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This project used the R programming language and would therefore like to recognise the efforts of the R-core team and those of RStudio in providing the tools and interfaces that made data analysis and visualisation possible and innovative. This project also used the R\LaTeX\ typesetting system. We would like to recognise the contributors to this system.

A special thanks to Dr Michael Sumner for all his efforts upskilling our team in programming, workflow management, geospatial data and a host of specific programming packages we used within this project.

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Australia’s Wine Future — A Climate Atlas

Foreword

My interest in viticultural climatology goes back to the late 1970s when Richard Smart and I published a climatic classification of Australian wine regions by means of novel indices of temperature, rainfall, aridity, sunshine hours and relative humidity. This was the first time that this had been done in Australia and our aim was to aid vineyard site selection and to provide guidelines for varietal selection, at a time of major change in the Australian wine industry. In hindsight, our methods were relatively simplistic, but they did provide a good platform for inter-regional comparison and a better basis for the discussion of the impact of climate on wine style and quality.

Therefore, I was delighted to learn that a team of well-credentialed climate scientists from the University of Tasmania had been engaged to produce a climate atlas of Australian wine regions. This method of presentation of climatic information is well overdue and will prove to be a most valuable resource. The graphical presentation of climatic indices in a true atlas format allows for easy interpretation, while the details to describe the methodology and approaches that underpin the climate modelling, scenarios development and data analysis are there for those who are technically inclined.

The first part of the atlas is a comparison of the current period (1997 to 2017) with the base period (1961 to 1990). The authors have utilised well known climatic indices, such as Growing Season Temperature, rainfall and aridity, which clearly demonstrate the significant changes that have taken place in all regions over the past few decades. They have also created some novel indices, designed to better represent the physiological requirements of grapevines over the entire year. By doing so they have been able to capture the influence of heat units, for example, at the beginning of the season on the timing of key phenological events (as we are well aware, we have observed the earlier occurrence of budburst and flowering in many regions over the past 20 years). Also, Non-Growing Season Rainfall change since the base period clearly shows the influence of the drying trend in most regions.

The second part of the atlas presents the projected climate across all Australian wine regions out to 2100. This includes detailed presentations for each individual wine region (or Geographic Indication), grouped for each State (WA, SA, NSW, Vic., Tas. and QLD). The evidence is clear. The industry faces many challenges in the future, not only in terms of diminished productivity and declining wine quality in a warming and drying climate but also in terms of increased likelihood of risk of heat stress of vineyard workers.

Congratulations to the authors and to Wine Australia on the production of this seminal work.

Dr Peter Dry AM
Adjunct Associate Professor, University of Adelaide
Emeritus Fellow, The Australian Wine Research Institute
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<td>Australian Gridded Climate Data</td>
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<td>AI</td>
<td>Aridity Index</td>
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<td>AWAP</td>
<td>Australian Water Availability Project</td>
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<td>B-M</td>
<td>The Australian Bureau of Meteorology</td>
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<td>BARRA</td>
<td>The Australian Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia</td>
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<td>CSIRO's Conformal Cubic Atmospheric Model</td>
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<td>Coupled Model Intercomparison Project</td>
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<td>- Has three most common variations CMIP3 and followed by CMIP5 and the current CMIP6, which indicate the experimental configuration of the intercomparisons</td>
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<td>CORDEX</td>
<td>Coordinated Regional Downscaling Experiment</td>
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<td>Commonwealth Scientific and Industrial Research Organisation</td>
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<td>EHF</td>
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<td>Ensemble member</td>
<td>The output from one CCAM simulation driven by one of the six global models</td>
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<td>European Centre for Medium-Range Weather Forecasts re-analysis</td>
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<td>Global Climate Model</td>
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<td>GDD</td>
<td>Growing Degree Days</td>
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<td>RCP</td>
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<td>- Comes in the flavours RCP2.6 (best case), RCP4.5, RCP6.5 and RCP8.5 (worst case, business as usual)</td>
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<td>WCRP</td>
<td>World Climate Research Programme</td>
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Introduction

Over the last century, Australia’s climate has warmed by 1°C, and few regions have been unaffected (CSIRO and Bureau of Meteorology, 2018). Hotter average temperatures, hotter summers, longer heatwaves, more frequent bushfires and changes to rainfall intensity and seasonality have already had impacts across the country, and these trends are expected to continue. Rapid and ongoing climate change has the potential to affect all aspects of the wine industry, including vineyard performance, pest and disease incidence, wine quality and market competitiveness. In recognition of these challenges, Wine Australia funded a collaborative research project to consider the impact of climate variability and longer-term trends in climate on the wine industry.

Australia’s wine future (2016–2019) was a collaborative research project that brought together researchers from a range of disciplines, including climate scientists, viticulturalists and adaptation specialists. The project was led by the Antarctic Climate Ecosystem Cooperative Research Centre (ACE CRC, University of Tasmania) in partnership with the South Australian Research and Development Institute (SARDI), the Australian Wine Research Institute (AWRI), CSIRO Marine and Atmospheric Research and the Tasmanian Institute of Agriculture (TIA).

The Australian wine sector is likely to face challenges as the climate continues to warm, but, in general, grape growers are experienced in responding to short-term climate surprises. In the short- to medium-term, adaptation approaches may be learnt from the regions that are currently experiencing the climate conditions that Australia is predicted to see in the future. Fine-scaled climate information tailored for particular sector applications is vital for identifying such adaptation needs.

Australia’s wine future generated the finest available climate projections for South-eastern Australia and provided detailed information about how the climate may change in the near, mid and long-term time horizons. In addition to providing climate information, the project focused on how climate information can be used to inform adaptation decisions and identify lessons that might be transferable across regions already managing a range of climate challenges.

The main legacy of the project is this atlas of climate information for all Australian wine regions, providing information to grape growers and wine makers about climate trends for the near, mid- and long-term horizons. The atlas showcases the most up-to-date climate information at the finest resolution available in Australia, based on the CSIRO’s Conformal Cubic Atmospheric Model (CCAM). Viticultural indices are presented that describe temperature, heat accumulation, heatwaves, rainfall, and moisture indices. Future trends in mean climate conditions, variability and extremes are visualised with reference to the current and historical climate. High resolution maps and time series for each region are presented to show the projected change in climate indices over time, highlighting the variability within and across the wine regions of Australia. The new atlas will help to answer the question — What will my region’s climate look like in the future? This is essential knowledge for making good management decisions and supporting strategic decisions over the longer term such as changing varieties or vineyard sites both within and between regions. The atlas is an important resource that will help the wine industry understand how climate change could affect grape yield, profitability and wine styles across Australia into the future.
Part I

Introducing the Atlas
Climate change

Natural Greenhouse effect

Greenhouse gases such as carbon dioxide keep the earth warm by allowing radiation from the sun to enter the atmosphere, while trapping a greater portion of outgoing radiation within the climate system. This maintains an average global temperature at +15°C. Without greenhouse gases, the average temperature on Earth would be ~-18°C, too cold to sustain life as we know it.

The amount of energy that the Earth receives from the sun changes over time naturally in response to variations in the sun’s activity and the tilt of the Earth’s axis. The climate of a location is affected by latitude, topography, altitude and proximity to large bodies of water and the associated currents and can only be assessed over long time periods in order to incorporate the natural variability that occurs over several years.

Climate variability

Weather describes what is happening in the atmosphere on a day-to-day basis or at a specific location. This changing state of the atmosphere is a result of interactions between the ocean and atmosphere, and the internal radiation cycles occurring within the sun itself. Additionally, the distribution of tectonic plates influences the climate, especially in the eastern Pacific and the Atlantic, as well as the direction and intensity of weather systems (e.g., hurricanes, tornadoes).

What are climate projections?

Climate projections are outputs from computer models used to represent the Earth’s mean climate state and variability. They are not intended to predict the weather on particular dates but rather to produce a simplified representation to be incorporated into the model.

Regional Climate Models (RCMs)

The complexity of GCMs results in them being configured for coarse resolution (spatial resolution of 50 to 200km, temporal resolutions of 6 hourly timesteps), due to the limitations of current supercomputers. As a result, certain features in the regional climate are poorly represented by GCMs including mountain ranges, coastlines, urban areas and other atmospheric phenomena such as storms and rainfall processes. Downscaling methods are sometimes employed to address this limitation of the GCMs, providing higher spatial and temporal resolution climate simulations for a region (typically improved resolutions of between 1 to 5km resolution, and temporal resolutions of 1 minute to 1 hour timesteps).

Two popular downscaling methods are statistical downscaling and dynamical downscaling. Statistical downscaling relies on historical statistical relationships between observations and climate models to estimate atmospheric variables. Dynamical downscaling employs Regional Climate Models (RCMs) that are based on modelling techniques that are like those used by GCMs, but with the computing resources focused over a region and with a focus on the atmosphere and surface components (i.e., a traditional model where there is less space coverage), including more complex processing power and improved understanding and representation of atmospheric dynamics within climate models.

What are climate predictions/forecasts?

Climate forecasts aim to accurately and precisely predict the weather that will be experienced at a precise place and time in the future. In order to achieve this, climate forecasts use observations to configure the atmosphere within a climate model as it represents the configuration of the actual atmosphere as accurately as possible (at a particular time, usually today or on the day of the forecast). The more accurately the atmosphere is configured, the more likely it is that a forecast model will predict the future. Forecasting has improved such that the accuracy and precision of a 5 day forecast in 2017 is more reliable than a 2 day forecast in the 1970s. Climate models have been improved by advances such as higher resolution observational data archives (due to satellite and surface ocean measurements), increased computer processing power and improved understanding and representation of atmospheric dynamics within climate models.

How well do climate models replicate the climate at different scales?

Scale is a key component of understanding the climate and fundamental to detecting climate change signals. GCMs are run at low resolution, so do not perform well when compared with observations from specific locations, as the gridpoint is representing the average of a vast area rather than a single point, which is affected by local microclimatic characteristics. This means that the grid-scale processes such as cumulus clouds, convection, updrafts and downdrafts in storms are not well represented. These phenomena are linked to small-scale processes that can only be simulated by the GCMs, but with limitations in computing power or limited scientific understanding of the physical processes. They do a good job at simulating global and continental scale-climate and provide a general overview of how the climate is changing. Long term averages of parameters like temperature and rainfall, but other parameters like ocean temperatures, boundary currents and ice cover, are well represented by the GCMs. They are also adept at simulating aspects of regional climate variability, such as the monsoon systems and seasonal changes in temperature, often driven by these dynamic parameters.

Detecting climate change signals at different scales

Detecting climate change signals is about the signal versus the natural variability (or noise) ratio for the area of interest. The larger the area, the more the day-to-day variability is smoothed out, as the area is larger and the amount of data is larger. In other words, the amount of data helps to reduce the variability in the system. This is why it is important to have a good understanding of the natural variability before attempting to detect a climate change signal, as it is often difficult to separate the signal from the noise of the system.

Climate models are used to simulate the Earth’s mean climate and are important tools to understand how the global climate may change due to the warming influence of increased greenhouse gas concentrations. Global Climate Models simulate the different components of the Earth’s system, including the atmosphere, ocean, land-surface, sea-ice, aerosols and the carbon cycle.

What are weather reanalysis products?

Weather reanalysis products (such as the ERA-Interim method within the methods) are climate model outputs specifically designed for climatic variables at locations or times between observations. A climate model is configured using observations and then run forward in time until the next set of observations can be incorporated. Reanalysis data products provide data archives that are consistent (use the same assumptions and equations), have full spatial coverage across the target domain (no missing data points), are consistent with constraints and maps atmospheric state that either were not measured or cannot be measured. Reanalysis products aim to provide a better estimate of the observed climate state.

What are GCMs?

Global Climate Models (GCMs) are used to simulate the Earth’s climate and are important tools to understand how the global climate may change due to the warming influence of increased greenhouse gas concentrations. Global Climate Models simulate the different components of the Earth’s system, including the atmosphere, ocean, land-surface, sea-ice, aerosols and the carbon cycle.

The foundation of climate modelling is a set of mathematical equations that describe the ocean-atmosphere system, including the atmosphere, ocean, land-surface, sea-ice, aerosols and the carbon cycle.

How can climate models respond to changes in climate forcings?

Climate models can respond to changes in climate forcings in a variety of ways.

Temperature changes in the climate system can be caused by changes in the Earth’s orbit, variations in solar radiation, changes in the Earth’s rotation, or changes in the composition of the atmosphere. Climate models can simulate these changes and their effects on the climate system. For example, if the concentration of greenhouse gases in the atmosphere increases, climate models can simulate the resulting warming of the Earth’s surface and atmosphere.

Regional climate simulations for a region (typically improved resolutions of between 1 to 5km resolution, and temporal resolutions of 6 hourly timesteps, due to the limitations of current supercomputers). Regional climate simulations are used to study the regional climate and are important tools to understand how the global climate may change due to the warming influence of increased greenhouse gas concentrations. Regional Climate Models simulate the different components of the Earth’s system, including the atmosphere, ocean, land-surface, sea-ice, aerosols and the carbon cycle.
Internal variability

Internal variability is due to the year-to-year changes in the weather which are independent of climate change. This timescale is difficult for the climate models to simulate as they are driven by incorrect processes (that are often at smaller scales than the grid resolution). This uncertainty remains present throughout the model runs but has less weighting as time goes on due to the other sources growing. The smaller the area of interest, the more this internal variability dominates the total uncertainty, however it is still significant at the global scale. This is linked to phenomena such as ENSO and other drivers of natural variability.

Model uncertainties

Model uncertainties are either due to different representations of the same process within different model configurations (i.e., solving different equations to solve the same problem); parameterisations due to differing model resolutions, poor understanding and simulation of processes within the model (i.e., the equations or parameterisation schemes are unable to represent the processes correctly). Many of these model uncertainties would be greatly improved with higher model resolution; however, there will always be model uncertainty because mesoscale processes are impossible to fully simulate. These uncertainties will always grow as a model run goes further into the future.

