Department of Planning and Environment

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Climate datasets for assessing climate risk in regional water strategies

Volume 1: Design approach

July 2023

Acknowledgement of Country

The Department of Planning and Environment acknowledges that it stands on Aboriginal land. We acknowledge the Traditional Custodians of the land and we show our respect for Elders past, present and emerging through thoughtful and collaborative approaches to our work, seeking to demonstrate our ongoing commitment to providing places in which Aboriginal people are included socially, culturally and economically.

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Executive summary

The NSW government through the Department of Planning and Environment -Water (DPE Water) undertakes policy development and planning to provide for water availability and water security outcomes for the various key water dependent sectors, including human needs, environment, cultural needs, and industry. The department has been developing regional water strategies to understand the water availability and security outlook several decades into the future. These strategies are underpinned by a comprehensive understanding of water availability and demand.

Policy and planning settings need to be evidence based, with much of this derived from the department's water models. The key input to the water models for understanding water availability in time and space is rainfall and evaporation. Until recently the department relied on historical observational data as representative of future climate, and therefore adequate for water policy and planning. However, several lines of evidence have emerged that this data has limitations in understanding plausible future climate that will affect water availability.

These lines of evidence include the major droughts experienced in the last two decades and at the other extreme the recent floods in NSW. More and longer paleoclimate records are also being completed that better describe rainfall variability for past centuries and millennia before we started collecting rainfall data. These paleoclimate records reveal periods in the past where extended dry conditions were far more prevalent than in recent times. The other principal line of evidence that the future will be different than the past is derived from the climate models used to assess the change in climate caused by increasing greenhouse gas emissions.

The department along with the research community has developed an approach to better understand the plausible future climate by integrating these three lines of evidence; the deep past from paleological climate evidence, the recent past and current from observed climate data. These were used as inputs to a stochastic model to develop 10,000-year extensions of natural climate variability. These were then combined with projections of future changes from NSW government's regional climate modelling program. This approach is an evolution of the method used to develop climate risk data for the Greater Hunter regional water strategy commenced in 2016.

Given the innovations with this approach and the scale of this implementation, a draft of this report describing this approach was presented to an independent expert panel to review the suitability of the approach for the intended purpose. The following report includes some refinements of that initial draft. Further detail of outcomes from the independent expert panel review and work we have done towards implementing this will be published in more technically detailed reports.

Introduction

Water planning in NSW

The NSW Government bases water policy development and planning on community expectations and on our understanding of water systems and resources. We have developed our understanding from lived experience of existing climate conditions, and from data that our communities have recorded. These data include historical hydroclimatic data such as streamflow, rainfall, temperature and evaporation.

We use these data as inputs to computer models that represent the physical, behavioural and management aspects of our river systems. Allocation rules for managed river systems in NSW guide how we share water between the environment and holders of different classes of water access entitlements. Legislation and policy guide the allocation rules, with input from the community. We use computer models to assess outcomes of these water allocation arrangements.

Regional water strategies

The NSW Government, through the Department of Planning and Environment – Water (the department), is developing 12 regional water strategies for the long-term resilience of water resources. The objective of the Regional Water Strategy program is to deliver resilient water resources for the environment, towns and communities, Aboriginal and Torres Strait Islander communities, agriculture and other industries.

These strategies include policy, planning and infrastructure solutions. The department will base the strategies on evidence to ensure that they meet current and future water needs. The evidence will include improved data and knowledge about the risks arising from climate variability and change. This will improve the strategies, and so improve our ability to deal with extreme events.

Other uses for climate data

The department uses climate data for the strategies and for other ongoing and program-based areas of water management, including:

- policy development
- water-sharing plan development
- annual and long-term diversion compliance
- determining floodplain harvesting entitlements
- infrastructure business case analysis.

Changes to data needs

Procedures for deciding how water is shared between different user groups were developed using historical observed climatic conditions. Our understanding of conditions is based on rainfall and temperature data collected since the 1890s and evaporation data collected since the 1970s. We use climate data in computer simulation water models of NSW river systems. These models assess how well we achieve outcomes for water-dependent sectors for different climates, management arrangements and levels of development.

Concerns are increasing that changes in climate resulting from increased greenhouse gas emissions may make average climate conditions drier, and droughts more severe, in NSW.

The greatest risk to water security is during extreme droughts. At these times, not enough water is available to meet critical demands. The vulnerability of water-dependent sectors to extreme droughts is a concern, especially for critical human water needs, high-value permanent plantations, and key environmental assets. This vulnerability increases if we encounter droughts more severe than those in the data collected since 1890. Based on long-term paleoclimate records, such droughts are not only possible but probable, and climate change may make them more severe.

New ways of modelling climate variability and change

The Regional Water Strategy program committed to fully assessing such vulnerabilities by developing a deeper understanding of the climate risks that will affect water security. This includes extending our understanding of extreme drought occurrence under natural variability and working to understand how the climate will be different, based on contemporary climate change science.

The department will assess the resilience of water systems to more extreme variability and climate change under modelled water management outcomes. We will do this by testing it with a wider range of plausible climate datasets than we used to develop existing water management arrangements (NWC 2010). For a given scenario, our water models will be used with various input datasets, each of which will lead to a corresponding output dataset.

This will test our existing water-sharing arrangements and identify vulnerabilities in important outcomes for water security, such as urban centres running out of water for extended periods, insufficient water to maintain ecosystem health, and decline in reliability of water supply for agriculture. We will assess these effects within a risk framework of consequence and likelihood and formulate and test options to reduce these vulnerabilities.

The outputs of the models will still include significant uncertainty. The department must understand and communicate this uncertainty, and its effects on modelled water-security outcomes. We must consider this alongside other sources of physical and behavioural uncertainty that affect the availability and use of water in our river systems.

These new methods for modelling climate variability and change are a major improvement compared with historical practices, and they provide a better basis for understanding climate risk to water security. We have designed these methods to allow for better data and methods as science and policy evolve.

Purpose of the report

The department has prepared this report to describe how we develop the climatic risk datasets for regional water strategies. Reporting has also allowed an independent expert panel to review our approach and has given us an opportunity to explain our reasoning to the community as part of the regional water strategy program.

The paper is not meant to be highly technical; more technical information is in the references. Also, while this report primarily discusses science that informs climate risk, other sources of uncertainty such as economic and societal factors also affect decision-making (Dessai et al 2009; NWC 2010). Methods to deal with scientific uncertainty and other sources of uncertainty are also discussed in Brown et al (2012) and Culley et al (2016).

In the time elapsed since the first independent expert review, much work has been done to implement this approach for most regional areas of NSW. This work will be reported in more detail in planned reporting, including publishing reports from consultancy work we commissioned to develop the new climate data sets and to advance the science.

Water modelling framework

The department is the regulator and policy maker for water resource management in NSW. We build and use water models to inform water policy, planning proposals and decisions about water availability and use. These complex water models consider the interactions between many different biophysical and management processes (Figure 1). The department has developed water models for all regulated and most unregulated river systems in NSW.

