percentage change in highest annual one day rainfall total from the ACS CMIP6 ensemble data for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2).

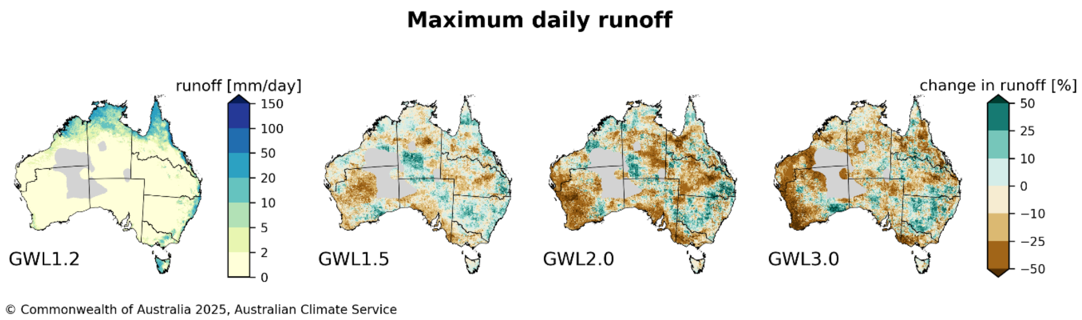

Figure 27: The median percentage change in Max1-day runoff from the NHP data for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2).

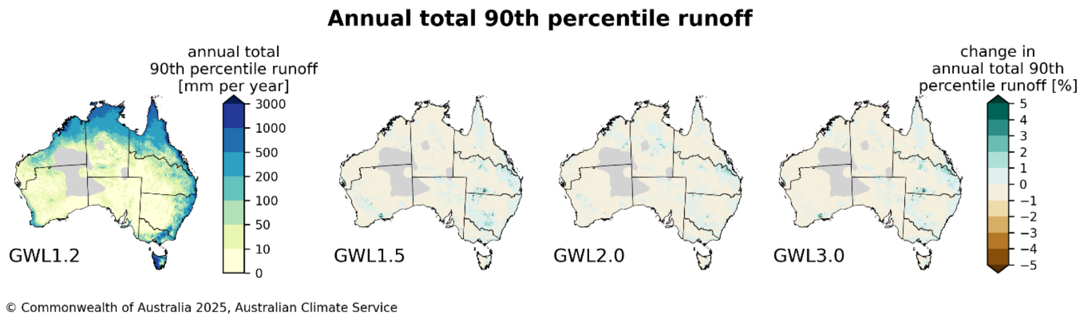

Figure 28: The median percentage change in annual total 90th percentile runoff from the NHP data for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2).

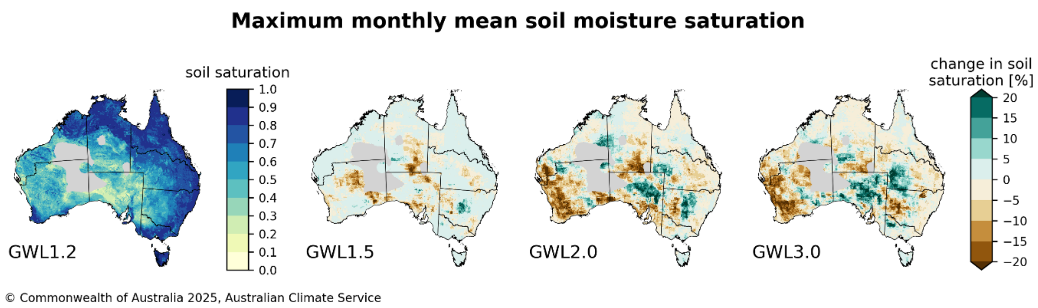

Figure 29: The median percentage change in Max monthly soil saturation from the NHP data for each future warming scenario (GWL1.5, 2 and 3) compared to the current climate (GWL1.2).

Regional Picture

Future trends

Key insights include a projected increase in rainfall and flow intensity in Queensland as well as in New South Wales, with implications for riverine flooding in these parts of Australia. In the northwest, regions around Fitzroy Crossing in Western Australia, are projected to see more intense flood preconditioning under future global warming levels, with implications for socio-economic impacts for isolated communities and transport routes.

The Northern Rivers and Murray-Darling Basin were included in the assessment due to their importance socio-economically. Both basins are projected to have increases in rainfall and flow intensity across GWL 2.0 and 3.0 as well, which implies that there will be potential issues for water management as well as flood risk in those basins.

Description

Changes in regional flood indicators across identified global warming levels are detailed is summarized in Table 18 and Table 19.

The Northern Rivers (NR) basin is crucial for flood risk assessment due to its history of severe floods impacting cities like Grafton and Lismore. Its unique topography and meteorology lead to rapid, large-magnitude floods in wide floodplains, posing significant risks to communities. Understanding these factors is key for effective flood management.

The Murray-Darling Basin (MD) is a complex and interconnected river system with diverse climate, landscape, and hydrological characteristics. But more importantly, it represents much of Australia's food bowl. The MD exhibits very high spatial and temporal streamflow variability with floods and droughts being common features (Zhang, et. al., 2024).

Summary of future flooding indicator changes – Regional

Table 18: Summary of maximum 1-day rainfall statistics for the ACS QME ensemble across NCRA regions.

Rainfall intensity – Max 1-day							
Region	**Median GWL1.2**	**Median GWL1.5 – GWL1.2**	**Median GWL2.0 – GWL1.2**	**Median GWL3.0 – GWL1.2**	**Confidence/likelihood at GWL2.0 – direction of change**	**90th percentile at GWL2**	**What lines of evidence were used to produce this statement?**
National	58.8 mm	Unclear	Unclear	+12%		+14%	ACS QME ensemble
WA North	74.6 mm	+2%	+8%	+11%	Likely increase	+13%	ACS QME ensemble
WA South	39.6 mm	+3%	+7%	+11%	Likely increase	+11%	ACS QME ensemble
NSW/ACT	53.9 mm	+2%	+6%	+15%	Likely increase	+11%	ACS QME ensemble
VIC	46.2 mm	+2%	Unclear	+14%		+15%	ACS QME ensemble
SA	36.2 mm	Unclear	Unclear	Unclear		+18%	ACS QME ensemble
TAS	55.5 mm	+5%	+6%	+7%	Likely increase	+12%	ACS QME ensemble
NT	71.2 mm	Unclear	Unclear	+11%		+21%	ACS QME ensemble
QLD North	88.4 mm	Unclear	+2%	+13%	Likely increase	+17%	ACS QME ensemble
QLD South	59 mm	Unclear	+5%	+12%	Likely increase	+13%	ACS QME ensemble
Notes	Data from ACS QME ensemble Excludes regions 20-30S, 122-132E Values are reported for the multi-model median of the regional mean % change (method 3) "Unclear" indicates where less than 65% of models agree on the sign of the change						

Table 19: Summary of maximum 1-day runoff statistics for the NHP ensemble for RCP 8.5 across NCRA regions.