Emission scenarios

Uncertainty regarding emission scenarios are based on Representative Concentration Pathways (RCPs, discussed above). These are storylines of how humans act into the future and are represented by the resulting change in average global radiative forcing by 2100. The four RCPs are numbered according to the change in radiative forcing by 2100: +2.6, +4.5, +6.0 and +8.5 watts per square meter. The spread in these emission scenarios add uncertainty to GCM projections which always increase through time. Until 2050, all scenarios result in similar climate change impacts, so do not add much uncertainty to the future outcome. However, past 2050, they begin to diverge rapidly, eventually becoming the dominant source of uncertainty when estimating the future climate.

Impotence of uncertainties with scales and parameters

When investigating global mean temperature, at first the internal variability is the main source of spread, with the different models and emission scenarios having less of an impact early on in the projections. From 2000 to 2050 the model uncertainties begin to dominate the overall uncertainty, whereas the emission scenarios, still have little influence (although for some variables, such as global mean precipitation, model uncertainty is by far the largest contributor throughout). Past 2050 it is the uncertainty surrounding the emissions scenario, the socio-economic pathway the global community chooses to take, that drives uncertainty around global (and in turn local) temperatures.

How can uncertainty be dealt with when using projections?

Research into understanding why the uncertainties in the models exist and what can and can’t be relied on in key to dealing with these uncertainties. The models produce plausible futures, rather than a single certain one, giving us an insight into what the future may look like. This means that we need to adapt to possible futures and be aware of the worst case scenarios. Using multi-model ensembles of simulations provides information covering all potential futures, allowing decision makers to apply a risk management approach with regards to imminent decisions being made today, while providing useful insights into what the longer term future may be to enhance the strategic decisions begin developed over the medium and longer terms.

The Coupled Model Intercomparison Project (CMIP)

The Coupled Model Intercomparison Project (CMIP) is a collaborative effort designed to improve our knowledge of climate change. CMIP provides an archive of outputs from a collection of global climate models contributed from the international climate modelling community. The CMIP archive facilitates the study of climate models in a standardised way, enabling a diverse community of scientists to better understand how the climate is represented by simulations; implement changes that improve simulations of the Earth’s climate; and interpret the impact that differing plausible futures may have on humanity. This multi-model approach allows the global community to identify the most plausible impacts that will be realised following different socio-political pathways into the future. The range of Global Climate Models included in CMIP5 represent the most diverse range of independent climate models and projections of how the global climate will change.

The CMIP collaboration is now within its 6th phase (CMIP6), due to be completed in 2020. This is based on CMIP5 model output. The CMIP5 series of global climate simulations were designed to test how various climate drivers impact upon the Earth’s climate. Instead of the SRES emissions scenarios (e.g., A2, B1), which were used in previous CMIP archives, CMIP5 presented a series of experiments called the Representative Concentration Pathways (RCPs). These were designed to test the impact of different concentrations of heat-trapping gases (e.g., atmospheric CO\textsubscript{2} concentrations) over a range of time sections (see section below on RCPs). To further appreciate the depth and breadth of CMIP5 experiments scope, as well as develop an understanding of the value and implications realised by this internationally coordinated research effort, we recommend referring to:


Emissions scenarios

One of the main sources of uncertainty around climate change is what choices humans make regarding the amount of greenhouse gases we release in the future. Different emissions scenarios are used to describe a range of socio-economic pathways the global community may follow, and the resulting influence on the Earth’s climate. Some scenarios are based on the business as usual pathway, where humans continue to be dependent on fossil fuels. Other scenarios are based on low emissions pathways, with a range from making small, deliberate actions to reduce emissions, to actively removing greenhouse gases from the atmosphere.

The resulting range reflects the uncertainty inherent in quantifying human activities and their influence on climate. Scenarios are essentially a set of storylines based on population projections, demographics, international trade, flow of information and technology, and other social, technological, and economic characteristics of plausible future worlds.

To ensure that the projections of GCMs can be compared in a sensible way, various scenarios of future greenhouse gas emissions are applied consistently to all GCMs. The latest scenarios used by the climate modelling community are known as Representative Concentration Pathways (RCPs). These are not emission scenarios in the traditional sense but encompass all of the changes in the storyline leading to range in average global radiative forcing (change in temperature due to change in atmospheric composition) by 2100.

The RCPs include RCP2.6, RCP4.5, RCP6.0 and RCP8.5. The size of the number indicates more energy (in the form of heat, in units of W m\textsuperscript{-2}) being trapped in the Earth system so that RCP8.5 leads to a significantly warmer future climate than RCP2.6. The highest is RCP8.5 which is the business as usual scenario (though by no means the upper limit), whereas RCP2.6 is ambitious in that it achieves net negative carbon dioxide emissions before the end of the century by including a policy option. The other RCPs have different pathways and represent different future worlds, which result in different levels of overall warming.

- RCP2.6 — following a low emissions, intensive mitigation scenario where the heat trapping capacity of the Earth is 4.5 W m\textsuperscript{-2}.
- RCP4.5 — following a late start to a low emissions, intensive mitigation scenario where the heat trapping capacity of the Earth is 4.5 W m\textsuperscript{-2}.
- RCP6.0 — following a moderate emissions, limited mitigation scenario where the heat trapping capacity of the Earth is 8.5 W m\textsuperscript{-2}.
- RCP8.5 — following a high emissions, limited mitigation scenario where the heat trapping capacity of the Earth is 4.5 W m\textsuperscript{-2}.
General methods

Observations

Observed climate between 1997 and 2007 is summarised for each region, based on the Australian Gridded Climate Data products (AGCD). These are national gridded climate data between 1997 and 2007 is summarised for each wine region, based on the understands that show a range of possible futures, the downscaled simulations provide scenarios to explore reductions in rainfall (see Table 1). Note that because we are selectively downscaling GCMs to show a range of possible climate futures such as changes in the amount of warming and rainfall, it is important to note that the downscaled climate projections are not necessarily consistent with each other or with other studies.

Description of the regional climate modelling approach

To develop high-resolution climate simulations for South Eastern Australia, we used the Conformal Cubic Atmospheric Model (CAM) developed at CSIRO (McGregor 2005) and McGregor and Dix (2008). Unlike most RCMs, CAM is a global atmospheric model with a variable resolution that can be used to explore the impacts of different climate change scenarios. In this way, CAM can generate a more realistic climate simulation, which is consistent with the large-scale behaviour of the global 50km resolution simulation, but is still coupled to the larger scale atmospheric circulation. The CAM model has been successfully downscaled to a 5km resolution for the south-eastern Australian regions with regards to spatial resolution, available variables and political actions as of 2019. Moving forward, if action to mitigate the impacts of climate change becomes more urgent, we can expect to better simulate extreme rainfall events that may lead to flooding.

METHODS AND INTERPRETATION

General methods

Host GCM for downscaling Relevance for downscaling regional climate

<table>
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<tr>
<th>Host GCM for downscaling</th>
<th>Relevance for downscaling regional climate</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO-BOM-ACCESS1-0</td>
<td>A hot, dry model that is representative of the consensus of GCM projections in Southern Australia. Warming exceeds 2.7°C across most of Australia, and &gt;3.7°C in central Australia. Drying is projected over most areas. This model shows a high skill score with regard to historical climate.</td>
</tr>
<tr>
<td>CNRM-CERFACS-CNRM-CM5</td>
<td>A hot, wet model, consistent with the consensus of GCM projections in Southern Australia. It has a good representation of extreme El Niño in CMIP5 evaluations.</td>
</tr>
<tr>
<td>NOAA-GFDL-GFDL-ESM2M</td>
<td>A hot, very dry model, with warming in central regions exceeding 3.9°C. Drying is projected across most of the continent, with annual precipitation projected to decline more than 20% in many areas.</td>
</tr>
<tr>
<td>MHI-CsiroGEM2-CC</td>
<td>A hot, dry model, with warming typically &gt;2.7°C and &gt;3.7°C in central regions. Annual precipitation is projected to increase in central Australia and decline elsewhere, including the horticultural zone. GCMs project significant reduction in winter. Maximum consensus for many regions.</td>
</tr>
<tr>
<td>MIROC-MIROC5</td>
<td>A hot, wet model for Australia, especially the south-eastern region. Warming does not exceed 2°C, and slight drying is expected. In annual precipitation is projected to decline in north-east Queensland and south-west Australia.</td>
</tr>
<tr>
<td>NCC-NOESM-M</td>
<td>A low-warming, wetter model, representative of the wettest scenarios within the CMIP archive. Warming over most of Australia exceeds 2°C. Little change in annual precipitation is projected, particularly in the south-east, although there is drying in south-west WA.</td>
</tr>
</tbody>
</table>

Table 1: The six host GCMs used for dynamical downscaling and the reasons for their selection.

The high-resolution downscaled climate simulations available at the time of publication were only for the RCP4.5 scenario. This scenario was used as of 2015 at the time of publication of this report. The scenario most representative of trajectory the Earth is following based on social, economic and political actions and achievements as of 2015. Moving forward, if action to mitigate the impacts of climate change becomes more urgent, we can expect to better simulate extreme rainfall events that may lead to flooding. The results presented for this model are computationally expensive, so new fine-scale projections were only done for south eastern Australia and Tasmania, where the greatest added value would be achieved over the mountains and coastal areas. For Western Australian regions and South Burnett in Queensland, we investigated the usefulness of using dynamically downscaled simulations available from other archives, particularly those produced over the south west western Australia. We compared these archives for compatibility with the key archive we have used for the south-eastern Australian regions with regards to spatial resolution, available variables and both spatial and temporal domain (coverage). In order to be consistent with the rest of Australia, these alternative archives required continuous temporal coverage from the 1960s to 2010. Unfortunately alternative archives investigated were not continuous. This introduced confusion when visualising many of the outputs, and thus could not be used. An alternative approach was adopted that made use of the 5km resolution CFA2019 ensemble output, as this model domain was global, which had coverage over all other Australian regions. However, this coarse resolution provided limited value when investigating the small wine regions. In order to transform the 5km outputs into more valuable forms, these were statistically downscaled to 5km resolution (using a quantile-quantile bias adjustment method Grumison et al 2013), based on the Australian Gridded Climate Data product. This produced far more useful, reasonable representations of the regions of interest to the project, providing the best continuous estimates currently available of climate changes into the future.
Bias adjustment

Model biases introduce systematic errors which vary from place to place, as these errors are heavily dependent on the topography, altitude, latitude and distance from large water bodies. The biases are due to insufficient spatial resolution and the subsequent limited representation of meteorological processes (Rauscher et al. 2010). This is not a problem when investigating climate change as the interest is on the relative changes over time rather than the absolute values. However, when looking at climate impacts, the absolute values are needed, particularly when investigating temperature extremes. Therefore, in order to make the atlas more useful, there was a need to statistically bias adjust the CCAM model outputs prior to climate impact assessment (Christensen et al., 2008).

Bias adjustment is a statistical method that adjusts the climate model output so that it matches the observations over the entire probability distribution. This adjustment is then applied to each quantile of the probability distribution into the future period, preserving any changes to the distribution projected by the climate models. The raw CFAP2019 ensemble outputs were bias-adjusted using the quantile statistical transformation, which has been widely used for adjusting modelled variables, especially temperature and rainfall (Gudmundsson et al., 2013). Temperature and rainfall were bias adjusted using the qmap package (Gudmundsson et al., 2013) within the R programming language. Specific parameter settings were: method = quant; step = 0.001 ; wet.day = FALSE for Temperature and TRUE for rainfall. Observation data inputs were from the Australian Gridded Climate Data product (Jones et al., 2009).

An example of the impact bias adjustment can have on the distribution of values is presented in Figure 2. The probability distribution of the model output has been adjusted such that it reflects the distribution of observed values.

Time periods

Time periods were calculated based on Australian growing years, which are the period from July to June each annual cycle, winter to winter in the Southern Hemisphere. Growing years were labelled as the calendar year in which July fell. Time periods used within this atlas are defined as:

<table>
<thead>
<tr>
<th>Time period</th>
<th>Start and end month</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997–2017</td>
<td>July 1997 to June 2018</td>
</tr>
<tr>
<td>2001–2020</td>
<td>July 2001 to June 2021</td>
</tr>
<tr>
<td>2021–2040</td>
<td>July 2021 to June 2041</td>
</tr>
<tr>
<td>2041–2060</td>
<td>July 2041 to June 2061</td>
</tr>
<tr>
<td>2061–2080</td>
<td>July 2061 to June 2081</td>
</tr>
<tr>
<td>2081–2100</td>
<td>July 2081 to June 2100</td>
</tr>
</tbody>
</table>

Table 2: Start and end months for each time period

Wine Regions / Geographic Indications (GIs)

The terms Wine Regions and Geographic Indications (or GIs) are used interchangeably throughout this atlas. They are determined, registered, managed and curated by Wine Australia (Wine Australia, 2019). Shapefiles of all wine regions were provided by Wine Australia.
Evaluation of the CFAP2019 ensemble

The following section evaluates the CFAP2019 ensemble for the period 1986–2005 by comparing the results to observations. In this section we use the Australian Gridded Climate Data products (AGCD), which are produced by the Australian Water Availability Project (AWAP), a collaborative effort of CSIRO and the Bureau of Meteorology (BoM). These national gridded datasets at 5km resolution of observed daily rainfall and daily maximum and minimum air temperature at 2m. AGCD data is based on interpolated weather station measurements and hence there are some gaps where the station network is less densely populated (e.g., in the Victorian Alps). We also used ERA-Interim reanalysis for evaluating the large-scale performance of the CFAP2019 ensemble such as mean sea level or winds at 850 hPa. The ERA-Interim reanalysis is a combination of model simulations and observations. As such, it is a reconstruction of the weather through time, providing information about surface conditions (e.g., temperature, precipitation, wind speed and direction, humidity, evaporation and soil moisture), information in pressure and model levels, and information on solar radiation and cloud cover. It provides a reasonably accurate representation of past weather over a number of years, so is valuable to validate the model output over the same time period. The Bureau of Meteorology Australian Regional Reanalysis for Australia (BARRA) was under development at the time of atlas development and publication, so was not yet available.