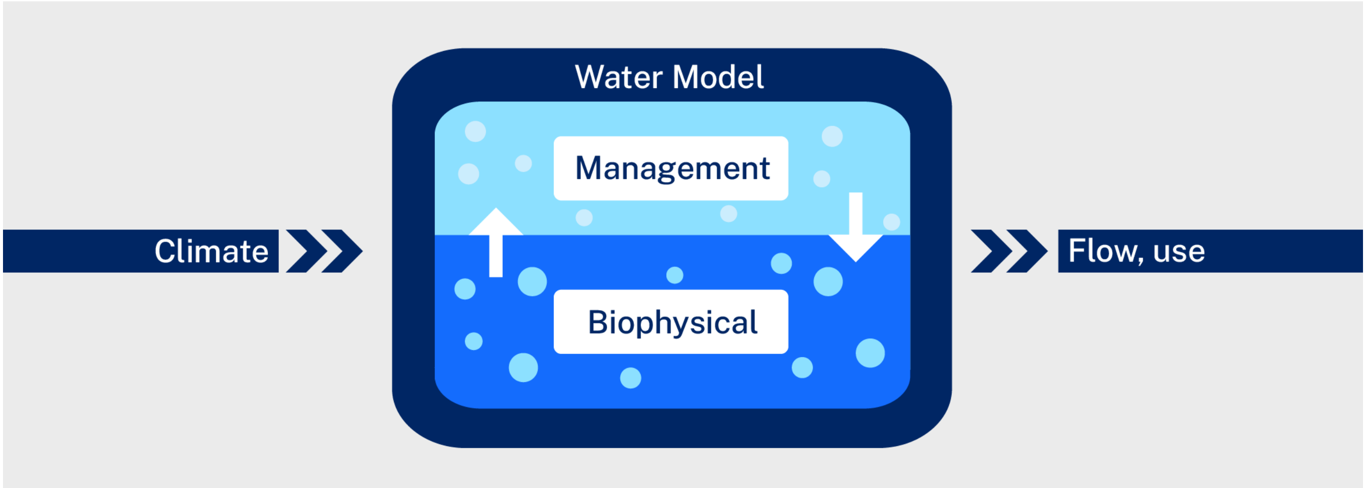


Figure 1. Simplified illustration of water models used to inform the Regional Water Strategy program

What we measure

For simplicity, Figure 1 indicates that the models only produce flow and use data, whereas the models can produce a vast array of different types of results at many locations in the river system, which help us understand water security and flow variability. Examples of metrics include:

- flow events that produce environmental benefits and how often they happen, their size, and the length of time between these events
- the percentage of time that water cannot meet urban demand
- the reliability of supply for the irrigated agriculture sector.

Figure 2 shows an example of modelling the volume of water stored in a headwater storage over 16 years, with changes caused by inflows, evaporation, and releases of water to meet downstream environmental and consumptive demands. The plot shows that the storage is partially filled at times, and at other times is empty. Low-volume periods are periods of low water security caused in part by dry conditions. A metric of the percentage of time a storage is empty, assessed over a significant period of climate variability, helps us understand vulnerability in water security for urban supply this storage provides. Other metrics give information for other categories of user or environmental outcomes.

The effects of climate change on these metrics will depend on how much rainfall patterns change and the potential loss of water through evaporation. We can calculate effects on water security when we route all such inflows through the water model.

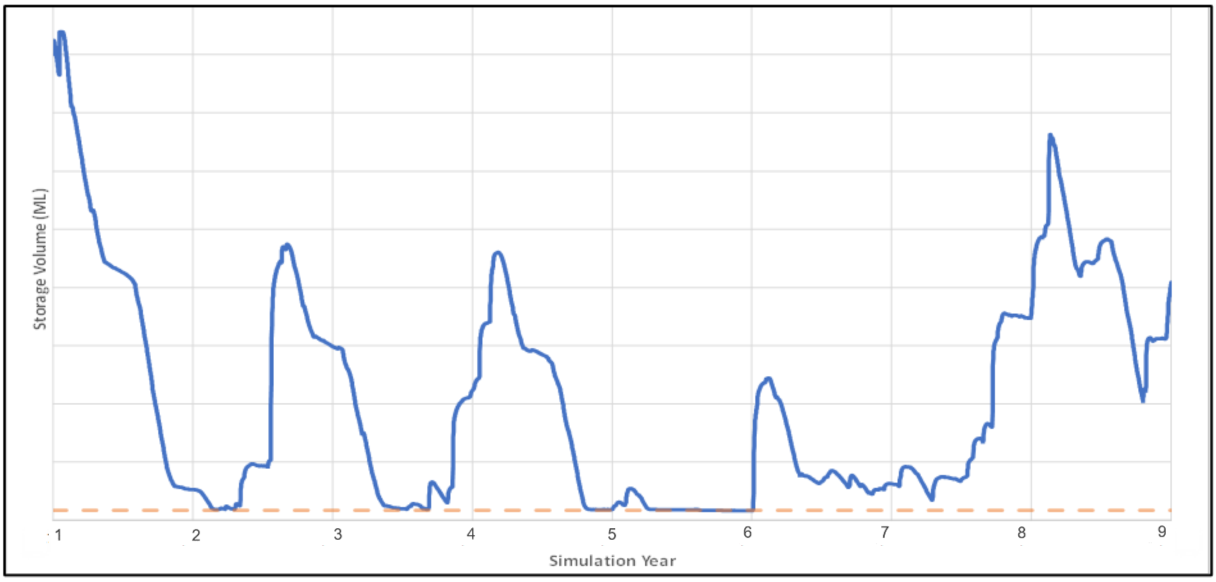


Figure 2. Modelled volume of water stored behind a headwater dam over 9 years

Figure 3 is an example of how sensitive inflows are to climatic changes. This example shows reduced flow when there are higher evaporation rates, as we would expect when the same rainfall is on a drier soil, and from the combination of lower rainfall and higher evaporation. Note the effect is more pronounced when there is lower rainfall.

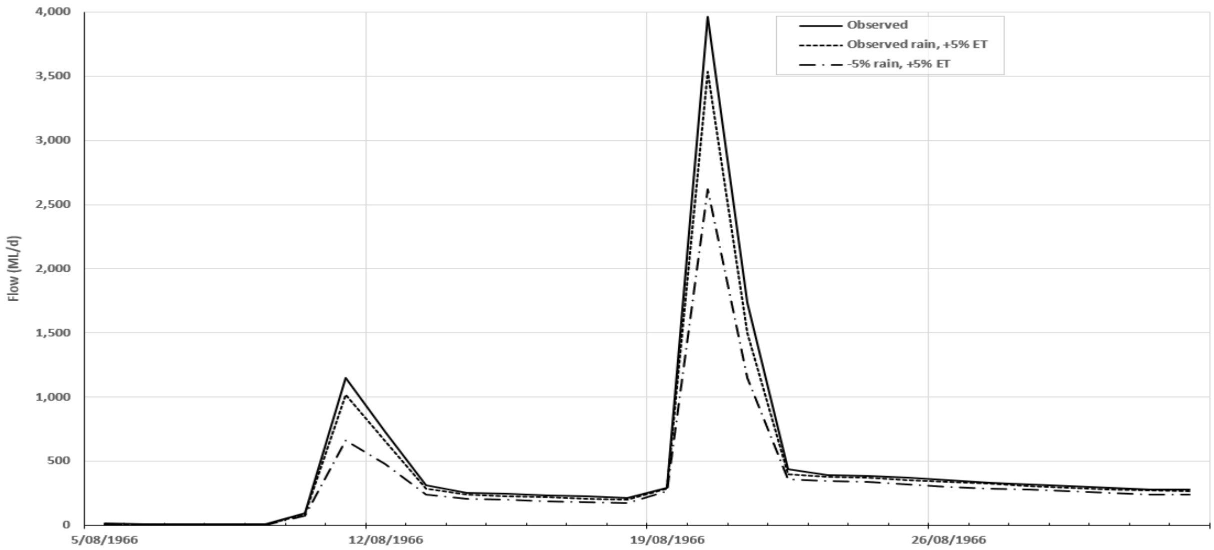


Figure 3. Modelled sensitivity analysis of changes in flow from historic climate, with 5% increase in potential evapotranspiration, and combined with 5% decrease in rainfall

Climate data for risk assessment

Adaptation to climate risk

We have developed climate risk datasets that will better inform risks to water security. These datasets allow the department to use a more thorough understanding of climate variability and plausible climate change.

To represent past climate variability comprehensively, we are developing stochastic datasets. We base these on the statistical characteristics of climatic conditions over the past 500 years, which we reconstruct using indirect measures of climatic conditions, known as paleoclimate data.

Ongoing analysis of global climate modelling inform the development of our datasets. These show plausible future changes in climate. Confidence in the direction and scale of these changes varies, and there are challenges in turning these results into a form we can use in our water models.