Runoff intensity – Max 1 Day							
Region	**Median Max 1-day runoff GWL2.0 – GWL1.2**	**Median Max 1 GWL3.0 – GWL1.2**	**Median GWL2.0 – GWL1.2**	**Median GWL3.0 – GWL1.2**	**Direction of Max 1-day runoff change at GWL2.0**	**Direction of max soil saturation change at GLW2.0**	**What lines of evidence were used to produce this statement?**
National	-3%	-4%	2%	1%	Decrease	Increase	NHP ensemble
WA North	7%	-12%	4%	Unclear	Increase	Increase	NHP ensemble
WA South	-15%	-13%	-3%	-1%	Decrease	Decrease	NHP ensemble
NSW/ACT	11%	18%	Unclear	-1%	Increase	Unclear	NHP ensemble

VIC	-17%	-14%	-2%	4%	Decrease	Decrease	NHP ensemble
SA	Unclear	-6%	Unclear	10%	Unclear	Unclear	NHP ensemble
TAS	Unclear	3%	Unclear	1%	Unclear	Unclear	NHP ensemble
NT	-3%	-1%	-2%	-1%	Decrease	Decrease	NHP ensemble
QLD North	2%	7%	-1%	Unclear	Increase	Decrease	NHP ensemble
QLD South	-13%	5%	-1%	Unclear	Decrease	Decrease	NHP ensemble
Northern Rivers Basin	8%	4%	Unclear	-2%	Increase	Unclear	NHP ensemble
Murray Darling Basin	7%	11%	-5%	-2%	Increase	Decrease	NHP ensemble
Notes	Data from NHP ensemble Values are reported for the multi-model median of the regional mean % change (method 3) "Unclear" indicates where less than 65% of models agree on the sign of the change						

Priority catchments

A summary of the key changes for the priority catchments at GWL2 are given in Table 20. 'Unclear' means that either there is low multi-model agreement on the direction of change or that there is not a significant change.

Table 20: *Summary of the changes in the flood indicators for the priority catchments.*

Catchment (NCRA region)	Median changes in rainfall intensity	Median changes in flow intensity	Median changes in flood impact potential
Hawkesbury (NSW)	+6 %	+11 %	-1 %
Sydney – Coast- Georges River (NSW)	+6 %	+11 %	-1 %
Mary River (QLD South)	Unclear	+5 %	Unclear
South Coast (QLD South)	Unclear	+5 %	Unclear
Brisbane River (QLD South)	Unclear	+5 %	Unclear
Torrens River (SA)	Unclear	Unclear	+10 %
Yarra River (VIC)	+2 %	-17 %	+4 %
Bunyip River (VIC)	+2 %	-17 %	+4 %

Confidence

The ACS Projections dataset does not include the full range of CMIP6 models and therefore might not capture the full range of plausible changes in rainfall. However, the models that were chosen were subject to the following criteria:

- Adequately capture the multi-model spread,
- Adequately model Australian climate drivers and processes.

The National Hydrological Projections dataset does not encompass the full range of CMIP5 models and therefore might not capture the full range of plausible changes in runoff and soil saturation. However, the models that were chosen were subject to the following criteria:

- Adequately capture the multi-model spread,
- Adequately model Australian climate drivers and processes,
- Contain daily fields of hydrological model inputs.

Therefore, the individual ensemble members represent the range of plausible futures and are a key element of establishing scenario driven hazard assessments.

The confidence in changes for the hydrological indicators is assessed as ***low*** due to limitations in GCM availability (see NHP data, Wilson et al., 2022), the ability of models to simulate processes, consistency with other studies, and our understanding of mechanisms. Although, it should be noted that the direction of changes are consistent with the recently published State of the Climate reports (2020-2024).

The confidence in changes for the climate indicators is assessed as ***medium to high*** due to the larger spread of models and updated model physics for the CMIP6 GCM data.

References:

Su CH, Stassen C, Howard E, Ye H, Bell S, Pepler A, Dowdy AJ, Tucker SO, Franklin C *(2022)* BARPA: New development of ACCESS-based regional climate modelling for Australian Climate Service, *Bureau Research Report 69,* http://www.bom.gov.au/research/publications/researchreports/BRR-069.pdf

Wilson L and Coauthors (2022) A national hydrological projections service for Australia. *Clim. Serv.*, 28, 100331, https://doi.org/10.1016/J.CLISER.2022.100331.

Zhang, L., Chiew, F., & Hatton. (2022). Hydroclimate of the Murray-Darling Basin. *Australian Academy of Technological Sciences and Engineering.* *https://www.atse.org.au/media/ydpd1vmb/mdb-essay-1-zhang.pdf* *https://doi.org/10.60902/3h4q-w402*.

5.4. Coastal hazards

Contributors

Ben Hague, Julian O'Grady, Xuebin Zhang

The National Climate Risk Assessment identified two coastal hazards as a priority: coastal and estuarine flooding, and coastal erosion and shoreline change. These are combined into a single section as some indices provide information on both hazards.

Key findings

- Present-day extremes and flood events will become increasingly frequent, and eventually, chronic under the sea-level rise increments considered for the 21st century. On average, minor flooding occurs 15 days per year in the current climate (0.06 m sea-level rise increment), but will increase to 39 days, 102 days and 208 days per year once sea-level rise reaches 0.2 m, 0.38 m and 0.60 m increments.
- A typical 1-in-100-year event (1% annual exceedance probability, AEP) becomes an annual occurrence at most locations with only 0.32 m additional sea-level rise.
- Flood extents associated with a 1% AEP will increase with further sea-level rise. Queensland currently has the largest flood extents (median 229 km^2 per LGA) and expects the largest increases in flood extent in terms of area (median 29 km^2 per LGA) with 0.54 m additional sea level rise. Under the same scenario, New South Wales has the greatest percentage-wise increase in flood extent, more than doubling from a median 3.54 km^2 per LGA to 10.05 km^2 per LGA.
- Based on the current available science, episodic coastal erosion will increase, but we cannot say with confidence whether long-term coastal erosion and shoreline change will increase or decrease in the future.

Indices

The indices we used to deliver coastal hazard insights on coastal and estuarine flooding (CEF) and coastal erosion and shoreline change (CESC) are summarised in Table 21. Four coastal flood metrics were used, each employing a different approach to assess impacts. These metrics indicate the frequency of high tide flooding at specific locations, the area of land within an LGA inundated during extreme events, and the increased frequency of extreme flooding in both estuarine and open ocean environments due to sea level rise around the Australian coast.

Hazard indices are applicable to different combinations of hazards and environments. Two environmental classifications are considered – sheltered and open coasts. Sheltered coasts include harbours, bays and estuaries, where waves do not make substantial contributions to coastal hazards. In contrast, open coasts include beaches and cliffs where waves do make substantial contributions to coastal hazards.

Table 21: Indices for coastal hazards.