The region of Victoria was used to assess the capability of the model because it covers a large number of the Australian wine regions and has a range of climate zones (coastal, open plains, low elevation hills through to high elevation alpine mountains).

Temperature

The CFAP2019 ensemble variables average daily maximum and minimum air temperature (at 2m, i.e. screen temperatures) between 1986–2005 are compared to the AGCD interpolated observations and the host GCM models in Figures 3 and 4. The ensemble mean for CFAP2019 ensemble and six host GCMs are presented. The results indicate that CFAP2019 ensemble better represents the temperatures for mountain regions and coastlines than the GCMs when compared to AGCD. The CFAP2019 ensemble also show a significant improvement (compared to the host GCMs) in daily minimum temperature, as well as much better representation of coldest daily minimum temperatures for alpine regions of Victoria. The host GCMs tend to show a warm bias in the daily minimum temperatures over Victoria that is not apparent in the CFAP2019 ensemble. However, for maximum temperatures there is a warm bias apparent in the CFAP2019 ensemble in summer, particularly for eastern Victoria. The spatial pattern of this warm bias is not apparent in the future projected change in daily maximum temperature, suggesting that the issue is related to the diagnosis of the 2m air temperature for tall vegetation (e.g., forests). Some caution is therefore advised in interpreting the projected changes in climate for daily maximum temperatures within or nearby forested regions.

Another example of how the CFAP2019 ensemble has improved the daily minimum temperature can be seen by examining the Urban Heat Island (UHI) for Melbourne. Urban areas result in an increased daily minimum temperature compared to the surrounding natural vegetation of typically 1°C to 2°C, depending on the density of the urban area and the amount of green space. Urban areas are generally poorly resolved in GCMs. However, regional models like CCAM include special parameterisations to account for the building materials, urban drainage, shading effects and changes to air circulation within the urban canyon. Figure 5 shows the difference in daily minimum temperature between an inner-city weather station (BoM Melbourne Regional Office) and three outer-city weather stations (Laverton RAAF — Blue dot, Coldstream - Green dot and Cranbourne Botanic Gardens — Yellow dot). Location of the weather stations are shown in the top plot and the observed and simulated difference in temperatures between the inner-city site and the three outer city sites is shown in the bottom plot.

Figure 3: Comparison of average daily maximum 2m air temperature between 1986–2005 for AGCD interpolated observations (left column), CCAM 5km resolution simulation (middle column) and host GCM (right column). The CCAM and GCM results are averaged over the six GCMs used for downscaling. The rows from top to bottom correspond to December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON), respectively.

Figure 4: Comparison of the daily minimum 2m air temperature between 1986–2005 for AGCD interpolated observations (left column), CCAM averaged over the six downscaling simulations (middle column) and the average of the six host GCMs (right column). The rows from top to bottom correspond to December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON), respectively.

Figure 5: Comparison of the Urban Heat Island (UHI) measured as the difference in average daily minimum temperature over 1986–2005 between an inner-city weather station (BoM Melbourne Regional Office — Red dot) and three outer-city weather stations (Laverton RAAF — Blue dot, Coldstream - Green dot and Cranbourne Botanic Gardens — Yellow dot). Location of the weather stations are shown in the top plot and the observed and simulated difference in temperatures between the inner-city site and the three outer city sites is shown in the bottom plot.

METHODS AND INTERPRETATION

Evaluation of the CFAP2019 ensemble
Rainfall

A comparison of the average rainfall simulated for different seasons from 1986–2005 by CCAM with AGCD interpolated observations and the host GCMs can be seen in Figure 6. The CCAM 5km resolution simulations better represent the average rainfall over the Victorian Alps than the GCMs where the mountains are poorly resolved. CCAM also represents increased rainfall along the southern coastline that was not represented by the GCM simulations. The simulated average rainfall from the CCAM 5km resolution simulations is higher than what is measured for the AGCD interpolated observations. However, the AGCD interpolated observations can also underestimate the rainfall in mountain regions due to a more sparse network of observing stations.

Another aspect where downscaling should improve the simulated climate is extreme rainfall. We used the 99th percentile of daily rainfall over the 1986–2005 period as an indicator of CCAM’s ability to represent extreme rainfall. A comparison of the 99th percentile of daily rainfall between 1986–2005 for AGCD, CCAM and the GCM is shown in Figure 7. The extreme rainfall is underestimated by CCAM when compared to AGCD interpolated observations, although CCAM significantly improves on the extreme rainfall from the GCMs which do not represent the high rainfall for the Alpine regions at all. As for average daily rainfall, the AGCD interpolated observations may underestimate the size of the extreme rainfall for mountain regions due to the sparse observing network, which is also suggested by comparing the results to BARRA (not shown). Nevertheless, CCAM is able to represent extreme rainfall that could not be captured in the GCM simulations.

Extreme rainfall

Another aspect where downscaling should improve the simulated climate is extreme rainfall. We used the 99th percentile of daily rainfall over the 1986–2005 period as an indicator of CCAM’s ability to represent extreme rainfall. A comparison of the 99th percentile of daily rainfall between 1986–2005 for AGCD, CCAM and the GCM is shown in Figure 7. The extreme rainfall is underestimated by CCAM when compared to AGCD interpolated observations, although CCAM significantly improves on the extreme rainfall from the GCMs which do not represent the high rainfall for the Alpine regions at all. As for average daily rainfall, the AGCD interpolated observations may underestimate the size of the extreme rainfall for mountain regions due to the sparse observing network, which is also suggested by comparing the results to BARRA (not shown). Nevertheless, CCAM is able to represent extreme rainfall that could not be captured in the GCM simulations.

Mean Sea Level Pressure and 850 hPa winds

Although the use of CCAM simulations is primarily for downscaling the regional climate, it is also important to consider the large-scale behaviour of the CCAM atmospheric simulation. This large-scale behaviour can influence the projections of the climate model simulations and is useful for interpreting the outputs of CCAM in the context of the ensemble of CMIP5 GCM projections. As discussed when describing CCAM, the use of bias corrected SSTs can allow CCAM to differ from the host GCM in some respects.

Figure 8 compares the simulated Mean Sea Level Pressure (MSLP) averaged between 1986 and 2005 for the six CCAM 50km global simulations with the ERA-Interim reanalyses and the average of the six host GCMs. When compared to ERA-Interim, the CCAM 50km simulations are somewhat biased towards easterly flow in the MSLP compared to the host GCMs, most noticeable in autumn and winter. This can lead to winds too easterly as indicated with the 850 hPa winds shown in Figure 9. Figure 9 compares the average 850 hPa wind speed and direction for different seasons over 1986–2005 between the ERA-Interim reanalyses, the average of the six CCAM 50km global simulations and the average of the six host GCMs. The 850 hPa wind represent the winds at approximately 1 to 1.5km above the surface, where ERA-Interim is less influenced by smaller scale mountains. Although the CCAM simulations are a reasonably good representation of the 850 hPa winds, the wind speed is too strong and the wind direction is too easterly in autumn and winter. This result is consistent with the easterly bias within MSLP results for those seasons. The CCAM simulation results are still a reasonable representation of the global climate and the projected future changes in climate are physically reasonable. Nevertheless, we can expect some differences in the larger scale changes projected by the CCAM simulations compared to the host GCMs.

Figure 8: Comparison of Mean Sea Level Pressure averaged over 1986–2005 between ERA-Interim reanalyses (left column), the average of the six CCAM 50km global simulations (middle column) and the average of six host GCMs (right column).

Figure 9: Comparison of average wind speed and direction at 850 hPa (approximately 1 to 1.5km above the surface) between 1986–2005. The ERA-Interim reanalysis is shown on the left column, the average of six CCAM 50km global simulations in the middle column and the average of six GCMs on the right column.

Figure 10: Comparison of the 99th percentile of daily rainfall between 1986 and 2005 from AGCD interpolated observations (left column), the average of six CCAM simulations (middle column) and the average of six GCMs (right column).
Methods and interpretation of figures

Infographic

Each regional section of the atlas starts with an infographic page that summarises the future changes in climate in general terms. This section describes the methods used to calculate each index.

Interpretation:

These infographics provide a snapshot of the projected climate across each region at different time periods. Values are summarised across space and time, so they give a good overall indication of change across the region, but may be less useful when interested in specific conditions or specific sites. These summaries enable easy and rapid comparisons between regions, or across time periods, in a broad, general sense.

Data sources

Values for the 1997–2017 (the current period) were calculated using the Australian Guided Climate Data product (Jones et al., 2009). Values for the time periods 2041–2060 and 2081–2100 were calculated from the Climate Futures Australian Projections 2019 (CFAP2019), produced collaboratively by the CSIRO, the ACERI and the University of Tasmania.

Mean values

Mean values are the spatial and temporal average of the target variable within a specific time-period, across all grid cells within each wine industry Australian Geographical Indicators (Wine Australia, 2019). For example, the mean GST value for the period 2041–2060 for the Barossa Valley is an average of 260 input values (13 grid-cells x 20 annual timesteps), summarised into a single value.

Interpretation:

Values are presented for selected 20-year periods representing the:

- current period (1997–2017) — reflecting recent memory;
- the mid-term future (2041–2060) — the high-likelihood future expected by 2050 (before which RCP scenarios are similar and after which they begin to diverge); this period is most relevant to strategic decision making; and
- far future (2081–2100) — providing a quantitative estimate of changes by the end of century (following the worst case scenario).

The three time periods indicate the rate of adaptation that may be required over the next 20 or 40 years while providing context to help guide planning over a longer time frame.

Temperature

Growing Season Temperature (GST) is defined as the mean atmospheric temperature at screen height (2m above the land surface) over the period from October to April of each annual cycle. This is calculated for every growing season year, for every grid-cell within the region. Annual values from all grid-cells and all annual timesteps are averaged.

Interpretation:

Growing Season Temperature (GST) increases into the future for every region across Australia. The rate of increase accelerates exponentially towards 2100. Values are summarised over space and time, so for regions with high topographic variability, average values are unlikely to reflect conditions at specific sites within the wine region, although they will give a reasonable indication of the direction and rate of change projected into the future.

Extemporanous Heat

Extemporanous Heat Factor (EHF) is an index that describes the severity of short term, acute heat impacts on humans during heatwaves. It accounts for how hot any three-day period is in relation to an annual temperature threshold at a particular location, as well as how hot the three-day period is with respect to the recent past (the previous 30 days). This reflects the recent past fact that people acclimatise, to a certain extent, to their local climate but may not be prepared for a sudden rise in temperature above that of the recent past.

The calculation is described in Nairn and Fawcett (2015). Annual values from all grid-cells and all annual timesteps are averaged.

Interpretation:

Extemporanous Heat Factor (EHF) represents the intensity of heatwaves within a region as experienced by humans, after accounting for any capacity to acclimatise to the typical conditions within a region. Increasing EHF indicates more intense heatwaves. As heatwaves are large synoptic scale features, regional variability is less influential than longer term climatic changes.

Aridity Index

The Aridity Index provides an indication of available water by considering the magnitude of rainfall compared to the magnitude of evaporation. This is calculated as annual precipitation / annual pan evaporation. The aridity index is independent of site specific characteristics (e.g., soil type, vine varietal) or changes in vineyard management (e.g., shading, row orientation, mulching), but captures deviation, aspect, humidity and the influence of wind. Annual values from all grid cells and all annual timesteps are averaged.

Interpretation:

The annual cycle was defined as July to June, which is winter to winter in the southern hemisphere, as annual precipitation is the sum of all rainfall that has fallen within a single grid cell within the period July to June of each annual cycle. Annual pan evaporation is the sum of all evaporation that could occur if water was always present within a grid-cell over the period July to June of each annual cycle. This follows the approach of numerous published methods that have all devised similar (yet slightly different) methods of estimating aridity by dividing a measure of rainfall by a measure of evaporation (or similar variables such as evapotranspiration, potential evaporation, etc.) (Transeau, 1905; Vyssotsky, 1905; Oldekop, 1911; Thornthwaite, 1911; Ivanova, 1921; Konist, 1952; Hargreaves, 1971; UNESCO, 1979; Sarker and Brear, 1986).

Interpretation:

The Aridity Index (AI) reflects the difference between evaporation and rainfall over the year. High (low) values indicate more (less) rainfall than evaporation. In a rapidly warming climate, evaporation rates increase substantially, so in order to maintain similar AI values rainfall must increase sufficiently to offset evaporative losses. Temperature increases have high certainty, thus evaporation increases are also highly certain. There are few places (globally) where rainfall is projected to increase at a rate fast enough to maintain AI values at their current levels. Therefore AI is expected to decrease in all wine regions across Australia. Values are summarised over space and time, so for regions with high topographic variability, average values are unlikely to reflect conditions at specific sites within the wine region, although they will give a reasonable indication of the direction and rate of change projected into the future.

Mean Growing Season Frost Risk Days are projected to decrease in all wine regions across Australia as temperatures continue to rise. Values are summarised over space and time. For regions with high elevations within the wine regions, average values will be higher (lower) than those expected in the lowlands (highlands).

Rainfall

Mean Growing Season Rainfall is the average sum of all precipitation that falls within the period from October to April of each annual cycle. Annual values from all grid-cells and all annual timesteps are averaged.

Interpretation:

Rainfall is one of the most uncertain components within the climate system. However, even modest increases in annual rainfall can actually result in decreased moisture availability across a region within a warming climate, as rainfall rates are required to increase in order to offset evaporative (and other) losses (see Aridity Index sections). Confidence in temperature, the warming trend and evapotranspiration demands is high, therefore large scale projections are less, very few simulations indicate increases in rainfall with sufficient magnitude to offset these projected losses. Rainfall should be viewed in context with Aridity Index projections.

Heat

Interpretation:

We have high confidence in how temperature will change into the future (depending on the emissions scenario). The physical drivers of how it changes within the climate system are well understood, as we can observe, model, and project the atmospheric processes that determine temperature and how it changes within the climate system. There is strong agreement across the CFAP2019 ensemble members regarding the rate and magnitude of warming projected into the future. As such, there is high confidence regarding projected variables related to temperature.