The level of confidence in modelled climate change outcomes varies across NSW. For some regions, different climate models show similar change outcomes which are supported by recent observations and meteorological principles. However, for other regions, different climate models show quite different outcomes, and recent observations do not indicate changes in rainfall.

The other challenges include the spatial resolution of the data and the comparatively short length of the daily time step datasets. We plan to use these results accordingly and will advise decision-makers how confident we are about these modelled datasets.

Historical data characteristics

Spatially extensive rainfall data have been collected since the late 19th century and are stored primarily on databases held by the Bureau of Meteorology. Standardised evaporation measurements have been collected since the early 1970s. These data are accessible through the Queensland Government's SILO database, which has infilled missing data to give consistent, complete data across Australia for all climate variables.

Figure 4 shows annual rainfall totals over the period 1890-2022 at a site in the Central West region of NSW, along with the cumulative departure from the mean of this data (also known as a residual mass curve – RMC). The positive or negative gradients for segments of the RMC indicate periods of above- or below-average rainfall, respectively. The annual rainfall totals are colour-coded as terciles. Red indicates the driest one-third of years and dark blue the wettest. This allows us to visualise variability over multiple decades and helps us interpret variability from year to year. The black line is the cumulative departure of these annual totals from the mean.

This figure shows a decade of positive gradient in the RMC, followed by 5 decades of negative gradient, then a further 5 decades of positive gradient. The average annual totals for these periods across multiple decades are 10% lower or higher than the long-term average, respectively. The annual totals show clusters of dry years during the RMC period with the negative gradient, and clusters of wet years during the RMC period with the positive gradient. 'The graph also illustrates how wet years still occur during overall dryer periods (for example 1896–1949), and dry years during overall wetter periods (such as 1950–2000). This characteristic is typical of much of inland NSW.

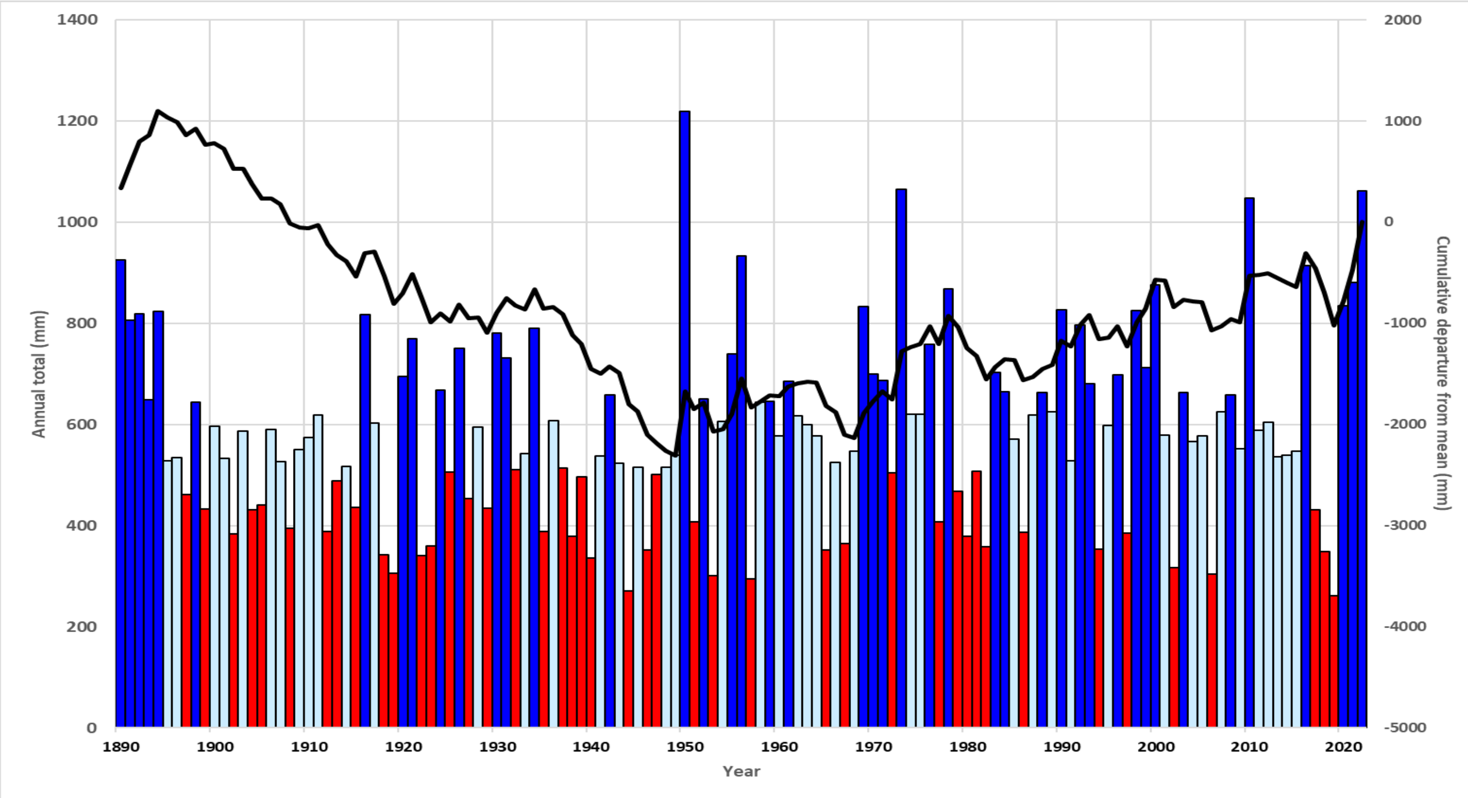


Figure 4. Rainfall variability from 1890 to 2022 in NSW's Central West region.

Note: dark blue columns represent years with rainfall in highest tercile (33%) of annual totals, light blue columns represent years with rainfall in middle tercile of annual totals, and red columns represent years with rainfall in the lowest tercile of annual rainfall. The black line represents the cumulative departure from the mean of the annual rainfall.

Climate drivers of rainfall

Understanding the key climatic drivers operating in the region of interest helps us develop better datasets to assess climate risk. This is consistent with the approach taken by Kiem and Verdon-Kidd (2013) for flood hazard assessment. Figure 5 shows those drivers affecting rainfall.

These drivers have a natural variability that could change with increasing greenhouse gas emissions. The strengths of these drivers depend in part on the distribution of unusual oceanic temperatures and their interaction with the atmospheric circulation pattern.

In some cases, how these may change is understood reasonably well from climate change science research and modelling. For example, the polar drift in the subtropical ridge and changes in the frequency and seasonality of east coast low weather systems (Pepler et al. 2016) are reasonably well understood. However, in most cases, we cannot be sure if these drivers will increase or decrease or by how much.

The relative importance of key climatic drivers varies for different parts of NSW. By characterising NSW as either north or south, and as either inland or coastal, we can summarise the dominant drivers:

- northern inland: Interdecadal Pacific Oscillation (IPO) and El Niño–Southern Oscillation (ENSO)
- northern coastal: IPO and ENSO
- southern inland: IPO, Southern Annular Mode and Indian Ocean Dipole
- southern coastal: East Coast Lows