Index name	Description	Relevant Hazard/s	Relevant Environments
Flood days	Days per year exceeding the impact-based minor flood threshold	CEF	Sheltered
Record days	Days per year exceeding the highest sea level recorded in the last 20 years	CEF	Sheltered
Flood extent	Area with a 1% chance of flooding annually	CEF	Sheltered & Open
Multiplication Factor (MF)	Storm-tide MF: Factor of frequency by which storm-tide-related coastal hazards will increase due to sea level rise.	CEF	Sheltered
	Total Water Level MF: Factor of frequency by which total water level-related coastal hazards will increase due to sea level rise.	CEF & CESC	Open

Data sources

'Flood days' and 'Record days' were based on peer-reviewed data produced through the ACS, derived from IPCC projections and the ANCHORS dataset (Hague and Talke 2024). The dataset is currently available on figshare: https://doi.org/10.6084/m9.figshare.24328903.v1.

Flood extent data is sourced from the CSIRO Probabilistic Coastal Inundation Layers product (O'Grady et al., 2024).

Data sources for the multiplication factor are those used to estimate extreme total water level in O'Grady et al. (2019a). This includes storm surge, tides, waves and beach slope datasets. The multiplication factor (see definition in Table 21) is computed from the resultant Gumbel scale parameters following the formula of Hunter (2012). For storm-tide only, Gumbel scale parameters are also estimated from Australian tide gauge records in a global tide gauge dataset (Haigh et al. 2022).

Limitations

All datasets leverage the 'mean sea level offset' approach, which is one of two projection methods recognised in the IPCC AR6 to project future changes in sea level extremes (Fox-Kemper et al. 2021). This approach first defines historical distributions of sea level (from gridded hindcasts or tide gauges) and then determines future distributions by shifting the distribution by a specified amount of mean sea level, increasing all values in the distribution (and associated statistics) by that increment. Using this approach leverages two key assumptions – there are no future changes in sea level variability on any timescale (stationarity of variance) and that thresholds of concern remain unchanged (stationarity of threshold) (Hague et al. 2024a). Each dataset then has its own unique additional assumptions. For example, Hague and Talke (2024) assume independence between storm surges and tides (Williams et al. 2016; Santamaria-Aguilar and Vafeidis 2018). Multiplication factors assume that return levels follow a Gumbel distribution, which implies that exceedances of all thresholds increase by the same factor, regardless of the threshold's present-day frequency (Buchanan et al. 2017).

Limitations arise from applying methods or interpreting results in circumstances where assumptions do not hold. Firstly, tidal ranges and storm surges have changed in the past (McInnes et al. 2024; Hague et al. 2023a) and are likely to continue changing into the future (Harker et al. 2019; Colberg et al. 2019), violating the stationarity of variance assumption. This limitation remains in the data, however we note that these changes in tidal range and storm surges are likely second-order effects on flood hazard changes compared to changes in mean sea level (McInnes et al. 2015; Hague and Talke 2024). Secondly, different flood thresholds at the same location have observed different changes in exceedance frequency (Hague et al. 2020), suggesting the Gumbel distribution fitted to the annual maxima does not hold once events become more frequent than annual occurrences (Stephens et al. 2018; Ghanbari et al. 2019; Hague et al. 2024a). This limitation is addressed by reporting multiplication factors greater than 200 (implying a "1-in-100-year" event becomes a "twice a year event") as "> 200", rather than reporting the exact value.

Additional factors not included in the models and data can influence coastal hazards, which could result in changes in hazards to be different to that expected based on presented indices. For flooding, the effects of freshwater inflows into estuaries are not (fully) represented in tide gauge observations and models. Hence, the metrics and data provided here do not consider compound flooding in estuaries. ACS has supported the development of a regional case study (Hague et al. 2024b) on how the influence of coastal flood drivers on estuarine flooding will change under sea-level rise. For erosion, our modelling does not account for processes including shifts in wave direction, degradation of protective coastal ecosystems (e.g., coral reefs, mangroves), and changes in sediment supply (e.g., from deeper waters or riverine discharge).

Identifying suitable indices for monitoring and predicting coastal erosion and shoreline change over time remains an area of active research. Ongoing sea-level rise has increased the frequency of extreme sea levels nationwide, leading to multiplication factors greater than one in all locations. Despite this, some studies show there is no net Australia wide trend towards increases in coastal erosion and shoreline change hazards on global or national scales (Ghanavati et al. 2023; Nanson et al. 2022; Bishop-Taylor et al. 2021). Furthermore, changes in wave direction have led to coastal erosion and shoreline change on local and regional scales (Gallop et al., 2020; O'Grady et al., 2019b). Sediment types are also a modulating factor (Leach et al. 2020; Thom et al. 2018). How these aspects influence the hazard cannot be considered in the multiplication factor.

Outputs

The following outputs are provided on the github page:
https://github.com/AusClimateService/hazards-coastal:

- Plots of coastal flood days under sea level rise increments
- Plots of multiplication factors under sea level rise increments
- Code to produce the above

The following outputs are provided on ia39:

- Data and plots of multiplication factor (g/data/ia39/ncra/coastal/MF/)
- Data (g/data/ia39/ncra/coastal/flood_days/) and plots (g/data/ia39/ncra/coastal/Plots/) of coastal flood days
- Shapefiles and statistics for flood extents for LGAs (g/data/ia39/ncra/coastal/flood_extents/)

Current maturity

The ACS Hazard Stocktake (Hirst et al. 2025) assessed the maturity of coastal and estuarine flooding as 'Developed', indicating a mostly mature capability within Australia with only one or two significant limitations. Coastal and estuarine flooding hazard capability was assessed as more mature than all other hazards, except for 'Heatwave and extreme heat' which was also assessed as 'Developed'.

The ACS Hazard Stocktake assessed the maturity of coastal erosion and shoreline change as 'Basic Research Online', indicating low confidence and experimental results.

Use for risk assessments:

To conduct a risk assessment, hazard information must be combined with information on exposure and vulnerability to the hazard, as well how risk management responses can change each component (Simpson et al. 2021). The World Meteorological Organization defines a hazard as a phenomenon "that poses a level of threat to life, property or the environment". Hence, sea level (a phenomenon) only becomes flooding (a hazard) once it reaches a certain height is associated with some degree of threat (Mahmoudi et al. 2024; Rasmussen et al. 2022).

Hazard indices are constructed to be useful for hazard assessments, and in combination with combined with exposure and vulnerability information for risk assessments.

- The use of flood days assumes that flood threshold relevant for decision-makers are exceeded
- The use of Multiplication factors assumes that the flooding is sufficiently rare so its frequency and height can be robustly estimated using a Gumbel extreme value distribution (Hunter 2012).

- The 1% AEP is presented here because of its utility for design storms. However, decision-makers will ideally consider a range of AEPs.

Based on the assessed maturity in the ACS Hazard Stocktake (Hirst et al. 2025), the current coastal erosion and shoreline change hazard information is "insufficient to address user needs at a qualitative level". However, the index could be intersected with coastal morphology data, to inform a vulnerability assessment for soft and hard shorelines. The information provided by the multiplication factors could identify locations where sea level extremes and soft shore coasts are most susceptible to sea-level rise for further investigation considering additional factors that influence the hazard on local scales (Sharples et al. 2020; Konlechner et al. 2020).