Each ensemble member describes a possible future, with different timing and sequencing of broad global drivers (such as the Southern Annular Mode (SAM), the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD)) and the extent and speed of warming or cooling can be out of phase with each other. This is a strength of an ensemble mean as the high and low expressions of the natural variability within the climate system are smoothed out, revealing the general climate trend. For some regions, variability between the different ensemble members is less than the variability that occurs spatially across a wine region. This is especially true for those regions with significant hills or mountains (e.g. Barossa Valley, Tasmania East Coast). For regions that are more uniform spatially (e.g. Riverland), the ensemble variability is more noticeable, expressed as clusters of points that escape the point cloud in some years. These high and low years are useful for understanding the likelihood of extremely hot or cold years over time. Often, the extremely hot years are indicative of the conditions to expect in the future. For example, the hot year (along with the associated extreme daily temperatures) observed in south east Australia during the 2015/2016 growing year is indicative of typical projected conditions in 2050. Similarly, cooler conditions (relative to the surrounding decades) can occur at any time (although even the coldest year by the end of century would be considered an average year today).

The trend lines highlight how typical conditions are projected to change over time — they are representative of the ensemble mean at warmer and cooler locations within the region. It is most interesting to determine when the cooler location becomes hotter than the warmer location (typically around 2030, depending on the region and the magnitude of spatial variability). It is important to note that interannual and decadal variability is present in the future climate projections, but the trend is clearly warming, especially from 2020 onwards.
METHODS AND INTERPRETATION

Methods and interpretation of figures

Underlying data source: Australian Gridded Climatic Data Project (Jones et al., 2009)

Growing Season Temperature (GST) was calculated as the average of all daily average temperature values for each day within the period from October to April of each growing season year. Growing Season Temperature is the average of all annual GST values over the current period (1997-2017). Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:

Each tile represents the mean Growing Season Temperature during the period 1997-2017, (which is the period of recent memory). This map reflects the level of variability across the region as it is currently experienced. Tiles are the resolution of the underlying data. Lower values typically correspond to higher elevation regions. Towns and roads are included to help identify specific sites within the region. Tiles have an average elevation of the area they represent, so they best represent regions that have similar elevations (±1km²) and thus are poorly represented. This can influence the representation of some climatic features and should be considered when interpreting these figures.

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019)

Growing Season Temperature (GST) was calculated as the average of all minimum and maximum temperature values for each day within the period from October to April of each growing season year. Growing Season Temperature is the average of all annual GST values over the current period (1997-2017), or the baseline period (1961-1990). The baseline period mean GST was then subtracted from the current period mean GST, resulting in the observed change in mean GST. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:

Each tile represents how mean Growing Season Temperature during the current period (1997-2017) has changed when compared to mean Growing Season Temperature during the historical period (1961-1990). Climate change is a large scale feature, so the level of change observed is relatively similar when viewed at level scales. Towns and roads are included to help identify specific sites within the region. Tiles have an average elevation of the area they represent, so they best represent regions that have similar elevations (±200m) across 5-10km² scales. Typically, the highest peaks occur at smaller scales (±1km²) and thus are poorly represented. This can influence the representation of some climatic features and should be considered when interpreting these figures.

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019)

Growing Season Temperature (GST) was calculated as the mean Growing Season Temperature during each 20-year period of 2021-2040, 2041-2060, 2061-2080, 2081-2100 (following the RCP8.5 scenario). These reflect the level of variability across the region, and the rate of change projected into the future. Tiles are the resolution of the underlying data. Lower values typically correspond to higher elevation regions. Tiles have an average elevation of the area they represent, so they best represent regions that have similar elevations (±200m) across 5-10km² scales. Typically, the highest peaks occur at smaller scales (±1km²) and thus are poorly represented. This can influence the representation of some climatic features and should be considered when interpreting these figures.

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019)

The curves represent the distribution of GST values from all grid cells and all ensemble members during each 20-year time period. The grey filled curves are calculated when selected within the warmer, average or cooler part of their region and thus can inform us where they are likely to sit within the point cloud, allowing us to extract more detail from these figures. Because these lines are the ensemble mean (the average of 6 values), extreme years have been smoothed out. This can be seen in the case of extreme events, the peaks and troughs indicated by the points are more helpful. The grey bars are the regional average for contrasting GI’s across Australia. They do not represent the regional variability within each of these GIs, but are intended to provide approximate climate analogues to aid interpretation. The coloured zones are intended to be used independently of the Growing Year (July to June) axis, allowing decisions to be made based on the expected magnitude of global warming (such as those national governments are committed to within the Paris Agreement), rather than being based on the passage of time. This allows these plots to be useful regardless of the emissions scenario the world eventually follows.

Interpretation:

Probability distributions reflect the spread and potential likelihood of values within a particular population of values. High, narrow peaks indicate low variability with a high frequency of particular values occurring within the population. Low, broad peaks indicate high variability, with few values occurring frequently. The probability distributions displayed in the atlas incorporate all spatial grid cell values, across each 20-year time period, from six ensemble members (i.e., independent simulations). Variability across spatial and temporal scales as well as across the CFAP2019 ensemble is represented with each curve. This has the advantage of reflecting the diversity that is found within each wine region (cooler vs warmer subregions) and across different types of years (e.g., hot, average or cold). Different ensemble members capture different climate configurations (e.g., El Niño, neutral, or La Niña phases of ENSO), thus better estimate the range of possible extremes. Low likelihood years (extreme hot or cold) can be included, indicating what is possible, while simultaneously representing the expected or typical conditions for a particular region. Curves with multiple peaks indicate either strong, stable spatial differences (highland vs lowlands conditions), or a strong modal character of the regions climate (e.g., a region is either very warm years, or very cold years but rarely is in between). The different colored curves indicate how conditions are expected to change into the future. As the curves are all distinct and the direction of change across the five time-periods is consistent, this indicates all ensemble members agree on the rate and direction of the change into the future. The future curves are typically lower and broader than their historical counterparts. Differences between the future and historical curves indicate high variability, with frequent occurrences of the range of values within the population.
Growing Degree Days

Growing Degree Days calculations are not standardised across Australia. Growers within each GI often have their own adaptation either for their vineyard or across their region. As such, GDD means different things to different people and the values are not interchangeable. For this atlas, we selected a method to calculate GDD that was standardised, relevant and useful across Australia. The two main limitations of existing methods were: 1) limiting the period where heat is accumulated to after October — this does not account for the effect of warm winter/spring periods, increasingly important under a warming climate; 2) limiting the influence of heat to daily values >10°C — this does not account for physiological responses that clearly occur at far lower temperatures, especially during the winter/spring period.

In response to these limitations, we established a new method to use daily climate values as inputs, take into account the influence of heat across the entire growing year (July to June) and reflect the physiological demands of grape vines as they change throughout the year. The method is simple enough to implement (and adjust) at the vineyard scale where required (by users external to the atlas) and remains relevant into warmer future conditions. The approach captures the importance of increased heat accumulation prior to October as the climate warms, also improving the utility of the GDD metric as a measure of heat accumulation within cooler climates (or cooler seasons) as it better reflects the influence of low temperature days relevant to grapevine physiology.

Method description

Growing Degree Days calculation

Growing Degree Days are calculated using this (standard) equation:

\[ \text{GDD} = \text{max}(T_{\text{max}} - T_{\text{base}}) \]

Where: \( \text{GDD} = \text{Growing Degree Days}; T_{\text{max}} = \text{Maximum daily temperature}; T_{\text{base}} = \text{Minimum daily temperature}; T_{\text{base}} = \text{the temperature threshold above which heat is considered of value to the vines.} \)

The value of \( T_{\text{base}} \) is altered for three different phenological stages: dormancy to budbreak, budbreak to leaf appearance, leaf appearance to harvest (or end of season), reflecting the physiological requirements of grape vines during these different periods of growth. We used the values determined by Moncur et al. (1989) and account for the most significant variations cultivated in Australia, for each phenological stage set as \( T_{\text{base}} = 2 \degree C \) from July 1st until budbreak, \( T_{\text{base}} = 7 \degree C \) from budbreak until leaf appearance, \( T_{\text{base}} = 10 \degree C \) from leaf appearance until June 30th.

The value of this adaptation is the additional information it provides earlier in the season, especially the influence of cooler days, which are particularly important within cooler climate regions. However, in order to implement this approach, accumulated GDD values that indicate when each threshold has been reached are required such that the timing of these trigger points within each year can be estimated. Given that cool climate varieties are more likely to be sensitive to this method than those suited to warmer climates, the thresholds were estimated using data provided by Moncur et al. (1989). Thus, the above transition points for \( T_{\text{base}} \) as defined by accumulated GDD thresholds were: budbreak = 150 GDD; leaf appearance = 1000 GDD. In order to provide a useful translation of different GDD approaches, boxplot tables are presented comparing the method used within this atlas (which we have called the GDD\text{method} method) and a range of methods used from across Australia. These are presented for four contrasting regions.
Figure 6: Probability distribution of Growing Degree Days

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

**METHODS AND INTERPRETATION**

Methods and interpretation of figures

**Figure 7: Projected annual cumulative Growing Degree Days**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

**Figure 8: Probability distribution of date when Growing Degree Days reaches threshold**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).
Rainfall projections from the bias adjusted CFA2019 ensemble are the highest accuracy, highest precision rainfall projections currently available for Australia. Rainfall is a well understood weather and climate variable, controlled by the ocean, atmosphere and uniform dynamics at large, medium and small scales across space and time. Large and medium scale processes are well realised within the CFA2019 ensemble, resulting in reasonable representation of the distribution of rainfall across Australia. This is exemplified with the representation of wet and dry subregions within some wine regions. However, it is those processes that occur at small spatial scales which are sometimes poorly resolved leading to inaccuracies or poor precision. As such, there is greater inaccuracy and precision within the projections of rainfall than there are for temperature. This means there is reduced levels of confidence (i.e. greater uncertainty) surrounding projections of this variable.

There is often greater variability across the ensemble than there is spatially across a region, reflecting the larger differences between wet and dry years across most regions. Each ensemble member describes a possible future, with different timing and sequencing of broad global drivers (such as the Southern Annular Mode (SAM), the ENSO Southern Oscillation (ENSO)) and the Indian Ocean Dipole (IOD)). This results in the timing of wet or dry years being out of phase with each other, resulting in dramatically different projections of any one year (sometimes seen as disconnected clusters of points). Because of this, 10-year or 25-year averages (or distributions) are far more useful for characterising the rainfall typical for a wine region. Annualised values are useful for identifying the possible extremes, especially the potential timing of their occurrence (for example, it is more likely to have a wet year now, or in 2100).

Figure 1: Observed mean Growing Season Rainfall

Underlying data source: Australian Gridded Climate Data Product (Jones et al., 2009).

Growing Season Rainfall (GSR) was calculated as the sum of all daily rainfall values within the period from October to April of each growing season year. Mean Growing Season Rainfall is the average of all annual GSR values over the current period (1997–2017). Grid cells selected were those within the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:
Each tile represents the mean Growing Season Rainfall during the period 1997–2017, which is the period of record (1961–1990). This map reflects the level of variability across the region as it is currently experienced, indicating subregions with higher or lower rainfall. Tiles are the resolution of the underlying data. Ticks and roads are included to help identify specific sites within the region. Rain shadows are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Figure 2: Observed change in mean Growing Season Rainfall

Underlying data source: Australian Gridded Climate Data Product (Jones et al., 2009).

Growing Season Rainfall (GSR) was calculated as the sum of all daily rainfall values within the period from October to April of each growing season year. Mean Growing Season Rainfall is the average of all annual GSR values over the current period (1997–2017), or the baseline period (1961–1990). The baseline period mean GSR was then subtracted from the current period mean GSR, resulting in the observed change in mean GSR. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:
Each tile represents how mean Growing Season Rainfall during the current period (1997–2017) has changed when compared to mean Growing Season Rainfall during the historical period (1961–1990). Change is presented in millimetres. Ticks and roads are included to help identify specific sites within the region. Rain shadows are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Figure 3: Projected mean Growing Season Rainfall

Underlying data source: Climate Futures Australasian Projections 2019 (CFA2019).

Growing Season Rainfall (GSR) was calculated as the sum of all daily rainfall values within the period from October to April of each growing season year for each member within the CFA2019 ensemble. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Mean Growing Season Rainfall is the average of all annual GSR values within each time period (2021–2040; 2041–2060; 2061–2080; 2081–2100). Those values were calculated for each ensemble member within the CFA2019. The 6 ensemble member values (for each cell) are averaged generating the mean ensemble value for each cell within the region.

Interpretation:
Each tile represents the mean Growing Season Rainfall during each 28-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). Those reflect the level of variability across the region, indicating subregions with higher or lower rainfall and how these are projected to change into the future. Tiles are the resolution of the underlying data. Ticks and roads are included to help identify specific sites within the region. Rain shadows are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Figure 4: Projected annual Growing Season Rainfall (October to April)

Underlying data source: Climate Futures Australasian Projections 2019 (CFA2019).

Blue points: Growing Season Rainfall (GSR) was calculated as the sum of all daily rainfall values within the period from October to April of each growing season year for each member within the CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Grey Bars: The grey bars represent the observed mean Non-Growing Season Rainfall for the current period (1997–2017) from contrasting wine industry Australian Geographical Indications (Wine Australia, 2019). Values were averaged across space and time, calculated from the Australian Gridded Climate Data product (Jones et al., 2009).

Colour zones: The coloured zones indicate the ensemble mean time when average global climate temperature increases by 2°C, 2.5°C or 3°C, following the Representative Concentration Pathway 8.5 scenario (RCP8.5), often referred to as the business as usual scenario). Those estimates were taken from the Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC-AR5), which are based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project - phase 5 (CMIP5) global climate model archive.