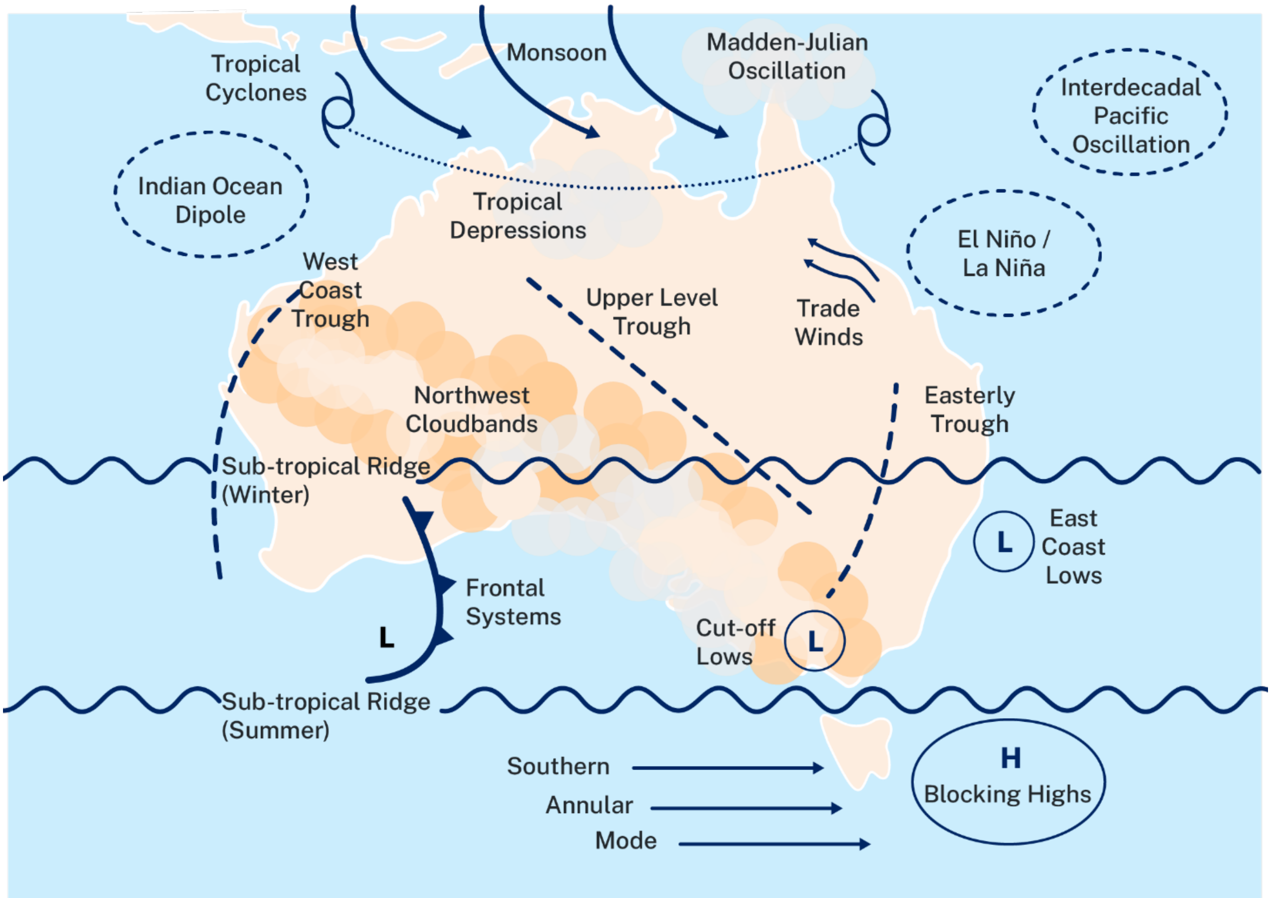


Figure 5. Climate drivers influencing rainfall across Australia. Source: Modified from www.bom.gov.au/watl/about-weather-and-climate/australian-climate-influences.shtml

The influence of the IPO on rainfall is illustrated by analysing the rainfall records based on whether the IPO is positive or negative. Figure 6 shows an instrumental record of IPO. An analysis of mean annual rainfall for sites in the Macquarie catchment based on IPO phase shows that rainfall is on average 10% lower in IPO-positive phases (refer to Figure 7).

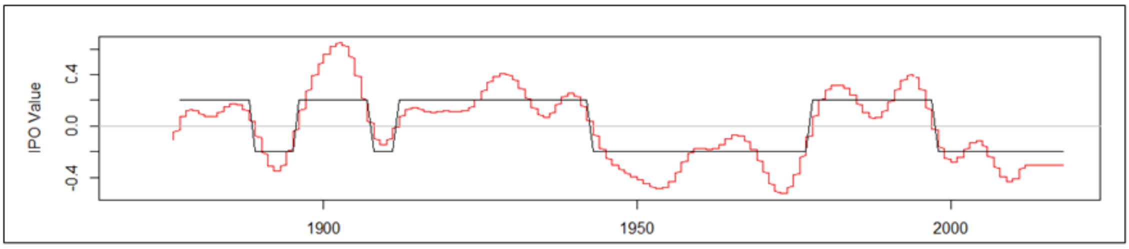


Figure 6. Time series of observations of the IPO (jagged red line) showing positive and negative states (angular black line) Sources: Henley et al. (2015), Leonard et al. (2019)

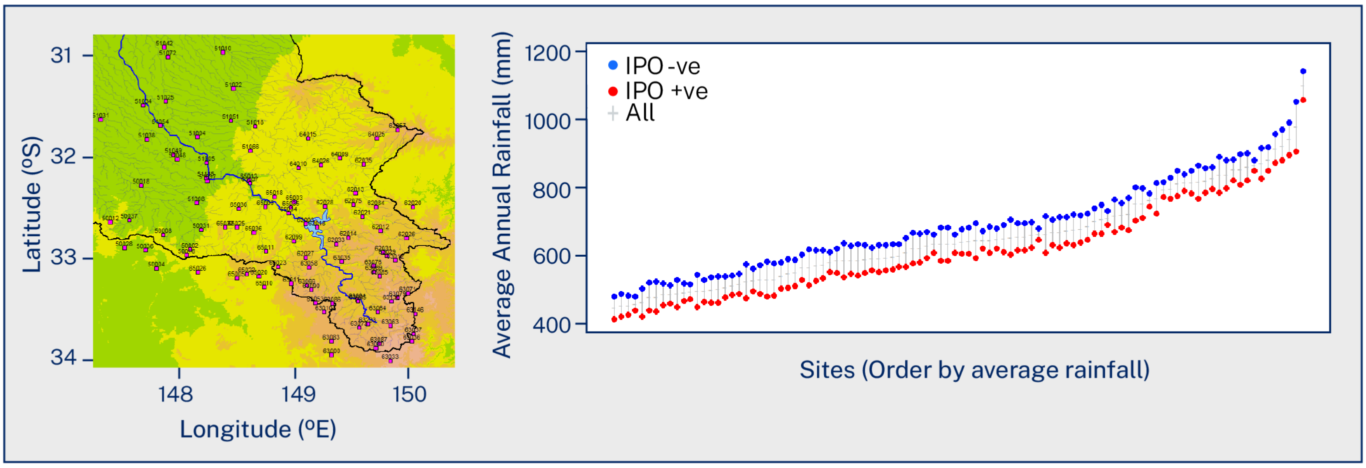


Figure 7. Rainfall sites in Macquarie catchment (left) with mean annual rainfall reported by IPO phase (right panel)

Source: Leonard et al. (2019)

Paleological climate

To learn what regional climates were like in the distant past, scientists study evidence such as tree rings, coral cores, cave deposits and ice-core salinity (see Gell et al. 2009; Vance et al. 2015). These records are expressed as a semi-quantitative time series of relative wetness or dryness. They give us information on how the climate varied from year to year, and wet and dry periods in the time before observational records.

An interpretation of several sets of these records was used to extend the IPO records shown in Figure 6 back to the mid-16th century (Figure 8). This shows that comparatively more time was spent in the positive IPO phases and previous centuries were likely drier than those for which we have observational records. A paleological record based on Antarctic ice-core salinity was developed extending back 1,000 years (Figure 9). This indicated there were droughts over several decades in the 11th to 14th centuries, a degree of persistence well outside the range in our observational record.

This tells us that using the observational record alone to characterise climate variability from year to year and over multiple decades underestimates extreme droughts. We should consider this in our methods to develop climate risk data.