Proposed future indices

We propose developing indices based on new sea level hindcast data. Future research is required to identify indices that are sensitive to how climate change, including both sea-level rise and weather pattern shifts, impact coastal erosion and shoreline change hazards. The application of the so-called 'Bruun Rule' (Bruun 1988) for this purpose has become controversial and is viewed as too simplistic by many scientists (e.g., Cooper et al., 2020; McCarroll et al., 2021). Indices for predicting coastal erosion and shoreline change on shorter timescales (e.g., Leaman et al., 2021; McCarroll et al., 2024) could be investigated in the longer-term context.

Results

Present-day extremes and flood events will become increasingly frequent, and eventually, chronic under the sea-level rise increments considered for the 21st century. On average, minor flooding occurs 15 days per year in the current climate (0.06 m sea-level rise increment), but will increase to 39 days, 102 days and 208 days per year once sea-level rise reaches 0.2 m, 0.38 m and 0.60 m increments (Figure 30**a**). An additional 0.14 m sea-level rise will result in an eight-fold increase in frequency of sea-level extremes on average. Under 0.32 m additional sea-level rise, this becomes an average 118-fold increase, and a more-than-200-fold increase under 0.54 m additional sea level rise (Figure 30**b**). This means a typical 1-in-100-year event becomes an annual occurrence at most locations with only 0.32 m additional sea-level rise. Contemporaneous work on developing impact-based flood thresholds and identifying past coastal flood events have allowed such projections to be contextualised based on recent impacts (Figure 31). This assists with communicating the consequences of sea-level rise to decision makers in a relatable way (Mahmoudi et al. 2024; Rasmussen et al. 2022).

Flood extents associated with a 1% annual exceedance probability (AEP) will increase with further sea-level rise. This is a flood extent that has a 1% chance of occurring each year in a baseline climate. The amounts by which the 1% AEP flood extent increases vary greatly between Local Government Areas (LGAs). Queensland currently has the largest flood extents (median 229 km^2 per LGA) and expects the largest increases in flood extent in terms of area (median 29 km^2 per LGA) with 0.54 m additional sea level rise (Figure 32). Under the same scenario, New South Wales has the greatest percentage-wise increase in flood extent, more than doubling from a median 3.54 km^2 per LGA to 10.05 km^2 per LGA.

While shorelines will move inland, we are not in a position to provide quantitative projections for changes in erosion and shoreline change. Coastal extreme water levels will become more frequent due to future sea-level rise but need more information to find out if these will lead to more frequent coastal erosion or larger shoreline changes both generally and locally. The largest increases are expected in Queensland (Figure 30c), although extreme total water level multiplication factors are less than storm-tide multiplication factors at all locations.

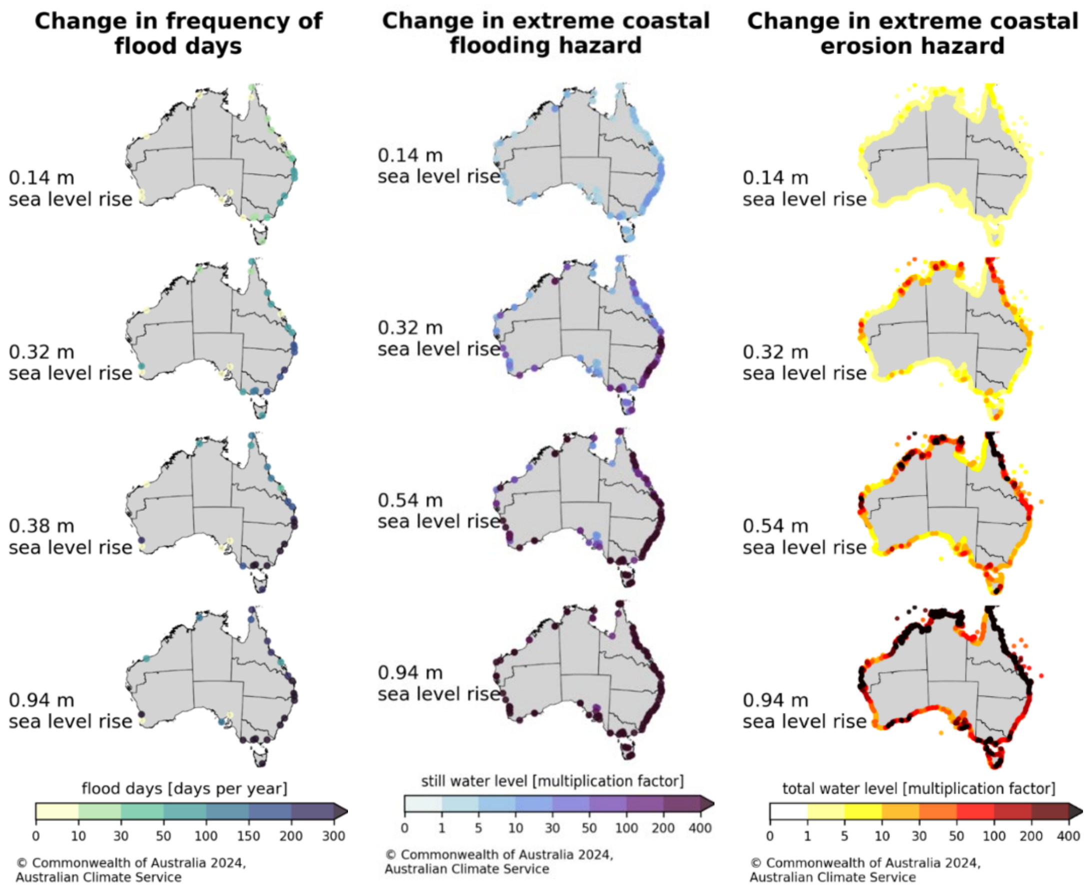

Figure 30: Median estimates of increase (a) minor flood days (left), (b) sea-level extremes (centre) and (c) extreme erosion (right), at 0.2 m, 0.38 m, 0.6 m and 1.0 m SLR increments, relative to the present-day (0.06 m increment).