Interpretation:
Each tile represents the annual Growing Season Rainfall for individual grid cells within the region for each separate CFA2019 ensemble member. For each year, the spread of points represents the spatial variability as well as the variability across the ensemble members. From 1961 to 2010, means and standard deviation are shown for the projected future, with no obvious influence of climate change across most regions. The grey bars are the regional average for contrasting GI’s across Australia. They do not represent the regional variability within each of those GIs, but are intended to provide approximate climate analogues to aid interpretation.

The coloured zones are intended to be used independently of the Growing Year (July to June) axis, allowing decisions to be made based on the expected magnitude of global warming (such as those national governments are committed to within the Paris Agreement), rather than being based on the passage of time. This allows these plots to be useful regardless of the emissions scenario the world eventually follows.

Figure 5: Projected annual Non-Growing Season Rainfall (May to September)

Underlying data source: Climate Futures Australasian Projections 2019 (CFA2019).

Non-Growing Season Rainfall is the sum of all daily rainfall values within the period from May to September of each calendar year (i.e., the May to September prior to the growing season). Non-Growing Season Rainfall is the sum of all daily rainfall values within the period from May to September of each calendar year (i.e., the May to September prior to the growing season).

Figure 6: Projected Non-Growing Season Rainfall (May to September)

Underlying data source: Climate Futures Australasian Projections 2019 (CFA2019).

Non-Growing Season Rainfall is the sum of all daily rainfall values within the period from May to September of each calendar year (i.e., the May to September prior to the growing season). Non-Growing Season Rainfall is the sum of all daily rainfall values within the period from May to September of each calendar year (i.e., the May to September prior to the growing season).
Each year and each ensemble member within the CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. All individual spatial and ensemble member values were included, no spatial or ensemble averaging is performed. The grey curves represent the distribution of observed seasonal rainfall values from all grid cells and all ensemble members during each different 20-year period. Time periods were: 2001–2020; 2021–2040; 2041–2060; 2061–2080; 2081–2100. The grey, filled curves represent the distribution of observed seasonal rainfall values from the current period (1997–2017) for contrasting wine industry Australian Geographical Indications (Wine Australia, 2019).

Figure 6: Projected monthly rainfall

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

Monthly Rainfall was calculated as the sum of all daily rainfall values within each month, for each year and each ensemble member within the CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Violin plots represent 20-years of values for each month within each time period (2021–2040; 2041–2060; 2061–2080; 2081–2100). All individual spatial and ensemble member values are included, no spatial or ensemble averaging is performed.

Figure 7: Probability distribution of seasonal rainfall

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

Seasonal Rainfall is the sum of all daily rainfall values within each calendar season (Winter, Spring, Summer, Autumn), for each growing season year for each ensemble member within the CFAP2019. Violin plots are those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. All individual spatial and ensemble member values were included, no spatial or ensemble averaging is performed. The coloured curves represent the probability distribution of seasonal rainfall values from all grid cells and all ensemble members during each different 20-year period. Time periods were: 2001–2020; 2021–2040; 2041–2060; 2061–2080; 2081–2100. The grey, filled curves represent the distribution of observed seasonal rainfall values from the current period (1997–2017) for contrasting wine industry Australian Geographical Indications (Wine Australia, 2019).

Interpretation:

Probability distributions reflect the spread and potential likelihood of values within a particular population of values. High, narrow peaks indicate low variability with a high frequency of particular values occurring within the population. Low, broad peaks indicate high variability, with few values occurring frequently. The probability distributions displayed in the atlas incorporate all spatial grid cell values, across each 20-year time period, from six ensemble members (i.e., independent simulations). Variability across spatial and temporal scales as well as across the CFAP2019 ensemble is represented with each curve. This has the advantage of reflecting the diversity that is found within each wine region (wetter vs drier subregions) and across different types of years (e.g., wet, average or dry). Different ensemble members capture different climate configurations (e.g., El Niño, neutral, or La Niña phases of ENSO), thus better estimate the range of possible extremes. Low likelihood years (extreme wet or dry) can be included, indicating what is possible, while simultaneously representing the expected or typical conditions for a particular region. Curves with multiple peaks indicate either strong, stable spatial differences (e.g., desert adjacent to alpine), or a strong modal character of the regional climate (e.g., a region either has wet years, or dry years but rarely average years). The different coloured curves indicate how conditions are expected to change into the future. The future curves are typically lower and broader as different simulations follow different trajectories, increasing the variability within the population of values. When curves for each time period are all distinct and the direction of change across the five time-periods is consistent, this indicates all ensemble members agree broadly on the rate and direction of warming into the future. In such cases there is increased certainty surrounding the projected future.

When the curves from all time periods are overlapping, natural variability dominates the climate change trend, with the future conditions projected to be much the same as at present. When the direction of change is confused between time periods, or the spread of the curves is significantly broadened (but the average conditions are more or less the same), ensemble variability is high, there is significant uncertainty regarding the projections of the future.

The grey curves are the probability distribution for contrasting Australian wine regions, selected to present the range observed across Australia, and indicate the approximate analogues a region may become similar to into the future. These grey curves are calculated using the Australian Gridded Climate Data product from the period 1997–2017.

The coloured curves are calculated using the bias-adjusted CFAP2019 ensemble during the period 2001–2020. As there are differences between these two archives, the 2001–2020 curves for some selected regions are slightly different to the grey curves. These differences are expected.

Figure 8: Probability distribution of number of rainy days during harvest

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

Harvest date was determined as the date within each year when each cumulative Growing Degree Days threshold (1000, 1500, 2000, 2500) was exceeded. The harvest period was determined as the 15-day period, starting 7 days before the harvest date and ending 7 days after the harvest date. Thus, there were 4 potential harvest periods, to account for different regional, seasonal or style preferences of different users of the atlas. The number of rainy days during harvest was calculated by counting the number of days with rainfall >10mm during the harvest period. Values were calculated for each cell and for each ensemble member within CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine region’s Geographical Indications (Wine Australia, 2019). The coloured curves represent the probability distribution of number of rainy days during harvest values from all grid cells and all ensemble members during each different 20-year period. Time periods were: 2001–2020; 2021–2040; 2041–2060; 2061–2080; 2081–2100. These are displayed separately for each GDD threshold (1000, 1500, 2000, 2500). Higher thresholds were often not reached in some regions. Only curves that represented >60 individual values were displayed (otherwise they were excluded, as they would only represent outliers).
Aridity

Figure 1: Observed mean annual aridity index

Underlying data source: Australian Gridded Climate Data Product (Jones et al., 2009).
Annual Aridity Index was calculated as \( P/E \) where: \( P \) = the sum of daily rainfall during the period from July to June each annual cycle, and \( E \) = the sum of daily evaporation during the period from July to June each annual cycle. Aridity Index values below 0.05 and above 2.00 were rounded up to 0.05 and values \( >2 \) were rounded down to 2. Mean Annual Aridity Index is the average of all Annual Aridity Index values over the current period (1997-2017). Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:
Each tile represents the mean annual Aridity Index during the period 1997-2017, which is the period of recent memory. This map reflects the level of variability across the region as it is currently experienced, indicating drier/wetter Aridity Index subregions (if they exist). Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region. Rain shadows or regions more exposed to evaporation are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Figure 2: Observed change in mean annual aridity index

Underlying data source: Australian Gridded Climate Data Product (Jones et al., 2009).
Annual Aridity Index was calculated as \( P/E \) where: \( P \) = the sum of daily rainfall during the period from July to June each annual cycle, and \( E \) = the sum of daily evaporation during the period from July to June each annual cycle. Mean Annual Aridity Index is the average of all Annual Aridity Index values over the current period (1997-2017), or the baseline period (1981-1990). The baseline period mean Annual Aridity Index was then subtracted from the current period mean Annual Aridity Index, resulting in the observed change in mean Annual Aridity Index (an absolute value). This was divided by the baseline period mean Annual Aridity Index and multiplied by 100 to produce the observed change in mean Annual Aridity Index as a percentage), which was considered more useful than the logarithmic scale of the aridity index. This is calculated for each growing season year and for each grid cell within the region. Each tile represents how mean annual Aridity Index during the current period (1997–2017) has changed when compared to mean annual Aridity Index during the historical period (1981–1996). Change is presented as a percentage, to allow regions with high variability to understand the rate of change within their subregion. Towns and roads are included to help identify specific sites within the region. Rain shadows or regions more exposed to evaporation are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Figure 3: Projected mean annual aridity index

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).
Annual Aridity Index was calculated as \( P/E \) where: \( P \) = the sum of daily rainfall during the period from July to June each annual cycle, and \( E \) = the sum of daily evaporation during the period from July to June each annual cycle. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:
Each tile represents the mean annual Aridity Index during each 20-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). Each tile represents the mean annual Aridity Index during each 20-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). These reflect the level of variability across the region, indicating drier/wetter subregions (if they exist) and how these are projected to change in the future. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region. Rain shadows or regions more exposed to evaporation are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Each wine Australian Geographical Indications area with Annual Aridity Index values that are decreasing into the future, indicating a drier, moisture constrained future.

Figure 4: Projected annual aridity index

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).
Blue points: Annual Aridity Index was calculated as \( P/E \) where: \( P \) = the sum of daily rainfall during the period from July to June each annual cycle; and \( E \) = the sum of daily evaporation during the period from July to June each annual cycle. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were averaged across space (a mean Annual Aridity Index was then calculated for each grid cell within the region). Each tile represents how mean annual Aridity Index during the current period (1997–2017) has changed when compared to mean annual Aridity Index during the historical period (1981–1996). Each point represents the annual Aridity Index for each grid cell within the region. Each point represents the annual Aridity Index for each grid cell within the region for each separate CFAP2019 ensemble member. For each year, the spread of points represents the spatial variability across the region. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region. Rain shadows or regions more exposed to evaporation are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Each wine industry Australian Geographical Indications area with Annual Aridity Index values that are decreasing into the future, indicating a drier, moisture constrained future. Differences between the months, or time periods is expressed as changes to the shape of the violin plots. Like a box-and-whisker plot, the shape is defined by the values within that population. The violin is created by mirroring the probability distribution of the values, plotted in the vertical direction, describing the frequency and spread of values in the y-axis space. Where there is a concentration of values, the violin is broad. Where there are few values the violin is narrow (possibly only a single line). As the probability distribution is continuous, where extreme outliers values occur, narrow lines can be drawn between the main body and the outlier (typical of high rainfall areas/months that may be particularly dry in some years).

Differences between the months, or time periods is expressed as changes to the shape of the violin plots. Like a box-and-whisker plot, the shape is defined by the values within that population. The violin is created by mirroring the probability distribution of the values, plotted in the vertical direction, describing the frequency and spread of values in the y-axis space. Where there is a concentration of values, the violin is broad. Where there are few values the violin is narrow (possibly only a single line). As the probability distribution is continuous, where extreme outliers values occur, narrow lines can be drawn between the main body and the outlier (typical of high rainfall areas/months that may be particularly dry in some years).

Figure 6: Probability distribution seasonal aridity index

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).
Seasonal Aridity Index is calculated as \( P/E \) where: \( P \) = the sum of rainfall within each calendar season (Winter, Spring, Summer, Autumn); and \( E \) = the sum of evaporation within each calendar season (Winter, Spring, Summer, Autumn). This is calculated for each growing season year and for each ensemble member within the CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Each individual spatial and ensemble member values are included, no spatial or ensemble averaging is performed.

Violin plots represent 20-years of values for each month within each time period (2021–2040, 2041–2060, 2061–2080, 2081–2100). Each point represents the annual Aridity Index for each grid cell within the region for each separate CFAP2019 ensemble member. For each year, the spread of points represents the spatial variability across the region. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region. Rain shadows or regions more exposed to evaporation are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Each tile represents the mean annual Aridity Index during each 20-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). Each tile represents the mean annual Aridity Index during each 20-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). These reflect the level of variability across the region, indicating drier/wetter subregions (if they exist) and how these are projected to change in the future. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region. Rain shadows or regions more exposed to evaporation are often visible, although the exact boundaries should be interpreted with caution, especially in small regions where grid cells may be large compared to the controlling topographic features.

Each wine Australian Geographical Indications area with Annual Aridity Index values that are decreasing into the future, indicating a drier, moisture constrained future. Differences between the months, or time periods is expressed as changes to the shape of the violin plots. Like a box-and-whisker plot, the shape is defined by the values within that population. The violin is created by mirroring the probability distribution of the values, plotted in the vertical direction, describing the frequency and spread of values in the y-axis space. Where there is a concentration of values, the violin is broad. Where there are few values the violin is narrow (possibly only a single line). As the probability distribution is continuous, where extreme outliers values occur, narrow lines can be drawn between the main body and the outlier (typical of high rainfall areas/months that may be particularly dry in some years).

Differences between the months, or time periods is expressed as changes to the shape of the violin plots. Like a box-and-whisker plot, the shape is defined by the values within that population. The violin is created by mirroring the probability distribution of the values, plotted in the vertical direction, describing the frequency and spread of values in the y-axis space. Where there is a concentration of values, the violin is broad. Where there are few values the violin is narrow (possibly only a single line). As the probability distribution is continuous, where extreme outliers values occur, narrow lines can be drawn between the main body and the outlier (typical of high rainfall areas/months that may be particularly dry in some years).

Differences between the months, or time periods is expressed as changes to the shape of the violin plots. Like a box-and-whisker plot, the shape is defined by the values within that population. The violin is created by mirroring the probability distribution of the values, plotted in the vertical direction, describing the frequency and spread of values in the y-axis space. Where there is a concentration of values, the violin is broad. Where there are few values the violin is narrow (possibly only a single line). As the probability distribution is continuous, where extreme outliers values occur, narrow lines can be drawn between the main body and the outlier (typical of high rainfall areas/months that may be particularly dry in some years).
The grey, filled curves represent the distribution of observed Seasonal Aridity Index values within the current period (1997–2017) for contrasting wine industry Australian Geographic Indications (Wine Australia, 2019).