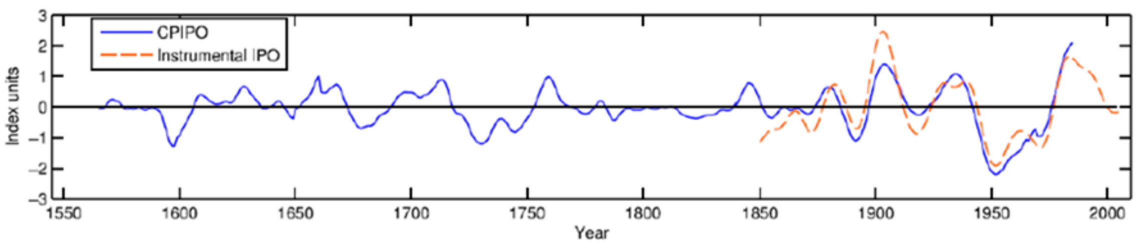


Figure 8. Comparison of the instrumental IPO time series to the combined paleo IPO time series, 1550 to 2000 CE
Source: Henley et al. (2011)

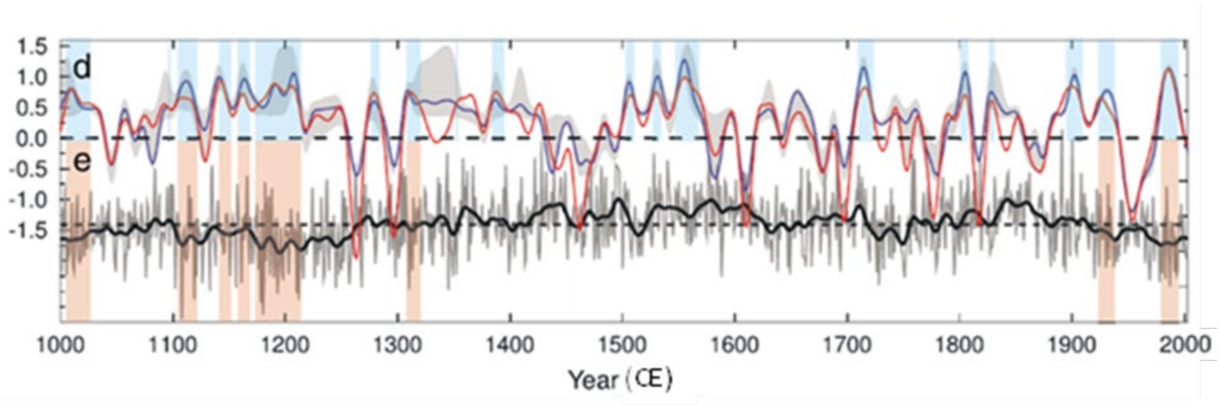


Figure 9. Paleological climate reconstruction from Antarctic ice-core analysis, 1000 to 2000 CE

Notes for Figure 9: Red and blue lines give reconstructions of the IPO index using two methods. Light blue banding gives IPO-positive phase. The solid black line gives sea salt concentrations and pink bands give likely droughts.

Source: Vance et al. 2015

Stochastically extended datasets of climate variability

Natural variability of wet and dry periods is an important characteristic of NSW's climate, so we must include variability as we use stochastic methods to understand climate more comprehensively. The process of extending climate data starts with simple stochastic generation from observational climate data. We can increase the complexity of data generation by considering persistence of climatic conditions and major drivers of natural variability.

For decades, scientists have analysed water security by stochastically generating extended climate sequences for climate risk. They have used the statistical properties of observed rainfall and combined these with a random component to generate multiple replicates of rainfall with similar statistical characteristics. We can incorporate persistence – in the form of extended sequences of wet and dry years – into statistical models to produce stochastic data with more extreme wet and dry sequences. From a sample of several decades of rainfall data, we can generate and analyse limitless years of data, although typically a few thousand years would be enough to characterise variability.

We generate climate sequences in such a way that they are synchronised across our regions that are naturally hydrologically connected such as in the Murray-Darling Basin, and regions where infrastructure options to transfer water between regions may be assessed.

The department's approach is to start by generating extended climate sequences for all climate stations used in our water models, using the historical dataset alone. We then repeat this, incorporating an extended paleoclimatological record of IPO to build in variability across multiple decades. It is mainly climate research institutions that have the expertise to do this work.

The steps in generating paleo-stochastic datasets are:

1. generate IPO-phase data
2. generate stochastic annual totals
3. generate monthly totals
4. generate daily totals
5. combine the data from steps 1 to 4.

Historical data are stratified based on whether they occur in the negative or positive phase of the contemporaneously observed IPO. The methods develop multisite statistics from these separate datasets for rainfall and potential water loss through evaporation. They generate separate sets of stochastic data for each IPO phase. An independent IPO phase is generated using a longer sample of IPO phases, which is developed from paleoclimatological studies. Figure 10 shows a 1,000-year sample of generated IPO phases.

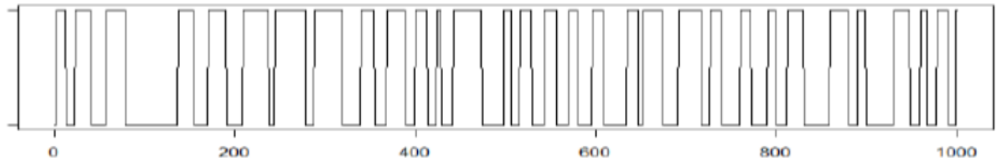


Figure 10. Generated IPO phases for a 1,000-year sample
Source: Leonard et al. 2019

The separate, stochastically generated datasets of rainfall for a corresponding length of time are then spliced together, depending on whether the IPO is in positive or negative phase. Figure 11 illustrates the full process.

Figure 11. Combining stochastically generated climate data with stochastically generated IPO-phase data

Climate change

The statistically extended datasets incorporating paleoclimate information represent climate variability comprehensively. However, these data assume climate is stationary. Climate change means this assumption is not valid, and that the future climate will be different. In this section, we discuss what that difference may be, and how the department will factor this difference into climate risk datasets.

The differences in which we are interested are in the primary climatic variables used in water balance modelling – rainfall and potential evapotranspiration. The characteristics of rainfall are of particular interest because they affect water availability. These characteristics include daily and seasonal distributions and variability between years and across multiple decades. Because of evapotranspiration's lower variability and its spatial coherence, we are mostly interested in changes in seasonal averages.

The main sources of information about change are observed data and climate models. It is statistically difficult to attribute climate change as a causal factor for observed data because of the high natural variability in NSW. It could, however, be considered as an additional line of evidence. For this reason, we rely on climate models for information on likely changes. These also have considerable uncertainties and limitations, and the challenge is working with these.

Climate models

Most of the predictions about how climate will change in the future come from general circulation models (GCMs). These are physically based simulation models. They mathematically represent the interactions between the physics and chemistry of the entire major atmospheric, oceanic and land-based processes that affect climate. To do this, the GCMs divide the globe into separate 3-dimensional layers from the deep ocean to the top of the atmosphere (Figure 12).

Major research institutions around the world develop these large, complex, computationally intensive models. The United Nations' International Panel on Climate Change (IPCC) bases its periodic assessments on GCMs. Fuller description of all 41 models, including assessments of their abilities to make realistic projections of climate, is beyond the scope of this paper, but are readily available (IPCC 2013).