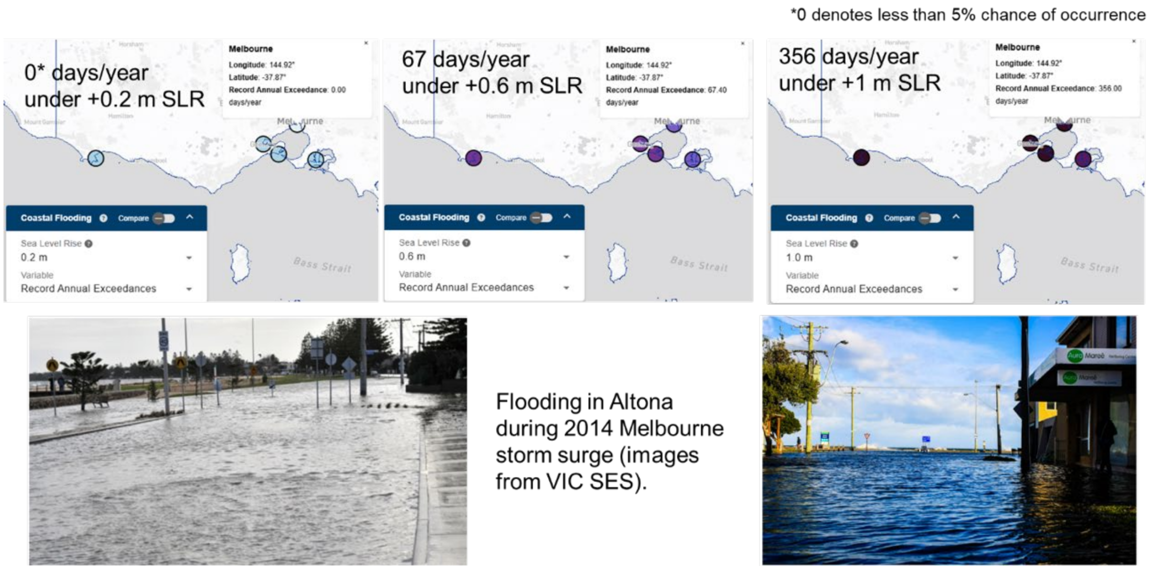

Figure 31: Example of relating future floods to their impacts to assist with briefings. This example shows the highest event in the last 20 years at Melbourne, and associated impacts, and how often these water levels are expected under 0.2, 0.6 and 1.0 m sea-level rise.

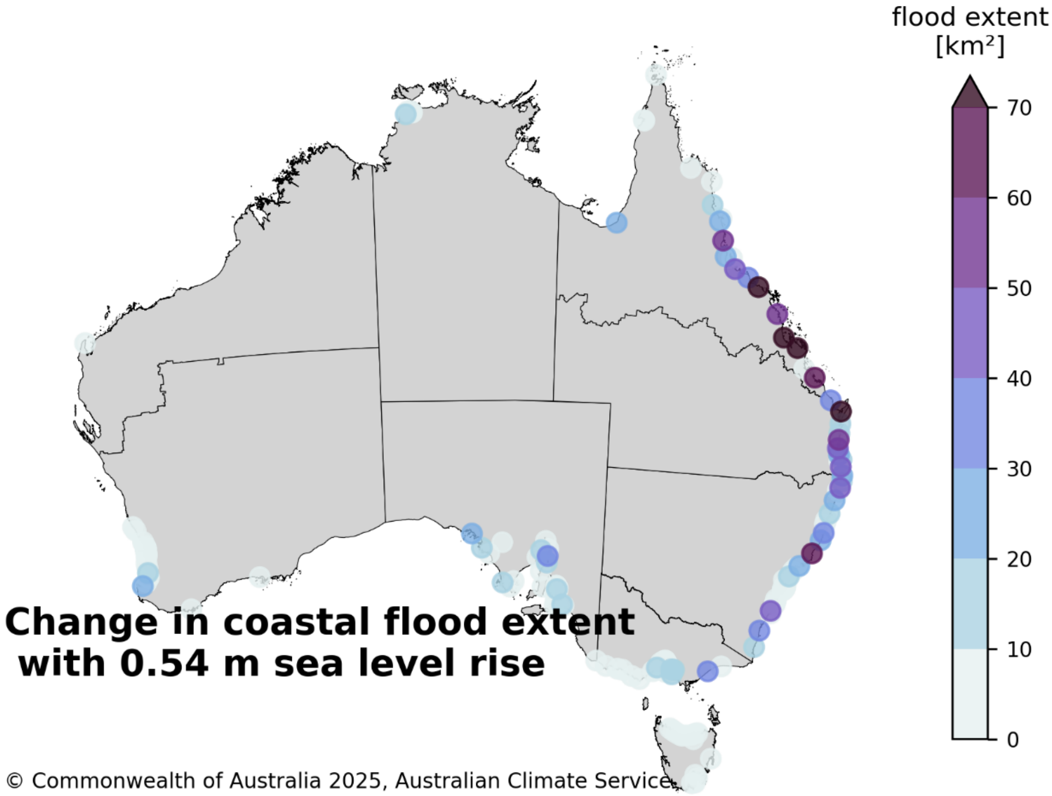

Figure 32: Flood extent for 1% AEP by LGA under 0.6 m SLR increment compared to present-day (0.06 m).

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5.5. Marine extremes

Contributors

Richard Matear (Lead), Pearse Buchanan

Key messages

- The ocean environment around Australia is warming and acidifying. These are observable trends that will continue for all GWLs (high confidence) (Table 23).
- Ocean warming occurs everywhere, with a hotspot in the Tasman Sea where the poleward migration and intensification of the East Australian Current transports more warm water south (high confidence the region will experience enhanced warming)
- Ocean warming increases the occurrence of heat extremes. By GWL 3.0 a near-permanent heatwave state occurs in the Tasman Sea, and conditions for extensive coral bleaching in Northern Australia
- For the heat stress metrics, there is an acceleration in severity as one goes from GWL 2.0 to GWL 3.0
- Ocean acidification occurs in the surface water around Australia at nearly a constant rate.
- In shelf regions, the drop in aragonite saturation state at the ocean bottom is similar to the surface, and further offshore along the continental shelf, the undersaturated water at the ocean bottom shoals with increasing GWLs.
- Under-saturated surface conditions for aragonite will occur in the Southern Ocean by GWL 3.0, threatening calcifying plankton species.
- There is low confidence in the magnitude of the change in net primary productivity with medium confidence in the sign of change for the Australian region except in Northern Australia, where there is low confidence in the magnitude and sign of the change.

Introduction

Oceans play critical roles in the Earth's climate system by storing and transporting heat, fresh water and carbon. The storage of heat and carbon in the oceans slows the rate of atmospheric warming caused by human emissions of greenhouse gases, mainly carbon dioxide (CO2). This alters the ocean state and affects marine ecosystems that must adjust to changing conditions. Australia's climate and weather are also influenced profoundly by regional and global processes driven substantially by the oceans. The exchange of heat and moisture between the ocean and atmosphere drives key climate features that, in turn, directly affect the weather and climate of Australia's terrestrial environments, including rainfall, temperature, and the frequency and intensity of extreme weather events. Significant climate-driven changes in ocean environments are projected over the next century. This section briefly presents the oceanographic setting around Australia and discusses the projected changes in the ocean environment with rising Global Warming Levels (GWLs). The changes in the ocean environment manifest as changes in the mean state and in ocean extremes (Table 22).

Table 22: Ocean diagnostics used to characterise the change in the environment with global warming.

	Diagnostic	**Comments**
Warming	Sea surface temperature	Mean state
	Marine heatwave (MHW) duration and magnitude	Extreme
	Degree Heating Week (DHW)	Extreme
	Bottom Temperature	Mean state
Acidification	Surface Aragonite Saturation State	Mean state
	Surface pH	Mean state
	Bottom Aragonite Saturation State	Mean state
Other	Net Primary Productivity (NPP)_	Mean state
	Mixed Layer Depth	Mean state
	Bottom Stress	Mean state
	Sea Surface Height	Mean state

Oceanographic Setting

Australia sits at an oceanic crossroads, flanked by the Indian, Pacific, equatorial and Southern Oceans (Figure 33).