**Interpretation:**

Probability distributions reflect the spread and potential likelihood of values within a particular population of values. High, narrow peaks indicate low variability with a high frequency of particular values occurring within the population. Short, broad peaks indicate high variability, with few values occurring frequently. The probability distributions displayed in the atlas incorporate all spatial grid cell values, across each 20-year time period, from six ensemble members (i.e., independent simulations). Variability across spatial and temporal scales as well as across the CFAP2019 ensemble is represented with each curve. This has the advantage of reflecting the diversity that is found within each wine region (wetter vs drier subregions) and across different types of years (e.g., wet, average or dry). Different ensemble members capture different climate configurations (e.g., El Niño, neutral, or La Niña phases of ENSO), thus better estimate the range of possible extremes. Low likelihood years (extreme wet or dry) can be included, indicating what is possible, while simultaneously representing the expected or typical conditions for a particular region. Curves with multiple peaks indicate either strong, stable spatial differences (e.g., desert adjacent to alpine), or a strong modal character of the regions climate (e.g., a region either has wet years, or dry years but rarely average years). The different curves indicate how conditions are expected to change into the future. The future curves are typically shorter and broader as different simulations follow different trajectories, increasing the variability within the population of values.

When curves for each time period are all distinct and the direction of change across the five time-periods is consistent, this indicates all ensemble members agree broadly on the rate and direction of warming into the future. In such cases there is increased certainty surrounding the projected future.

When the curves from all time periods are overlapping, natural variability dominates the climate change trend, with the future conditions projected to be much the same as at present. When the direction of change is confused between time periods, or the spread of the curve is significantly broadened (but the average conditions are more or less the same), ensemble variability is high, there is significant uncertainty regarding the projections of the future.

The grey curves are the probability distribution for contrasting Australian wine regions, selected to present the range observed across Australia, and indicate the approximate analogue a region may become similar to into the future. These grey curves are calculated using the CFAP2019 ensemble during the period 2001–2020. As there are differences between these two archives, the 2001–2020 curves for these selected regions are slightly different to the grey curves. These differences are expected.

UNDERLYING DATA SOURCE: Climate Futures Australasian Projections 2019 (CFAP2019).

**Harvest date** was determined as the date within each year when each cumulative Growing Degree Days threshold (1000, 1500, 2000, 2500) was exceeded. Thus, there were 4 potential harvest dates, to account for different regional, varietal or style preferences of different users of the atlas. The **aridity index from season start until harvest** was calculated as $P/E$, where: P = the sum of rainfall from July 1st to harvest date, and E = the sum of evaporation from July 1st to harvest date. Values were calculated for each cell and for each ensemble member within CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine region’s Geographic Indications (Wine Australia, 2019).

The coloured curves represent the probability distribution of aridity index from season start until harvest for all grid cells and all ensemble members for all years during each different 20-year period, displayed separately for each GDD threshold. Time periods were: 2001-2020, 2021-2040, 2041-2060, 2061-2080, 2081-2100.

**Interpretation:**

Probability distributions reflect the spread and potential likelihood of values within a particular population of values. High, narrow peaks indicate low variability with a high frequency of particular values occurring within the population. Short, broad peaks indicate high variability, with few values occurring frequently. The probability distributions displayed in the atlas incorporate all spatial grid cell values, across each 20-year time period, from six ensemble members (i.e., independent simulations). Variability across spatial and temporal scales as well as across the CFAP2019 ensemble is represented with each curve. This has the advantage of reflecting the diversity that is found within each wine region (wetter vs drier subregions) and across different types of years (e.g., wet, average or dry). Different ensemble members capture different climate configurations (e.g., El Niño, neutral, or La Niña phases of ENSO), thus better estimate the range of possible extremes. Low likelihood years (extreme wet or dry) can be included, indicating what is possible, while simultaneously representing the expected or typical conditions for a particular region. Curves with multiple peaks indicate either strong, stable spatial differences (e.g., desert adjacent to alpine, or a strong modal character of the regions climate (e.g., a region either has wet years, or dry years but rarely average years). The different curves indicate how conditions are expected to change into the future. The future curves are typically shorter and broader as different simulations follow different trajectories, increasing the variability within the population of values.

When curves for each time period are all distinct and the direction of change across the five time-periods is consistent, this indicates all ensemble members agree broadly on the rate and direction of warming into the future. In such cases there is increased certainty surrounding the projected future.

When the curves from all time periods are overlapping, natural variability dominates the climate change trend, with the future conditions projected to be much the same as at present. When the direction of change is confused between time periods, or the spread of the curve is significantly broadened (but the average conditions are more or less the same), ensemble variability is high, there is significant uncertainty regarding the projections of the future.
**METHODS AND INTERPRETATION**

**Methods and interpretation of figures**

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**Extreme Heat**

**Figure 1: Observed mean excess heat factor**

Underlying data source: Australian Gridded Climate Data Product (Jones et al., 2009).

**Excess Heat Factor (EHF)** is an index that describes the severity of short term, acute heat impacts on humans during heat waves. It accounts for heat hot a period of three days or more is in relation to a particular location, as well as how hot the period is with respect to the recent past (the previous 30 days). This reflects the fact that people acclimatise to a certain extent to their local climate but may not be prepared for a sudden rise in temperature above that of the recent past. The calculation is described in Nairn and Forrester (2015). In order to apply this assessment into the future, the baseline period used to calculate the typical annual temperatures needed to be applied on a rolling basis, to take into account acclimatisation. The baseline period was always calculated as the previous 30 years (rounded to the nearest 5 years, so for example: the baseline period for the year 1990 was 1985–1994, the baseline period for the year 2020 was 1990–2019). Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Heatwave days were identified as those days when EHF is positive for 3 consecutive days or more. Mean EHF is the average of all observed EHF values during heatwave days within the current period (1997–2017).

**Interpretation:**

Each tile represents the mean EHF during the period 1997–2017 (which is the period of recent memory). Higher (lower) EHF values indicate more (less) intense heatwaves. For more information refer to Nairn and Forrester (2015). This map reflects the level of variability across the region as it is currently experienced. Lower values tend to be in regions exposed to large water bodies (typically oceans) that can provide relief, particularly overnight. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region.

**Figure 2: Observed change in excess heat factor**

Underlying data source: Australian Gridded Climate Data Product (Jones et al., 2009).

**Excess Heat Factor (EHF)** is an index that describes the severity of short term, acute heat impacts on humans during heat waves. It accounts for heat hot a period of three days or more is in relation to a particular location, as well as how hot the period is with respect to the recent past (the previous 30 days). This reflects the fact that people acclimatise to a certain extent to their local climate but may not be prepared for a sudden rise in temperature above that of the recent past. The calculation is described in Nairn and Forrester (2015). In order to apply this assessment into the future, the baseline period used to calculate the typical annual temperatures needed to be applied on a rolling basis, to take into account acclimatisation. The baseline period was always calculated as the previous 30 years (rounded to the nearest 5 years, so for example: the baseline period for the year 1990 was 1985–1994, the baseline period for the year 2020 was 1990–2019). Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Heatwave days were identified as those days when EHF is positive for 3 consecutive days or more. Mean EHF is the average of all observed EHF values during heatwave days within the current period (1997–2017).

**Interpretation:**

Each tile represents the mean EHF during each 20-year period of 2011–2030, 2031–2050, 2051–2070, 2071–2090, 2091–2110 (following the RCP8.5 scenarios). These reflect the level of variability across the region as it is currently experienced. Lower values tend to be in regions exposed to large water bodies (typically oceans) that can provide relief, particularly overnight. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region.

**Figure 3: Projected mean excess heat factor**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

**Excess Heat Factor (EHF)** is an index that describes the severity of short term, acute heat impacts on humans during heat waves. It accounts for heat hot a period of three days or more is in relation to an annual temperature threshold at a particular location, as well as how hot the period is with respect to the recent past (the previous 30 days). This reflects the fact that people acclimatise to a certain extent to their local climate but may not be prepared for a sudden rise in temperature above that of the recent past. The calculation is described in Nairn and Forrester (2015). In order to apply this assessment into the future, the baseline period used to calculate the typical annual temperatures needed to be applied on a rolling basis, to take into account acclimatisation. The baseline period was always calculated as the previous 30 years (rounded to the nearest 5 years, so for example: the baseline period for the year 1990 was 1985–1994; the baseline period for the year 2020 was 1990–2019). Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Heatwave days were identified as those days when EHF is positive for 3 consecutive days or more. Mean EHF is the average of all EHF values during heatwave days within each time period (2001–2030, 2031–2060, 2041–2060, 2051–2080, 2061–2090, 2071–2090). These were calculated for each ensemble member within the CFAP2019. The 6 ensemble member values (for each cell) are averaged, generating the ensemble mean for each cell within the region.

**Interpretation:**

Each tile represents the mean EHF during each 20-year period of 2011–2030, 2031–2050, 2051–2070, 2071–2090, 2091–2110 (following the RCP8.5 scenarios). These reflect the level of variability across the region as it is currently experienced. Lower values tend to be in regions exposed to large water bodies (typically oceans) that can provide relief, particularly overnight. Tiles are the resolution of the underlying data. Towns and roads are included to help identify specific sites within the region.

**Figure 4: Projected mean number of extreme heat days**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

The annual number of days where daily maximum temperature exceeded either 38°C, 37°C, 40°C or 45°C was calculated for each cell and ensemble member within CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. Heatwave days were identified as those days when EHF is positive for 3 consecutive days or more. Mean EHF is the average of all observed EHF values during heatwave days within the current period (1997–2017), or the baseline period (1961–1990). The baseline period mean EHF was then subtracted from the current period mean EHF, resulting in the observed change in mean EHF.

**Interpretation:**

Each tile represents how mean EHF during the current period (1997–2017) has changed when compared to the mean EHF during the historical period (1961–1990). Climate change is a large scale feature, so the level of change observed is relatively similar when viewed at local scales. Higher (lower) EHF values indicate more (less) intense heatwaves. For more information refer to Nairn and Forrester (2015).

**Figure 5: Projected number of days with severe risk to humans working outside**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

Humans have physical limitations within which they can safely operate without adaptive technology or behaviours, with humidity contributing to heat stress. When temperatures are >38°C and humidity is >60%, conditions are classified as being a severe risk of heat stress for humans. Days when both these conditions were met were classified as high human heat stress days and the annual count calculated. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. All individual spatial and ensemble member values are included, no spatial or ensemble averaging is performed.

**Interpretation:**

The number of days identified as exhibiting conditions that expose humans working outside to severe risk of heat stress (>38°C and >60% humidity) is projected to increase in many regions. Those regions at greatest risk are those where moisture availability remains high enough to support high humidity days.

In most regions, increases are projected to increase exponentially, diverging from historical levels from around 2020 onwards. For some regions, projections indicate 40–60 days at risk (i.e., most of summer) by the end of the century (following RCP8.5).
Australia’s Wine Future — A Climate Atlas

METHODS AND INTERPRETATION

Methods and interpretation of figures

Figure 7: Probability distribution of daily minimum and maximum temperature
during a heatwave

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

Ensemble Heat Wave Factor (EHF) is an index that describes the severity of short term, acute heat
impacts on humans during heat waves. The calculation is described in Naim and Fawcett (2015). Heatwave days were identified as those days when EHF is positive for 3 consecutive
days or more.

Date of Heatwave Days was determined as the date within each year a heatwave occurred.
For multi-day events, all days were included and daily minimum and maximum temperature
values of those days were extracted. Values were extracted for each cell and for each ensemble
member within CFAP2019. Grid cells selected were those within (or intersecting with the
boundary of) the polygon that defined each wine region’s Geographical Indications (Wine
Australia, 2019).

The coloured curves represent the probability distribution of daily minimum temperature
and daily maximum temperature during a heatwave. Values are for all grid cells, all ensemble
members, for all years during each 20-year period. Time periods were: 2001–2020, 2021–2040,
2041–2060, 2061–2080, 2081–2100. All individual spatial and ensemble member values are
included, no spatial or ensemble averaging is performed.

Interpretation:
Probability distributions reflect the spread and potential likelihood of values within a
particular population of values. High, narrow peaks indicate low variability with a high
frequency of particular values occurring within the population. Short, broad peaks indi-
cate high variability, with few values occurring frequently. The probability distributions
displayed in the atlas incorporate all spatial grid cell values, across each 20-year time
period, from six ensemble members (i.e., independent simulations). Variability across
spatial and temporal scales as well as across the CFAP2019 ensemble is represented with
each curve. This has the advantage of reflecting the diversity that is found within each
wine region (wetter vs drier subregions) and across different types of years (e.g., wet,
average or dry). Different curve members capture different climate configurations
(e.g., El Niño, neutral, or La Niña phases of ENSO), thus better estimate the range of
possible extremes. Low likelihood years (extreme wet or dry) can be included, indicating
what is possible, while simultaneously representing the expected or typical conditions
for a particular region. Curves with multiple peaks indicate either strong, stable spatial
differences (e.g., desert adjacent to alpine), or a strong modal character of the regions
climate (e.g., a region either has wet years, or dry years but rarely average years).
The different curves indicate how conditions are expected to change into the future. The
future curves are typically shorter and broader as different simulations follow different
trajectories, increasing the variability within the population of values.

When curves for each time period are all distinct and the direction of change across the
five time-periods is consistent, this indicates all ensemble members agree broadly on the
rate and direction of warming into the future. In such cases there is increased certainty
surrounding the projected future.

When the curves from all time periods are overlapping, natural variability dominates the
climate change trend, with the future conditions projected to be much the same as at
present.

When the direction of change is confused between time periods, or the spread of the
curve is significantly broadened (but the average conditions are more or less the same),
ensemble variability is high, there is significant uncertainty regarding the projections of
the future.

Heatwaves are a specifically characterised event. The date of heatwave days for most
regions does not change significantly. Heatwaves are calculated relative to a 30-year base-
line period. However, within a climate change context, the 30-year baseline needs follow
behind the target year (to account for acclimatisation of organisms within the region as
the climate warms). This rolling 30-year baseline period warms with climate change.
This ensures that the latest 30-day threshold typically occurs at the peak of summer (with
a normally distributed spread surrounding this mean). The absolute temperatures of
heatwaves are much hotter and in many regions the EHF values increase, indicating an
increase in heatwave intensity, however, the chance of a heatwave in any month of the
year is projected to remain relatively constant into the future.