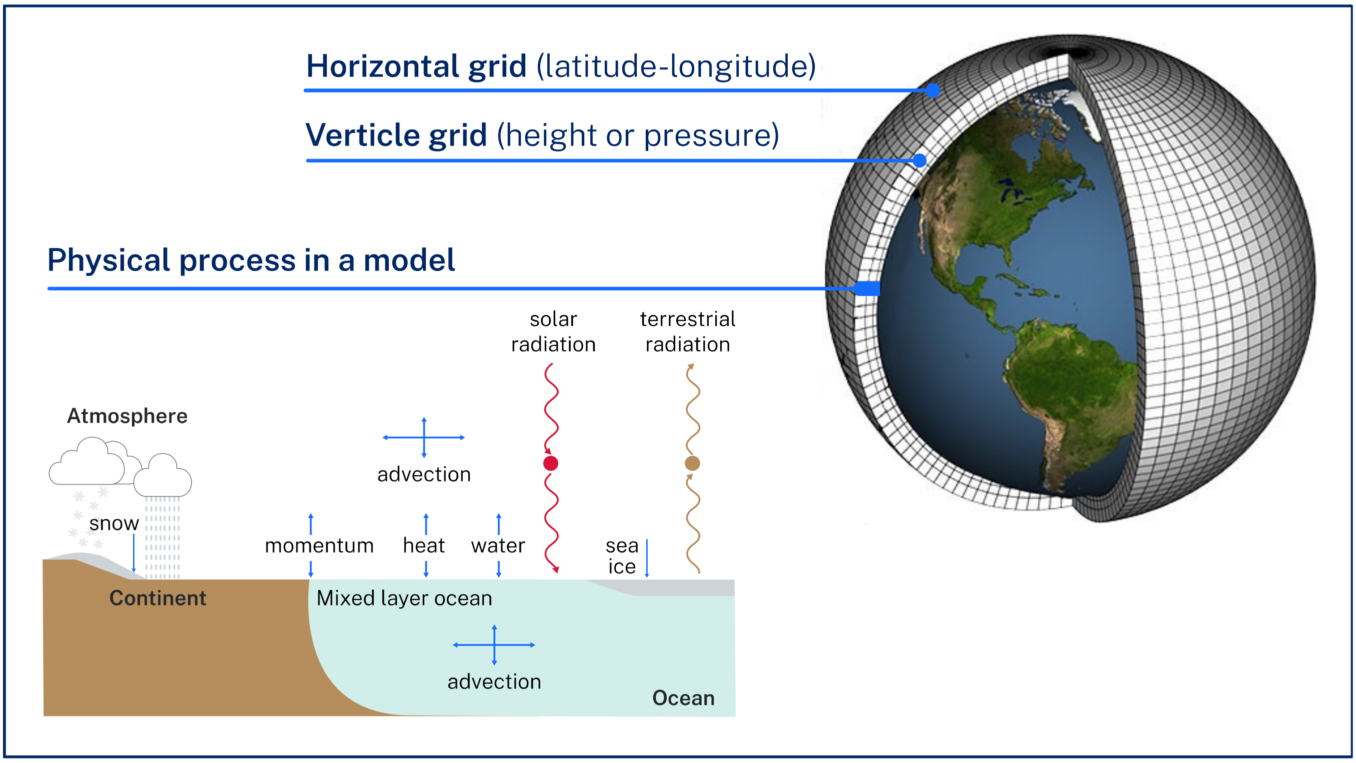


Figure 12. Simple schematic of a general circulation model
Source: www.climate.gov/file/atmosphericmodelschematic.png

The main challenges in using the information from GCMs for climate risk assessment include understanding the uncertainties in projected changes and formulating these changes as inputs to use in our water models.

The level of skill of GCMs in simulating climate parameters can inform the uncertainty in projections of change. This skill is assessed by comparing modelled results with observations. Higher skill scores indicate higher confidence that projected changes are robust. For example, GCMs have a high level of skill in simulating temperature, and therefore projected simulated increases in temperature are likely to be robust.

GCMs generally have less skill in modelling all aspects of rainfall variability, based on comparisons with observations. While the models may, for example, be able to reproduce a probability density distribution of daily rainfall well enough compared to observations (Perkins et al. 2007), they cannot generally satisfactorily reproduce important characteristics that affect water security. These include seasonal distributions and distributions between years or across multiple decades. This is a factor affecting uncertainty in projections of rainfall, given global warming.

An indication of uncertainty in GCM results comes from comparing modelled rainfall to observed rainfall. The GCMs used are simulated, analysed and reported as part of the Intergovernmental Panel on Climate Change Coupled Model Intercomparison Project (CMIP). Results of mean monthly modelled rainfall from the GCMs used in the fifth phase of this project (CMIP5) are shown compared against observed data for the whole of Australia and five selected regions (Figure 13). The observed data is from the Australian Water Availability Project for a 20-year period of record from 1986-2005.

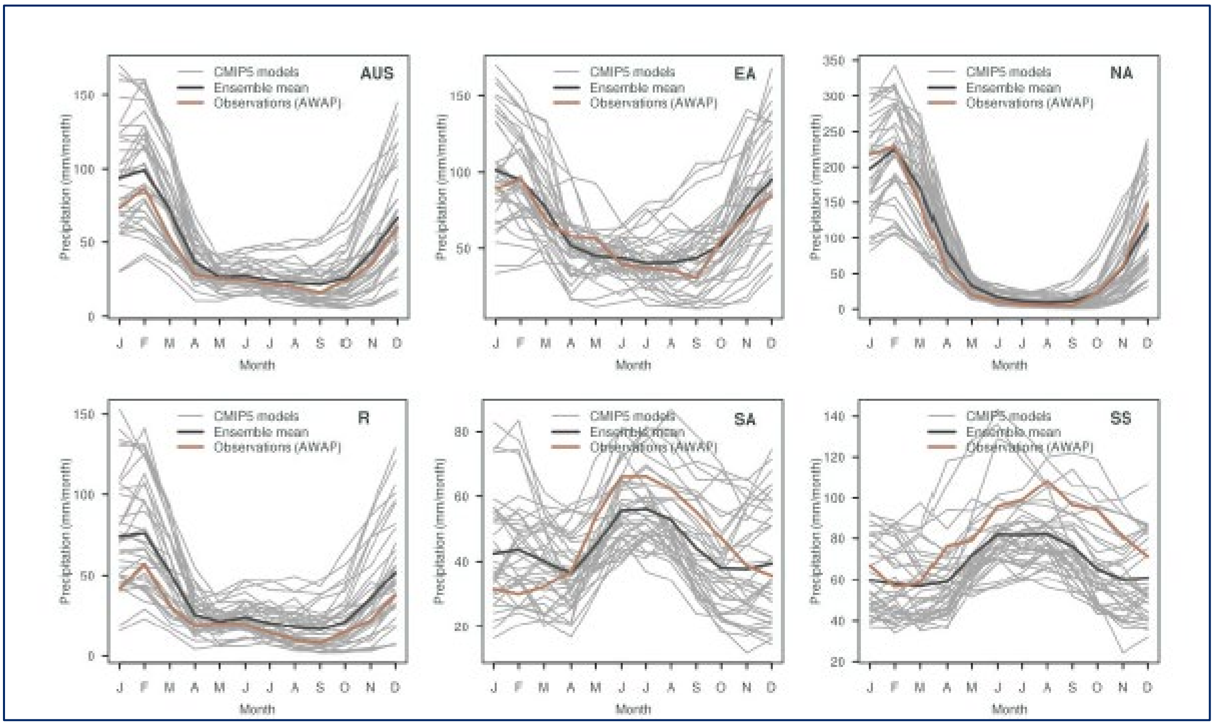


Figure 13. Average annual cycles of rainfall for Australia and selected regions from CMIP5 models

Note for Figure 13: The regions are respectively: Australia (AUS); East Australia (EA); North Australia (NA); Rangelands (R); Southern Australia (SA) and Southern Slopes (SS). Each grey line gives the results from a model simulation. The black line gives the ensemble model mean, and the brown line gives the average observations (averaged over period 1986 to 2005).

This low level of skill in reproducing past climate contributes to uncertainty in the robustness of future climate projections. A further issue concerns the methods often used to estimate percentage changes for rainfall which is highly variable. Because GCMs are computationally intensive, the methods typically calculate change projected as a percentage of average annual or seasonal rainfall for 20-year periods a certain time interval apart, for example 30 or 50 years. Depending on whether the 20-year reference period is relatively wet or dry (which depends on natural variability), the projected change could be positive or negative.

Regardless of the skill of a GCM in modelling rainfall, this method of computing change is not entirely robust. The issue with using this method is illustrated in Figure 14 using observed annual rainfall, effectively a 'perfect' model.