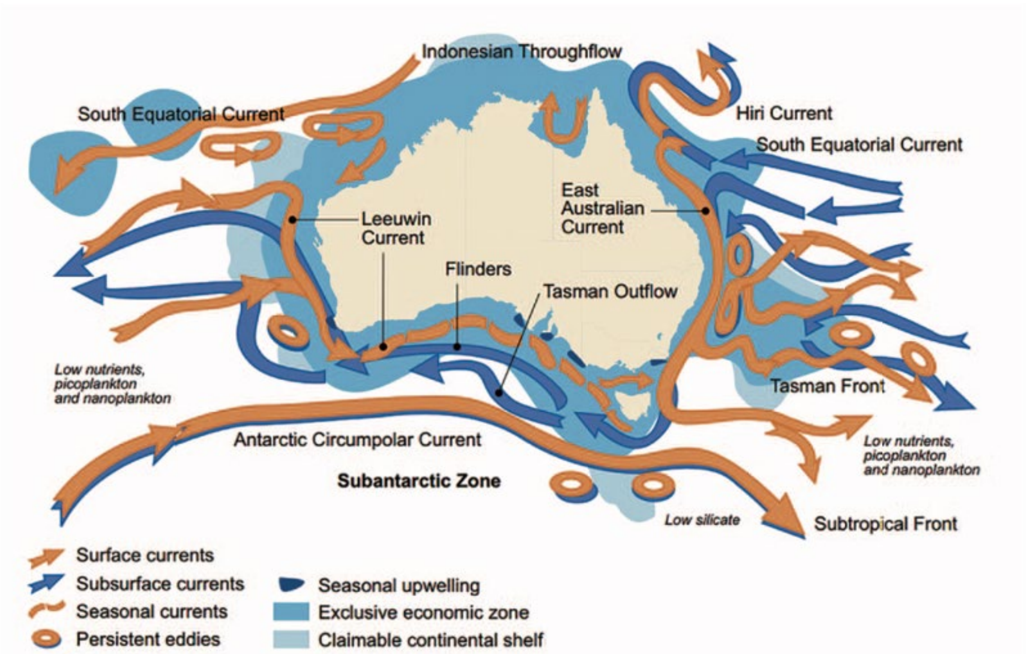

Figure 33: Schematic view of the major Australian surface ocean current systems (Source: adapted from the CSIRO report to DSEWPaC, 2011).

The Indonesian Throughflow carries relatively fresh seawater westwards from the Pacific to the Indian Ocean through the Indonesian archipelago. The Indonesian Throughflow feeds the southward flow of the Leeuwin Current off the west coast. The world's largest ocean current, the Antarctic Circumpolar Current, flows from west to east between Australia and Antarctica. The east coast of Australia is influenced by the East Australian Current, the western boundary current of the large anticlockwise gyre that spans the subtropical latitudes of the Pacific Ocean.

These large-scale ocean circulation patterns are linked to surface winds and their variability. The easterly trade winds near the tropics and westerly winds further south determine the strength of the subtropical gyres that span the Indian and Pacific Ocean basins. The Indonesian Throughflow and the Leeuwin Current vary primarily in response to winds over the tropical Pacific at seasonal, inter-annual and decadal timescales. Local winds drive variability of boundary currents, such as the East Australian Current, and the upwelling of nutrient-rich waters in some coastal locations. Therefore, the current systems near Australia respond to local and distant changes in wind patterns.

Ocean currents strongly influence Australia's terrestrial and marine environment by transporting heat, water, nutrients and organisms. Ocean currents along the equator are critical players in variations in the strength of the Leeuwin Current off Western Australia and are linked to the productivity of the West Australian lobster fishery. In contrast, a southward expansion of warm East Australian Current waters has catalysed a shift from kelp forest to urchin barrens along much of Tasmania's east coast. Knowledge of ocean currents is essential for the design of coastal and offshore infrastructure, effective search and rescue, defence operations and sustainable management of marine resources.

Atmospheric and oceanic processes influence the distribution of temperature, salinity, nutrients, and biological productivity around Australia. Sea-surface temperature decreases from north to south, warms in summer, and cools in winter. Warm waters extend further south along the east and west coasts, reflecting the southward flow of the East Australian and Leeuwin Currents, respectively.

Surface waters surrounding Australia generally lack nutrients, resulting in low biological productivity. Exceptions include the northern continental shelves and a wide band south of the continent known as the Subtropical Convergence, where deep winter mixing brings nutrients to the surface layer (Figure 33). Upwelling of nutrient-rich waters occurs off the Bonney coast of South Australia and Victoria in summer and sporadically off the West Australia and New South Wales coasts. Deeper, colder waters tend to be richer in nutrients and localised upwelling brings these nutrient-rich waters to the surface where they 'feed' shallower water ecosystems.

Future Projected Changes

We have relied on an ocean eddy-resolving model to provide a quantitative perspective on how the ocean environment changes with climate change (OFAM3, Oke et al., 2013). The future ocean simulation uses the multi-model mean trend CMIP5 atmospheric forcing fields from their RCP8.5 projections to drive this eddy-resolving ocean model

(Zhang et al., 2016). To characterise the changes in the ocean environment with global warming, 11 diagnostics were computed, summarised in Table 22. The future ocean simulation has been used in several studies to investigate how the ocean environment changes with global warming (see OFAM references listed below).

Warming and Heat Extremes

Oceans absorb ~90% of the additional heat in the Earth system as the planet's surface warms. However, the surface ocean around Australia tends to warm more slowly than the Australian land surface, 1.08 °C vs. 1.51 °C, since 1900 and 1910 respectively (BoM 2024). The ocean warming trend, as evident in the observations, will continue with global warming. Key indicators of ocean warming are changes in ocean temperatures and changes in the frequency and magnitude of extreme ocean temperatures.

At the surface, the annual mean temperature of the oceans around Australia warms from the current state of GWL 1.2°C (Table 23). The ocean surface warming increases with GWL levels, with the projected warming of the oceans around Australia being less than the global mean value. For example, at GWL 3°C, the global mean temperature increases by 1.8°C from GWL 1.2 while the ocean around Australia warms by an average of 1.3°C. The projected surface ocean warming occurs in all regions around Australia, with a slight reduction in warming as one goes poleward (Figure 34).

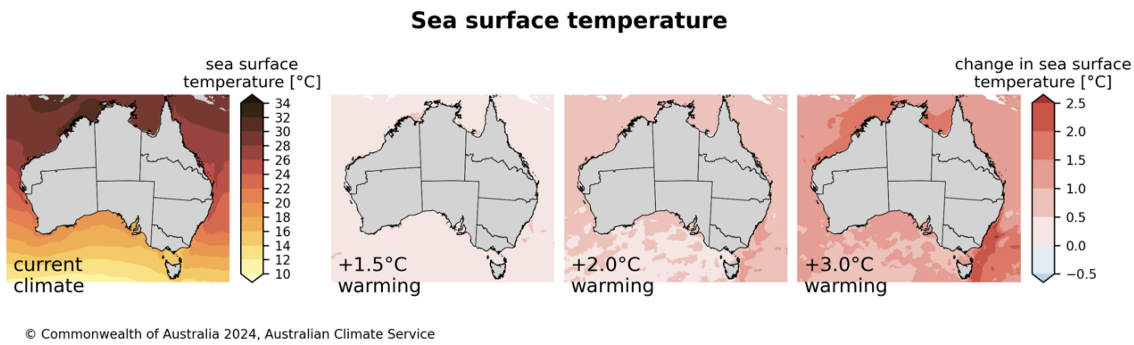

Figure 34: Sea surface temperature of the Australia region in the current climate, and the change in sea surface temperature at GWL 1.5, 2.0 and 3.0°C.