Figure 8: Probability distribution of date of heatwave days

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019).

Excess Heat Factor (EHF) is an index that describes the severity of short term, acute heat
impacts on humans during heat waves. A definition of how it is calculated is described in Naim
and Fawcett (2015). Heatwave days were identified as those days when EHF was positive.

Date of Heatwave Days was determined as date within each year a heatwave occurred.
For multi-day events, all days were included. Values were calculated for each cell and for each
ensemble member within CFAP2019. Grid cells selected were those within (or intersecting with the
boundary of) the polygon that defined each wine region’s Geographical Indications (Wine
Australia, 2019).

The coloured curves represent the probability distribution of Date of Heatwave Days values for
all grid cells and all ensemble members for all years during each 20-year period. Time periods
were: 2001–2020, 2021–2040, 2041–2060, 2061–2080, 2081–2100. All individual spatial and
ensemble member values are included, no spatial or ensemble averaging is performed.

Interpretation:
Probability distributions reflect the spread and potential likelihood of values within a
particular population of values. High, narrow peaks indicate low variability with a high
frequency of particular values occurring within the population. Short, broad peaks indi-
cate high variability, with few values occurring frequently. The probability distributions
displayed in the atlas incorporate all spatial grid cell values, across each 20-year time
period, from six ensemble members (i.e., independent simulations). Variability across
spatial and temporal scales as well as across the CFAP2019 ensemble is represented with
each curve. This has the advantage of reflecting the diversity that is found within each
wine region (wetter vs drier subregions) and across different types of years (e.g., wet,
average or dry). Different ensemble members capture different climate configurations
(e.g., El Niño, neutral, or La Niña phases of ENSO), thus better estimate the range of
possible extremes. Low likelihood years (extreme wet or dry) can be included, indicating
what is possible, while simultaneously representing the expected or typical conditions
for a particular region. Curves with multiple peaks indicate either strong, stable spatial
differences (e.g., desert adjacent to alpine), or a strong modal character of the regions
climate (e.g., a region either has wet years, or dry years but rarely average years).
The different curves indicate how conditions are expected to change into the future. The
future curves are typically shorter and broader as different simulations follow different
trajectories, increasing the variability within the population of values.

When curves for each time period are all distinct and the direction of change across the
five time-periods is consistent, this indicates all ensemble members agree broadly on the
rate and direction of warming into the future. In such cases there is increased certainty
surrounding the projected future.

When the curves from all time periods are overlapping, natural variability dominates the
climate change trend, with the future conditions projected to be much the same as at
present.

When the direction of change is confused between time periods, or the spread of the
curve is significantly broadened (but the average conditions are more or less the same),
ensemble variability is high, there is significant uncertainty regarding the projections of
the future.
**Annual frost risk days** is the number of individual frost risk day events that occur during the period from October to April each annual cycle. Mean frost risk days is the average of all annual frost risk days within the current period (1997–2017). Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:
Each tile represents the mean frost risk days during the period 1997–2017, which is the period of recent memory. Higher (lower) frost risk values indicate more (less) days where minimum temperatures were < -2 °C. For many regions, frost risk is very low (often less than 1 day per year). This map reflects the level of variability across the region as it is currently experienced. Tiles are the resolution of the underlying data. Higher values typically correspond to higher elevation regions. Tiles have an average deviation of the area they represent, so they best represent regions that have similar elevations (±1km²) and thus are poorly represented. This can influence the representation of some climatic features and should be considered when interpreting these figures. Towns and roads are included to help identify specific sites within the region.

**METHODS AND INTERPRETATION**

**Methods and interpretation of figures**

**Figure 3: Projected mean frost risk days**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019). A frost risk day was defined as any day when daily minimum temperature was < -2 °C. Annual frost risk days is the number of individual frost risk day events that occur during the period from October to April each annual cycle. Mean frost risk days is the average of all annual frost risk days within each period (2001–2020, 2021–2040, 2041–2060, 2061–2080, 2081–2100). These were calculated for each ensemble member within the CFAP2019. The 6 ensemble member values (for each cell) are averaged, generating the ensemble mean for each cell within the region. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell.

Interpretation:
Each tile represents the mean frost risk days during each 20-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). Higher (lower) frost risk values indicate more (less) days where minimum temperatures were < -2 °C. This map reflects the level of variability across the region as it is currently experienced and for many regions, frost risk is very low, often less than 1 day per year (so these figures have few features). Tiles are the resolution of the underlying data. Higher values typically correspond to higher elevation regions. Tiles have an average deviation of the area they represent, so they best represent regions that have similar elevations (±1km²) across 5-10km² scales. Typically, the highest peaks occur at smaller scales (±1km²) and thus are poorly represented. This can influence the representation of some climatic features and should be considered when interpreting these figures. Towns and roads are included to help identify specific sites within the region.

**Figure 4: Projected monthly minimum temperature**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019). Monthly minimum temperatures were extracted directly from the CFAP2019. Violin plots represent 20-years of values for each month within each time period (2021–2040, 2041–2060, 2061–2080, 2081–2100). All individual spatial and ensemble member values are included. Spatial or ensemble averaging is performed. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019).

Interpretation:
Violin plots are a combination of box-and-whisker plots and probability distribution curves. Like a box-and-whisker plot, this shape is defined by the values within that range. The violin is created by mirroring the probability distribution of the values, plotted in the vertical direction, describing the frequency and spread of values in the y-axis space. Where there is a concentration of values, the violin is broad. Where there are few values the violin is narrow (possibly only a single line). As the probability distribution is continuous, extreme outlier values occur, narrow lines can be drawn between the main body and the outlier (typical of high rainfall areas/months that may be particularly dry in some years).

Differences between the months, or time periods is expressed as a change to the shape of each violin. The 2001–2020 violin for each month is shadowed underneath future time periods, so that changes in future periods can be more easily determined. In all wine regions across Australia, minimum daily temperatures are projected to increase rapidly from 2030 onwards.

**Figure 5: Projected monthly frost risk days**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019). Frost risk days were defined as days when daily minimum temperature was < -2 °C. The monthly count of frost risk days was calculated for each month, within each year for each ensemble member within CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell and then averaged into a regional ensemble mean for each 20-year time period (i.e., a single summary value for each time period from all inputs across the region). Time periods were: 2001–2020, 2021–2040, 2041–2060, 2061–2080, 2081–2100.

Interpretation:
Average monthly frost risk days for each 20-year period of 2021–2040, 2041–2060, 2061–2080, 2081–2100 (following the RCP8.5 scenario). Differences between the months, or time periods is expressed as changes to the height of each column. The 2001–2020 column for each month is shadowed underneath future time periods, so that changes in future periods can be more easily determined.

For all Australian wine regions, accumulated frost intensity is projected to decrease into the future. As temperatures rise, days that are < -2 °C are projected to warm, decreasing the chill or frost intensity of these days. In many regions, these days are dominated by high elevation regions, rather than the true growing areas. However, they provide a strong indication of the direction and rate of change projected into the future. The decreasing trend appears to have been occurring since the 1960s (although it is possible it started earlier).

**Figure 7: Projected mean number of extreme cold days**

Underlying data source: Climate Futures Australasian Projections 2019 (CFAP2019). The annual number of days where daily minimum temperature fell below either -2 °C, -3 °C, or - 2 °C was calculated for each cell and ensemble member within CFAP2019. Grid cells selected were those within (or intersecting with the boundary of) the polygon that defined each wine industry Australian Geographical Indications (Wine Australia, 2019). Values were calculated for each grid cell. These values were then averaged into a regional ensemble mean for each year (i.e., a single summary value for each year from all inputs across the region).

Interpretation:
The number of days colder than selected thresholds (< -2 °C, -3 °C, or -2 °C) is projected to dramatically decrease into the future. The decreasing trend appears to have been occurring since the 1960s (although it is possible it started earlier). Interannual variability is high in most regions, but climate change is clearly the dominant influence over the long timescales.
Part II

Australia’s Wine Future — A Climate Atlas
Figure 1: Spatial representation of the Australian wine regions used within this atlas. For mainland Australia these are the Wine Australia Geographical Indications (GI). The Tasmania GI was divided into 8 regions based on Australian Bureau of Meteorology forecast districts, in recognition of the different climatic zones across the state.
Figure 2: Observed mean Growing Season Temperature across Australia’s wine regions

Current period (1997-2017)

Figure 2: Observed mean Growing Season Temperature (Oct-Apr) across all growing years from 1997-2017.
Figure 3: Observed change in mean Growing Season Temperature across Australia’s wine regions

Figure 3: The change in Growing Season Temperature between the current (1997–2017) and historical (1961–1990) periods. Growing Season Temperature has increased across the region over recent decades.
Observed Climate Across Australia’s Wine Regions

National Maps

Figure 4: Observed mean Growing Season Rainfall across Australia’s wine regions

Figure 4: Observed mean Growing Season Rainfall (Oct–Apr) across all growing years from 1997–2017.
Figure 5: Observed change in mean Growing Season Rainfall across Australia’s wine regions

Figure 5: Change in Growing Season Rainfall (Oct–Apr) between the current (1997–2017) and historical (1961–1990) periods. Negative values indicate a trend towards drier conditions. Positive values indicate a trend towards wetter conditions.
Figure 6: Observed mean Non-Growing Season Rainfall across Australia’s wine regions
Figure 7: Observed change in mean Non-Growing Season Rainfall across Australia’s wine regions

Change in Non-Growing Season Rainfall (May–Sep) between the current (1997–2017) and historical (1961–1990) periods. Negative values indicate a trend towards dryer conditions. Positive values indicate a trend towards wetter conditions.
Figure 8: Observed mean Growing Year Rainfall across Australia’s wine regions
Observed Climate Across Australia’s Wine Regions

Figure 9: Observed change in mean Growing Year Rainfall across Australia’s wine regions


Figure 9: Change in Annual Rainfall (Jul-Jun) between the current (1997–2017) and historical (1961–1990) periods. Negative values indicate a trend towards drier conditions. Positive values indicate a trend towards wetter conditions.
Figure 10: Observed mean Aridity Index across Australia's wine regions

Aridity Index is a value that characterises the ratio between the mean annual rainfall and mean annual evaporation. Low values indicate drier conditions. High values indicate wetter conditions.
Figure 11: Observed change in mean Aridity Index across Australia’s wine regions

Figure 11: Observed percentage change in mean Aridity Index between the current (1997–2017) and historical (1961–1990) periods. This shows the change already experienced across the country. Negative values indicate a trend towards drier conditions. Positive values indicate a trend towards wetter conditions.
OBSERVED CLIMATE ACROSS AUSTRALIA’S WINE REGIONS

Reference Bar Charts

Figure 12: Mean Growing Season Temperature for current period (1997–2017)

Figure 13: Mean maximum growing year Growing Degree Days for current period (1997–2017)
Australia’s Wine Future — A Climate Atlas

OBSERVED CLIMATE ACROSS AUSTRALIA’S WINE REGIONS

Reference Bar Charts

Figure 14: Wine regions of Australia ranked by total Growing Season Rainfall for the period 1997–2017. The growing season is defined to be October to April; e.g. the first growing season is October 1997 to April 1998, and the last growing season is October 2016 to April 2017.

Figure 15: Wine regions of Australia ranked by total Non-Growing Season Rainfall for the period 1997–2017. The non-growing season is defined to be May to September; e.g. the first non-growing season is May 1997 to September 1997, and the last growing season is May 2016 to September 2016.
OBSERVED CLIMATE ACROSS AUSTRALIA’S WINE REGIONS

Reference Bar Charts

Figure 16: Mean Growing Year Rainfall for current period (1997–2017)

Figure 17: Mean growing year Aridity Index for current period (1997–2017)

Figure 16: Wine regions of Australia ranked by total Annual Rainfall for the period 1997–2017. The annual period is defined to be July to June; e.g. the first annual period is July 1997 to June 1998, and the last annual period is July 2016 to June 2017.

Figure 17: Wine regions of Australia ranked by mean growing year Aridity Index for the period 1997–2017. The growing season is defined to be October to April; e.g. the first growing season is October 1997 to April 1998, and the last growing season is October 2016 to April 2017.
Figure 18: Representation of mean Growing Year Aridity Index vs mean Growing Season Temperature for each Australian Geographic Indication, averaged within the time periods (1961–1990, 1997–2017, 2021–2040, 2041–2060, 2061–2080, and 2081–2100), following the RCP8.5 scenario. Points represent observed conditions during the current period (1997–2017). Lines indicate the general direction of change experienced and projected into the future (based on the CFSR310 ensemble mean). Line segments represent the shorter-term direction of change projected between time periods. Values are regional and ensemble averages (i.e. a single value for each region, for each time period). The plot shows a tendency of regions to move towards warmer and drier conditions (i.e. higher mean Growing Season Temperature and lower mean Growing Year Aridity Index). Regions that currently experience quite wet conditions (points on the right-hand side of the plot) are projected to have challenges driven mostly by warming temperatures (pathways are more vertical).
Queensland
**Figure 1: Observed mean Growing Season Temperature (Oct–Apr) across all growing years from 1997–2017.**

**Figure 2: Projected mean Growing Season Temperature (Oct–Apr) for 20-year time periods from 2021 to 2100.**

**Figure 3: Projected change in Growing Season Temperature between the current (1997–2017) and historical (1961–1990) periods. Growing Season Temperature has increased across the region over recent decades.**

**Figure 4: Projected Growing Season Temperature (October to April).**

**Figure 5: Distribution of Growing Season Temperature.**

**Figure 6: Probability distribution of Growing Degree Days (GDD) across the growing year (July–June).**

**Figure 7: Cumulative Growing Degree Days (GDD) across the growing year (July–June).**

**Figure 8: Distribution of date when Growing Degree Days reaches threshold.**
Figure 1: Observed mean Growing Season Rainfall (Oct–Apr) across all growing years from 1997–2017.