If our 20-year reference period was for example pre-1950 – a dry period, and our period used to calculate change was 30 years later – a wet period, then the method would report a 20% increase in rainfall. Conversely, if our reference period was during the wet period from around 1970, and the period to calculate change was 30 years later during the Millennium Drought, our method would report a 7% decrease in rainfall. Each result is equally valid despite their very different outcomes.

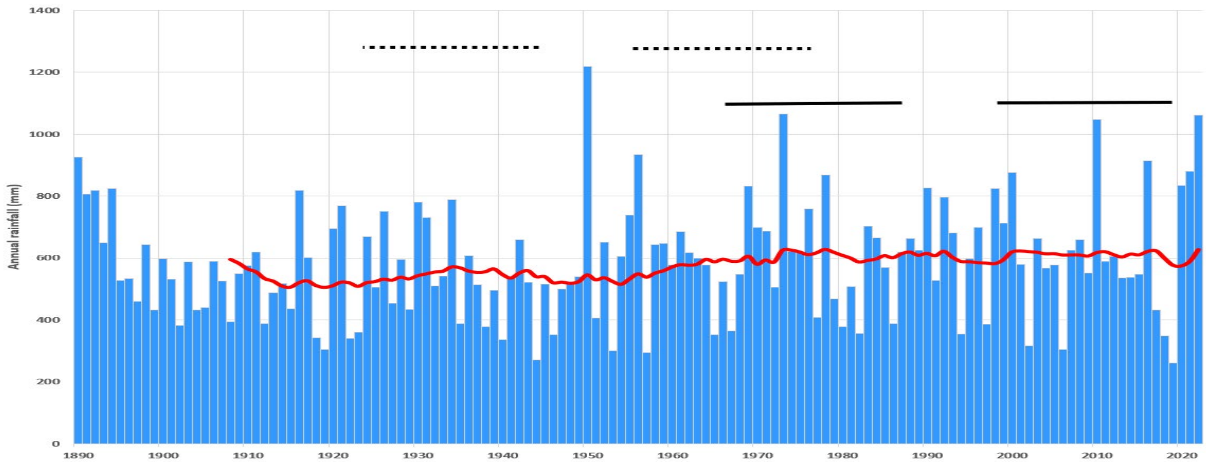


Figure 14. Impact of sampling on calculating change between 20-year rainfall totals for different periods within an observed rainfall time series

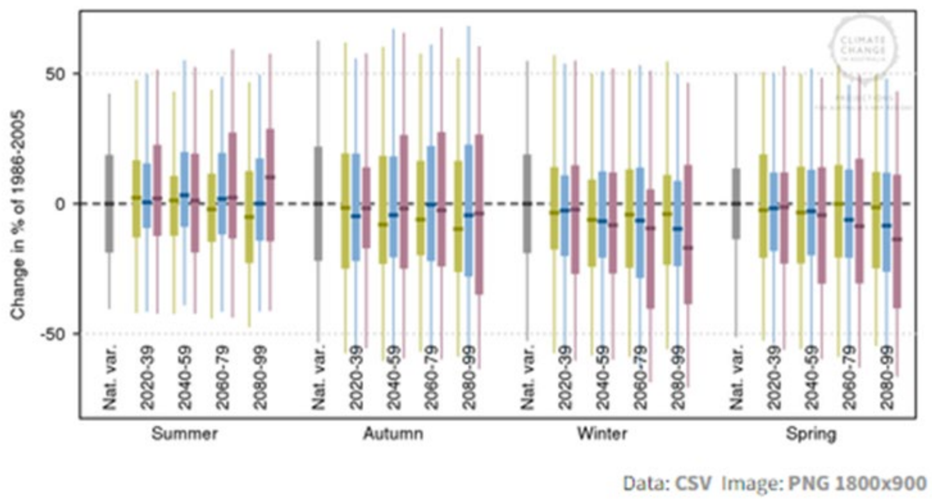
Note for Figure 14: Solid bars show comparison periods with a 7% decrease in rainfall, whereas dashed bars show comparison periods with a 20% increase.

All possible comparisons of this method for the observational data starting from 1890 were calculated by incrementing both the reference and comparison period by a year for the full period of record. These results are summarised in Table 1. Together with the range of individual model results shown in Figure 13 this demonstrates that statements such as '*… rainfall will decrease by 9%*', for example, should be treated with caution and considered with other lines of evidence if possible.

The low skill of GCMs and the short sampling periods used for change calculation combine to produce a wide range of projected changes in rainfall. This is illustrated in Figure 15, in which the range of projected rainfall from the 41 CMIP5 GCMs varies from -40 to +40%, i.e., could be 40% less rainfall or 40% more rainfall. This range generally increases as the level of greenhouse gas emission increases from the less intensive Representation Concentration 2.6 (RCP2.6) to the more emission intensive RCP4.5 and RCP8.5 scenarios. Most projected changes are within a narrower but still significant range of-20% to +20%. Even this narrower range equates to a 30% to 50% change in generated runoff.

Therefore, the uncertainty in changes projected by GCMs is important and would affect decision making related to water outcomes. Any design approach must justify selecting one or more models as a basis for change. Approaches to selecting projected changes predicted by one or more GCM depend on the modelling purpose and should be supported by other lines of evidence, including degree of model agreement on direction of change, observational trends, and other research.

There is relatively little agreement on how much seasonal rainfall in northern NSW will change and the direction change will take. Most projections fall within the range of natural variability. There is more consensus between models about significant reductions in winter and spring rainfall in the southern inland region of NSW, particularly the Murrumbidgee River and Murray River catchments. Other lines of evidence, including atmospheric physics based analysis and atmospheric observations (Timbal and Drosdowsky 2012), also support this drying trend.



Projected change in seasonal precipitation for 2090 (2080-99). Graphs show change in (from left) summer, autumn, winter and spring. Anomalies are given in % relative to 1995(1986-2005) under RCP2.6 (Green), RCP4.5 (blue) and RCP8.5 (purple). Natural climate variability is represented by the grey bar. Bar plots are explained in the 'Understanding the bar plots' section below the map on this webpage.

Figure 15. Projected changes to 2090 in seasonal precipitation compared with 1986 to 2005 for a region in NSW for different emission scenarios

Notes for Figure 15: Anomalies are given in percentages relative to 1995 (1986 to 2005) under RCP2.6 (green), RCP4.5 (blue) and RCP8.5 (purple). The grey indicates natural variability.

Source: www.climatechangeinaustralia.gov.au/en/projections-tools/summary-data-explorer/#

There is also evidence from modelled results of an increase in rainfall intensity, particularly for high rainfall days, a result which is supported by the physics-based explanation that a warmer atmosphere holds more water. For example, a summer rainfall event that may have been 100 mm under historical conditions may be 120 mm in the future, meaning that some medium-to-major floods may be larger.

The other important climatic factor in determining water availability is potential evapotranspiration. The results from GCMs for this are reasonably reliable, partly because potential evapotranspiration is closely related to temperature and the models have good skill in projecting changes in temperature. However, the conversion of potential evapotranspiration to actual evapotranspiration may change compared to the past based on vegetation having a different water requirement in response to increased carbon dioxide levels.

Downscaling climate risk datasets

Results from GCMs have coarse spatial resolution (typically 100-200km grid cells), but water models need data of much finer spatial resolution. Downscaling methods – including factoring, statistical and dynamical downscaling – have been developed to give the required detail (NWC 2010). Dynamical downscaling has been used on a subset of available CMIP3 models for the NSW and Australian Regional Climate Modelling (NARCliM) project (Evans et al. 2014).

In the first phase of this project 4 CMIP3 GCMs were remodelled onto finer resolution grids using 3 different regional climate models (RCMs) to produce a suite of 12 modelled results for 3 different 20-year climate periods (1990 to 2009, 2020 to 2039, and 2060 to 2079).