The most prominent spatial feature in the figures is the enhanced warming in South-east Australia (Tasman Sea). This region of rapid warming is apparent in the observations (Wu et al., 2012) and is attributed to the poleward shift and/or intensification in the East Australian Current (EAC). The rapid warming in the Tasman Sea is about 3x the average warming of the global ocean surface. It is projected to continue with global warming as the EAC shifts south and intensifies. The rapid warming of the Tasman is a robust feature of climate projections and is linked to the poleward shifts in the winds in the subtropical South Pacific (high confidence).

Northwest Australia is another region of slightly enhanced warming. The ENSO cycle significantly influences the region, with La Niña increasing Indonesian Through Flow and Leeuwin Current transport and warming the ocean off NW Australia. The enhanced warming in NW Australia is partly an artefact of the future atmospheric forcing used to force the ocean model because only the projected trend in the forcing comes from the CMIP5 projections. The weather and interannual variability come from the observed variability from 1981–2012 repeatedly three times (2006–2037, 2038–2069, and 2070–2101). The CMIP5 projected trend is applied on top of this variability. Over the historical period (1981-2012), there tended to be more La Niña-like state, which led to a warming bias in the region in the future projection. However, the CMIP6 climate projections generally project a more El Niño-like state, but this response may take several decades to emerge from interannual and decadal variability (Bai et al., 2023; Ying et al., 2022). Hence, there is low confidence in the enhanced surface ocean warming off NW Australia.

Ocean warming is not restricted to the surface. Ocean circulation and upper ocean mixing processes transport warmer surface water into the ocean interior, ensuring that the entire ocean will change with global warming. For water shallower than 200 m, the bottom temperature warming is similar to the surface warming showing that the benthic environment in these waters shows little delay in warming from the surface.

The warming trend in the ocean with global warming will also alter the occurrence of extreme temperatures in the ocean. The marine heat wave diagnostic (Hobday et al., 2016) characterises heat waves in the open ocean. For the Australian region, the mean annual duration of MHWs increases rapidly with GWLs from 22 days at GWL1.2 to 161 days at GWL 3 (Table 23). The increase in the MHW duration is most evident in Northern Australia, along the coasts and in the Tasman Sea (Figure 35). In these regions, specifically, conditions at GWL 1.5 are consistent with only a slight increase in MHW duration. However, at GWL 2, the MHW duration in these regions is about 140 days and by GWL 3 these regions' MHW duration is nearly permanent (greater than 320 days). The mean magnitude of the MHWs stays below 0.5°C for all GWLs except GWL 3 when Northern Australia and the Tasman Sea mean MHW magnitude exceeds 1°C. The mean magnitude present here is less than the previous analysis from the same simulation (Hayashida et al., 2020) because the reference period used for detecting MHW was based on the GWL 1.2 period. At GWL 3, MHW's magnitude and duration increase rapidly from the values at GWL 2.

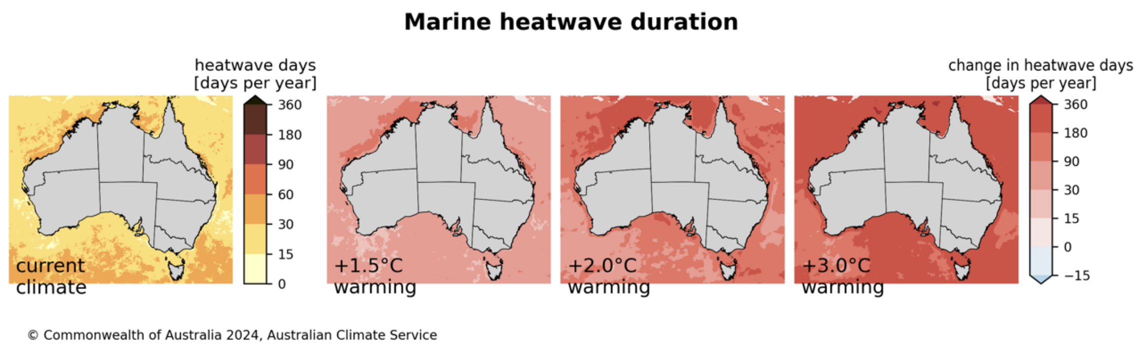

Figure 35: Marine heatwave days per year for the Australia region in the current climate, and the change in heatwave days per year at global warming levels 1.5, 2.0 and 3.0°C.

To quantify the cumulative thermal stress experienced by coral reefs, the thermal stress diagnostic Degree Heating Week (DHW) is used (Toscano et al., 1999). DHW greater than 4°C-weeks is associated with coral bleaching, and DHW greater than 8°C-weeks with widespread coral bleaching (Liu et al., 2006). The GWL 1.2 period determines the maximum monthly temperature threshold used in the DHW calculation. It is only at GWL 3 where DHW rapidly increases in Northern Australia and parts of the Great Barrier Reef and approaches 8°C-week, a value associated with widespread coral bleaching.

Acidification

About 28% of anthropogenic CO_2 emissions since 1800 have been absorbed by the oceans (Friedlingstien et al., 2022). This carbon added to the oceans affects seawater chemistry, making it more acidic. This process has been called ocean acidification (Orr et al., 2005). Ocean acidification is an observable long-term trend (BoM and CSIRO 2024) with chronic and acute impacts on marine organisms and ecosystems (Aze et al., 2014).

Ocean acidification is typically represented by changes in pH and in aragonite and calcite saturation states; the latter two diagnostics provide information on organisms' ability to calcify (e.g., coral reef for aragonite and coccolithophores for calcite). Here, we use pH and aragonite saturation state to represent ocean acidification. In the open ocean, CMIP6 simulations do represent the large-scale future changes in ocean acidification (Kwiatkowski et al., 2022). However, in the continental shelf regions of Australia, CMIP6 models are too coarse to represent the ocean dynamics and shelf regions, and the CMIP6 models under-estimate ocean acidification variability and change (Mongin et al., 2016).

At the surface, the aragonite saturation state declines with increasing GWLs consistent with rising atmospheric CO_2 and ocean CO_2 uptake. In the Australia region, the decline is ubiquitous, with a slightly reduced decline as one goes poleward. The pH changes show a similar behaviour (Figure 36). GWL 3, regions of the Southern Ocean become undersaturated with respect to aragonite (less than 1) and the surface water becomes chemically corrosive to the aragonite form of calcium carbonate that form the shells of calcifying plankton, such as pteropods. This change threatens to alter the community composition of Southern Ocean marine ecosystems.