The modelled results are at daily or sub-daily steps for a suite of climate variables, including rain and potential evapotranspiration. Using the NCEP/NCAR reanalysis dataset (Ji et al. 2016; Fita et al. 2016), dynamical downscaling has been shown to significantly improve the performance of modelled outputs compared with using the parent GCMs. The spatial representation of rainfall more closely aligns with the observed pattern (Figure 16).

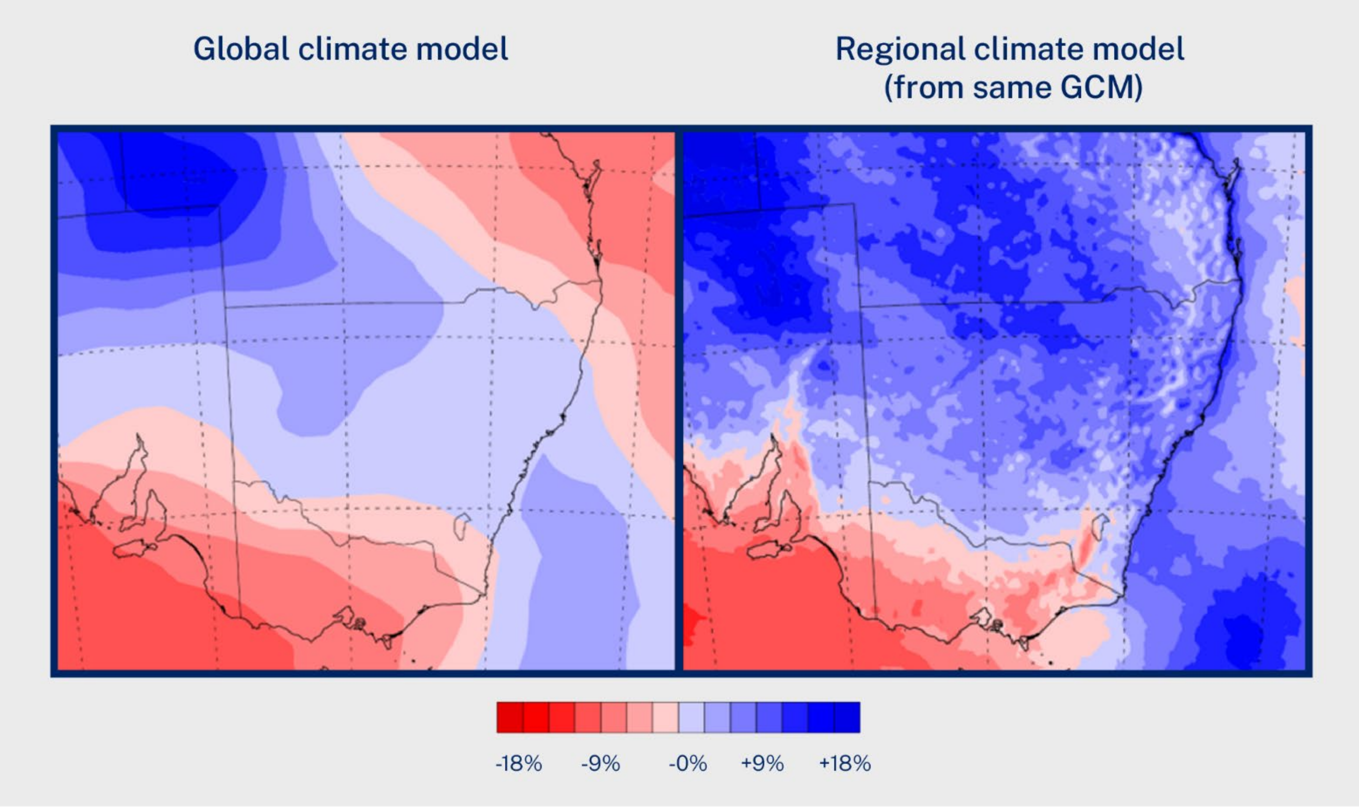


Figure 16. Improvements in spatial variability of changes in rainfall modelling based on NARCliM 1.0 results

Factoring in climate change

The advantages of the NARCliM project's dynamical downscaling approach are a strong reason to use this dataset for including climate change in our climate risk datasets. The conclusions of Ji et al (2016) about the improvement compared with the driving GCM, and the more coherent spatial variability, give a sound basis for using these results in preference to other methods. The dynamically downscaled results from NARCliM are effective for daily and seasonal scales.

However, the NARCliM results do not capture the climate risk arising from changes to variability as they are of comparatively short length. The low skill GCMs have at modelling changes to annual and decadal rainfall variability over longer periods is still an issue in regional climate models derived using these GCMs.

Dessai et al (2009) caution that relying too heavily on a small set of modelling results may underestimate the uncertainty in projections and does not give enough confidence for robust adaptive responses.

We want to include changes in rainfall at all temporal scales: daily, seasonal, between years and over multiple decades. This means that we cannot use dynamically downscaled results to model the characteristics of rainfall variability over the long-term. Variations in rainfall between years and over multiple decades are well represented in the paleo-stochastic data.

How we use the NARCliM rainfall data

We decided that best use of the NARCliM rainfall data at this stage is as a stress test of our water systems. For this reason, we have selected the GCM/RCM combination that had the lowest projected rainfall compared with the present day. We took the monthly ratios calculated over 20-year periods of projected to current rainfall data at the location of each climate station used in the water models. We calculated this from the bias corrected NARCliM datasets and used this to factor the stochastic dataset by multiplication. We also used the potential evapotranspiration results from the same NARCliM scenario to factor the stochastically generated potential evapotranspiration results.

We understand that this tacitly accepts the same limitations discussed with using these ratios (see Figure 14). However, the purpose of this change factoring is to give a lower-bound estimate of water availability to test the vulnerability of water-security outcomes. The models' limitations do not prevent us from using the results to test this objective; the model developed is fit for purpose and can answer the question we are asking.

We apply this method of generating stochastic data from historic and paleoclimate datasets, and then factoring by NARCliM results, to NSW's inland regions and north coast. For the south-coast region, we have based our analysis on changes to East Coast Low seasonal frequency informed by NARCliM. These changes were applied initially based on the available East Coast Low synoptic data (Pepler et al. 2016). We then generated stochastic data from the altered dataset.

Glossary

Term	Description
El Niño-Southern Oscillation (ENSO)	A recurring climate pattern linked to warming and cooling of water in the central and eastern tropical areas of the Pacific Ocean. This warming and cooling tends cycle over periods of 3-7 years, with extreme phases known as El Niño and La Niña, associated with dry and wet conditions respectively in eastern Australia.
Potential evapotranspiration	The theoretical upper limit of combined evaporation from water surfaces and transpiration by plants. Actual evapotranspiration is limited by crop type and growth stage and water availability.
General circulation models (GCMs)	Physically based, computer simulation models of the planet that mathematically represent interactions between the physics and chemistry of the entire major atmospheric, oceanic, and land-based processes that affect climate.
Interdecadal Pacific Oscillation (IPO)	A decadal to multi-decadal variation of climate in the Pacific Ocean basin, analogous to ENSO with a longer timescale and more expansive spatial structure. The different IPO phases have significant influence on rainfall in eastern Australia.
Paleoclimate	Climate of the past inferred from biophysical measurements that are correlated with prevailing climate conditions, such as from tree rings, ice cores, corals, stalagmites, and ocean and lake sediments.
Stochastic climate	Statistically generated time series of climate variables based on random numbers that are modified to preserve statistical properties of the observed climate data on which they are based.
Southern annular mode (SAM)	The north-south movement of a stream of strong westerly winds in the mid to high latitudes of the southern hemisphere, this is associated with rain-bearing cold fronts that bring rainfall to southern Australia.
Indian Ocean dipole (IOD)	A coupled ocean and atmosphere phenomenon in the equatorial Indian Ocean where changes in temperature gradients affect regions of rising and descending moisture and air. The IOD has a connection with ENSO which affects the severity of El Niño and La Niña events, contributing to rainfall variability in Australia.
Stationary/stationarity	Describing a state where statistical characteristics of data do not vary over time.

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