The aragonite saturation state naturally declines with ocean depth until undersaturation occurs. However, ocean acidification shoals the depth horizon at which this undersaturation occurs, otherwise known as the lysocline, as anthropogenic carbon is transported into the ocean interior. Around Australia, coastal waters at the ocean bottom have declining aragonite saturation values, with the lysocline rising on the continental slope. This may impact benthic ecosystems, including those comprised of corals.

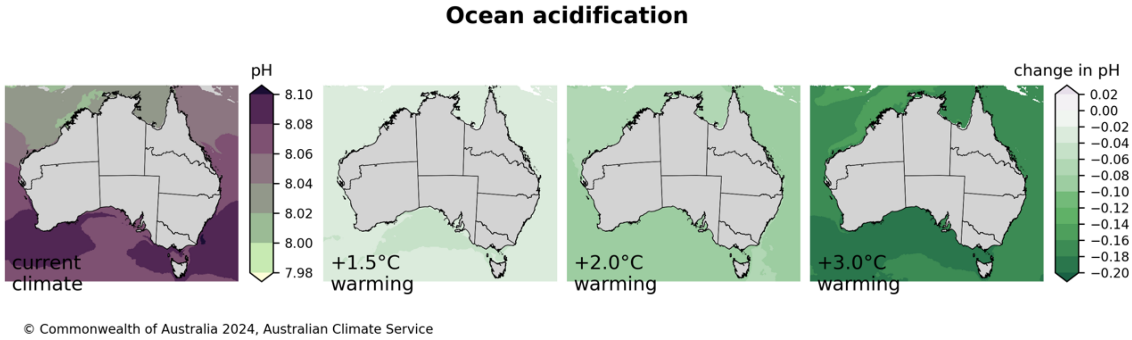

Figure 36: Ocean acidification (pH) for the Australia region in the current climate, and the change in pH at global warming levels 1.5, 2.0 and 3.0°C.

Productivity

In the ocean, microscopic marine plants (phytoplankton) are the primary organisms that take light and ocean nutrients and convert them into living tissues that ultimately feed most ocean ecosystems. This process is called primary production. Ocean net primary production is projected to decline as ocean warming and changing circulation reduce the supply of nutrients to the upper oceans. However, CMIP6 projections of changes in net primary production are highly variable regionally, and the pattern of changes generally shows the largest declines in the mid and low (tropical) latitudes, with slight increases in the Southern Ocean (Kwiatkowski et al., 2022). However, this pattern of change is uncertain, and recent studies with the eddy-resolving ocean simulations suggest increases in net primary production in the Tasman Sea and the western Equatorial Pacific (Matear et al., 2013 and 2015) that are not reflected by the non-eddy resolving models. In the Australian region, the changes in net primary production tend to decline along the east coast and increase along the north coast, the Tasman Sea and the Southern Ocean. As with ocean warming, the trend in Northern Australia is uncertain due to the La Niña bias in the atmospheric forcing fields used. The increasing net primary productivity in the Tasman Sea and Southern Ocean and declining productivity in the subtropical water off east Australia are consistent with previous studies (medium confidence). However, modelling net primary productivity is complex, resulting in low confidence in the magnitude of change.

Summary

The oceans absorb heat and carbon as rising atmospheric CO_2 warms the planet. Ocean warming and acidification are observable long-term trends with chronic and acute impacts on marine organisms and ecosystems. Warming and acidification are evident in all marine environments around Australia. The warming trend will change the occurrence of extreme heat events like marine heat waves.

Confidence

For ocean warming and ocean acidification, there is high confidence in the direction of change, medium confidence in the magnitude of change and low confidence in the ecological consequence of the changes. (consistent with IPCC AR6).

Limitation

The future ocean simulation presented is not well suited to representing the high-resolution dynamics and features of Australian coastal areas.

Table 23: Summary statistics for marine extremes.

	Current	Future		
Metric	**GWL 1.2**	**GWL 1.5**	**GWL 2.0**	**GWL 3.0**
Sea surface temperature [°C]	**23.4 °C**	**+ 0.3 °C** *High confidence*	**+ 0.7 °C** *High confidence*	**+ 1.3 °C** *High confidence*
Marine heatwave duration [days/year]	**18**	**+ 22 days** *High confidence*	**+ 77 days** *High confidence*	**+ 161 days** *High confidence*
Marine heatwave magnitude [°C]	**0.02 °C**	**+ 0.05 °C** *High confidence*	**+ 0.19 °C** *High confidence*	**+ 0.61 °C** *High confidence*
Degree heat week mean	**0.004**	**+ 0.03** *High confidence*	**+ 0.16** *High confidence*	**+ 2.07** *High confidence*
Aragonite saturation state – Acidity	**3.38**	**- 0.18** *High confidence*	**- 0.40** *High confidence*	**- 0.80** *High confidence*

Additional information

The github page contains code, figures and additional information https://github.com/AusClimateService/hazards-ocean.

References

The data displayed come from a future simulation that uses the multi-model mean forcings from RCP8.5 projection to drive an ocean eddy-resolving model (OFAM3). The references related to these OFAM simulations are summarised below:

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6. Accessing data, scripts and supporting information

6.1. Accessing data

Data on NCI

At the time of writing, ACS data and information on NCI is being held in three projects. Summary information is provided in Table 24. Note that project membership is required to access data in the project and a compute allocation is required to undertake analysis of data in-situ on NCI.

Climate projections data on NCI can be interrogated using a bespoke tool, the 'Data Finder'. The tool allows users to a) list available datasets filter them based on attributes such as the GCM or RCM and years. The tool and supporting documentation can be accessed at https://github.com/AusClimateService/dataset_finder.

Table 24: ACS Climate projections and hazard information on NCI.

Information	Regional climate change projections	Key hazard summary products	ACS Hazard Information
Project ID	kj66	bk45	ia39
Content	• One-stop shop for climate projections • Data have been regridded to common resolution of 5 km • Original and bias adjusted data are available	Key hazard products developed for Climate Hazard Portal	• Hazard information produced by ACS hazard teams (with some exceptions) • Includes intermediate steps, figures and summary statistics
Access	Requires project membership	Requires project membership	Requires project membership
Target audience	• Hazard Teams • ACS Partners, • Anyone requiring access to the underpinning climate projections (researchers, technically versed customers) • Potentially ACS Platform	Developers of the Climate Hazard Portal	• Hazard Teams – working area • NCRA Risk Teams – accessing hazard information • Users with technical skill to analyse large volumes of data

6.2. Metadata

Metadata for the hazard information presented in this report is summarised in a spreadsheet and can be accessed on the ACS GitHub pages https://github.com/AusClimateService/HazardMetadata/tree/main

This covers:

- The descriptive name of the dataset
- A description of the index used
- A DOI (where applicable)
- The period for which data is available
- The spatial extend over which the information is available
- The spatial resolution
- The Global Warming levels for which data is available
- Additional information
- The path to access the hazard information on NCI

6.3. Supporting documentation

Publicly accessible GitHub (https://github.com/AusClimateService pages provide supporting documentation on

- Hazard Information
- Bias correction
- Downscaling
- Model evaluation
- Links to relevant Python scripts