Figure 2: Observed change in Growing Season Rainfall between the current (1997–2017) and historical (1961–1990) periods. Negative values indicate a trend toward drier conditions. Positive values indicate a trend toward wetter conditions.

Figure 3: Projected mean Growing Season Rainfall (October to April) for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members.

Figure 4: Time series of Growing Season Rainfall (mm). Blue points are the annual values for each grid cell, for each of the 6 ensemble members. Horizontal grey bars represent the mean Growing Season Rainfall value during 1997–2017, 2021–2040, 2041–2060, 2061–2080, and 2081–2100. The shape of the curve is driven by the level of variability experienced within each 20-year period. Variability can occur spatially within the region, across years, or between ensemble members. Grey shapes represent the probability distribution of rainfall across the growing year. The current period (1997–2017) is shadowed underneath the future time periods to highlight any differences expected into the future. Coloured bars represent the projected mean global temperature change for each future time period, with each violin indicating the expected probability distribution of rainfall across the growing year. The current period (1997–2017) is shadowed underneath the future time periods to highlight any differences expected into the future.

Figure 5: As with Figure 4, but for Non-Growing Season Rainfall (mm). Horizontal grey bars represent the mean Non-Growing Season Rainfall value during 1997–2017 in selected regions across Australia.

Figure 6: Violin plots of monthly rainfall (mm) for 20-year time periods from 2001 to 2100. Each violin represents monthly totals for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. In each panel the monthly violins indicate the expected probability distribution of rainfall across the growing year. The current period (2001–2020) is shadowed underneath the future time periods to highlight any differences expected into the future. Horizontally, the violins indicate the expected probability distribution of rainfall across the growing year. The current period (2001–2020) is shadowed underneath the future time periods to highlight any differences expected into the future. Coloured bars represent the projected mean global temperature increase into the future (following the RCP 8.5 scenario). These can be used to make decisions based on projected temperature change rather than time.

Figure 7: Violin plots of monthly rainfall (mm) for 20-year time periods from 2001 to 2100. Each violin represents monthly totals for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. In each panel the monthly violins indicate the expected probability distribution of rainfall across the growing year. The current period (2001–2020) is shadowed underneath the future time periods to highlight any differences expected into the future. Coloured bars represent the projected mean global temperature increase into the future (following the RCP 8.5 scenario). These can be used to make decisions based on projected temperature change rather than time.

Figure 8: Number of rainy days during harvest for each 20-year period. Harvest refers to the date when Growing Degree Days (GDD) reach example phenological thresholds (1000, 1500, 2000, 2500) which were chosen to reflect development time of different grape styles and varieties. Rainy days during harvest were defined as days with >10mm of rain from 7 days before to 7 days after the date each GDD threshold was reached. Variability can occur spatially within the region, across years, or between ensemble members. A shift in the curve to the left (right) indicates a change toward drier (wetter) conditions.
Australia’s Wine Future — A Climate Atlas

SOUTH BURNETT

Aridity

Figure 1: Observed mean annual Aridity Index across all growing years from 1997–2017. Aridity Index is a value that characterizes the ratio between the mean annual rainfall and mean annual evaporation. Low (high) values indicate drier (wetter) conditions.

Figure 2: Observed percentage change in mean annual Aridity Index between the current (1997–2017) and historical (1961–1990) periods. This shows the change already experienced across the region. Negative (positive) values indicate a trend towards drier (wetter) conditions.

Figure 3: Projected mean annual Aridity Index for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Increasing (decreasing) values indicate a trend towards drier (wetter) conditions.

Figure 4: Time series of annual Aridity Index. Points are the annual means for each grid cell in the region, for each of the 6 ensemble members. Aridity Index values >2 all indicate very wet conditions. There is no meaningful difference past this value, so higher values were not presented. Horizontal grey bars represent the mean annual Aridity Index from selected regions across Australia — these provide an example of conditions this region may transition towards in the future. Coloured bars represent the projected global temperature increase expected in the future (following the RCP 8.5 scenario) which can be used to make decisions based on projected temperature change rather than time (for example, if the rate of warming rapidly increases, where temperature changes are experienced earlier, useful information can still be extracted from these figures by using the coloured bars instead of the time-axis).

Figure 5: Violin plots of monthly Aridity Index for 20-year time periods from 2001 to 2100. Each violin represents monthly averages for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. In each violin panel the violin indicates the expected probability distribution of Aridity Index for each month across the growing year. The current period (2001–2020) is shadowed underneath the future time periods to highlight any differences expected into the future. Dots represent the mean monthly Aridity Index for each violin. If the violin shifts lower (higher) this indicates a change towards drier (wetter) conditions.

Figure 6: Distribution of seasonal Aridity Index (Winter, Spring, Summer, Autumn), presented as a probability distribution for each 20-year period. Variability can occur spatially within the region, across years, or between ensemble members. A shift to the left (right) indicates drier (wetter) conditions. A missing time period indicates that the specific phenological threshold was not reached within the growing year (July–June).

Figure 7: Mean annual Aridity Index accumulated from start of the growing season (July) to date of harvest, presented as a probability distribution for each 20-year period. Date of harvest refers to the date at which Growing Degree Days reach some example phenological thresholds (1000, 1500, 2000, 2500), chosen to reflect development time of different grape styles and varieties. Variability can occur spatially within the region, across years, or between ensemble members. A shift to the left (right) indicates drier (wetter) conditions. A missing time period indicates that the specific phenological threshold was not reached within the growing year (July–June).
Figure 1: Observed mean Excess Heat Factor (EHF) during heatwaves (as per Nairn and Fawcett (2013)), across all growing years from 1997–2017. EHF is an index that characterises heatwaves, high values indicate more intense heatwaves. The mean EHF is the mean value from all heatwaves that occurred from 1997–2017.

Figure 2: Observed change in mean Excess Heat Factor 1997–2017 versus 1961–1990. EHF is an index that characterises heatwaves, high values indicate more intense heatwaves. The mean EHF is the mean value from all heatwaves that occurred from 1997–2017.

Figure 3: Projected mean EHF during heatwaves for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Increasing (decreasing) values indicate a trend towards more (less) intense heatwaves.

Figure 4: Projected mean number of extreme heat days for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Increasing (decreasing) values indicate a trend towards more (less) intense heatwaves.

Figure 5: Projected number of days with severe risk to humans working outside. Positive (negative) values indicate a trend towards more (less) intense heatwaves.

Figure 6: Projected range of hot summer days. Positive (negative) values indicate a trend towards more (less) intense heatwaves.

Figure 7: Distribution of daily minimum and maximum temperature during a heatwave. Low values indicate a trend towards more (less) intense heatwaves.
Figure 1: Observed mean number of days at risk of frost during the growing season (October to April) over the period 1997–2017. Days at risk of frost are those with a daily minimum temperature <2°C. High (low) values indicate high (low) frost risk.

Figure 2: Change in the mean number of days at risk of frost during the growing season (October to April) between the current (1997–2017) and historical (1961–1990) periods. Days at risk of frost are days with a minimum temperature <2°C. High (low) values indicate increased (decreased) frost risk.

Figure 3: Projected mean number of days at risk of frost during the growing season (October to April) for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Increasing (decreasing) values indicate a trend towards higher (lower) frost risk.

Figure 4: Violin plots of daily minimum temperature (°C) for each month for 20-year periods from 2001 to 2100. Each violin represents daily data for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. Each violin shows the distribution of daily minimum temperatures for the period 2001–2020, for each grid cell in the region, for each of the 6 ensemble members. The current period (2001–2020) has been shadowed underneath future time periods to highlight any differences expected into the future. Dots represent the means for each violin. If the violin shifts lower (higher) this indicates a change towards colder (warmer) conditions.

Figure 5: Projected monthly minimum temperature

Figure 6: Projected monthly frost risk days

Figure 7: Projected accumulated frost intensity

Figure 8: Monthly average cumulative frost days for 20-year periods from 2001 to 2100. Values are a summary across all grid cells, for all years within each 20-year period, for each of the 6 ensemble members. This reflects how frost risk varies across the year within each 20-year period. The current period (2001–2020) has been shadowed underneath future time periods to highlight any differences expected into the future.

Figure 9: Timeseries of accumulated frost intensity, which is the cumulative total of temperatures less than 2°C over a growing season. This index characterises exposure to cold conditions. High values indicate cold winters/springs. Points are for each grid cell, averaged across the 6 ensemble members.

Figure 10: Time-series of the number of days per growing year when temperature falls below selected thresholds (<−2°C, <−5°C, <−8°C). Areas indicate the number of days with individual thresholds in each growing year. Values are averaged across all grid cells and the 6 ensemble members. Fewer instances reflect a warming climate.
Figure 1: Observed mean Growing Season Temperature (Oct–Apr) across all growing years from 1997–2017.

Figure 2: Observed change in mean Growing Season Temperature between the current (1997–2017) and historical (1961–1990) periods. Growing Season Temperature has increased across the region over recent decades.

Figure 3: Projected mean Growing Season Temperature for 20-year time periods from 2021 to 2100. Growing Season Temperature is expected to increase steadily into the future. Each grid cell is the mean of the 6 ensemble members.

Figure 4: Projected Growing Season Temperature (October to April) for the Granite Belt region. The figure shows how the mean Growing Season Temperature is expected to change in the future compared to the past (1961–1990). The projections are based on different climate models and scenarios.

Figure 5: Distribution of Growing Season Temperature. The probability distribution of growing season temperature across the region is shown for the current period (1997–2017) and for future periods (2021–2100). The distribution is skewed towards higher temperatures in the future.

Figure 6: Distribution of Growing Degree Days (GDD) across the growing year (July–June). The distribution shows the range of dates at which the example phenological thresholds (1000, 1500, 2000, 2500) are reached for each time period. Variability can occur spatially within the region, across years, or between ensemble members.

Figure 7: Cumulative Growing Degree Days (GDD) across the growing year (July–June). Dashed lines show GDD values (1000, 1500, 2000, 2500) for some example phenological thresholds. Each growing year is represented by a colored line. In future time periods, heat accumulates faster, thresholds are reached earlier and maximum GDD reached is higher.

Figure 8: Probability distribution showing the range of dates at which the example phenological thresholds (1000, 1500, 2000, 2500) are reached for each time period. Variability can occur spatially within the region, across years, or between ensemble members. A shift to the left (right) indicates earlier (later) harvest dates. A missing time period indicates that the specific phenological threshold was not reached within the growing year (July–June).
Figure 1: Observed mean Growing Season Rainfall (October–April) across all growing years from 1997–2017.

Figure 2: Change in Growing Season Rainfall (October–April) between the current (1997–2017) and historical (1961–1990) periods. Negative values indicate a trend towards drier conditions. Positive values indicate a trend towards wetter conditions.

Figure 3: Projected mean Growing Season Rainfall for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members.

Figure 4: Time series of Growing Season Rainfall (mm). Blue points are the annual values for each grid cell, for each of the 6 ensemble members. Horizontal grey bars represent the mean Growing Season Rainfall during 1997–2017 in selected regions across Australia. These provide a comparison between current conditions (1997–2017) elsewhere and future conditions in this region and help identify future analogue regions. Coloured bars represent the projected mean global temperature increase into the future (following the RCP 8.5 scenario). This can be used to make decisions based on projected temperature change rather than time.

Figure 5: As with Figure 4, but for Non-Growing Season Rainfall (mm). Horizontal grey bars represent the mean Non-Growing Season Rainfall value during 1997–2017 in selected regions across Australia.

Figure 6: Violin plots of monthly rainfall (mm) for 20-year time periods from 2001 to 2100. Each violin represents monthly totals for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. In each panel the monthly violins indicate the expected probability distribution of rainfall across the growing year. The current period (2001–2020) is shadowed underneath the future time periods to highlight any differences expected into the future. Dots represent the mean monthly rainfall for each violin. If the violin shifts lower (higher) this indicates a change towards drier (wetter) conditions.

Figure 7: Seasonal rainfall (Winter, Spring, Summer, Autumn) (mm), presented as a probability distribution for each 20-year period. The shape of the curve is driven by the level of variability experienced within each 20-year period. Variability can occur spatially within the region, across years, or between ensemble members. Grey shapes represent the probability distribution of seasonal rainfall for contrasting regions during 1997–2017. Differences in the shape of curves between the current and future periods indicate a change in the typical conditions. A shift to the left (right) indicates an increase in drier (wetter) conditions.

Figure 8: Number of rainy days during harvest for each 20-year period. Harvest refers to the date when Growing Degree Days (GDD) reach example phenological thresholds (1000, 1500, 2000, 2500) which were chosen to reflect development time of different grape styles and varieties. Rainy days during harvest were defined as days with >10mm of rain from 7 days before to 7 days after the date each GDD threshold was reached. Variability can occur spatially within the region, across years, or between ensemble members. A shift in the curve to the left (right) indicates fewer (more) rainy days during harvest. A missing time period indicates that the specific phenological threshold was not reached within the growing year (July–June).
Figure 1: Observed mean annual Aridity Index across all growing years from 1997–2017. Aridity Index values < 2 all indicate very wet conditions. There is no meaningful difference past this value, so higher values were not presented. Horizontal grey bars represent the mean annual Aridity Index from selected regions across Australia — these provide an example of conditions the region may transition towards in the future. Coloured bars represent the projected global temperature increase expected in the future (following the RCP 8.5 scenario) which can be used to make decisions based on projected temperature change rather than time (for example, if the rate of warming rapidly increases, where temperature changes are experienced earlier, useful information can still be extracted from these figures by using the coloured boxes instead of the time-axis).

Figure 2: Observed percentage change in mean annual Aridity Index between the current (1997–2017) and historical (1961–1990) periods. This shows the change already experienced across the region. Negative (positive) values indicate a trend towards drier (wetter) conditions.

Figure 3: Projected mean annual Aridity Index for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Decreasing (increasing) values indicate a trend towards drier (wetter) conditions.

Figure 4: Time series of annual Aridity Index. Points are the annual means for each grid cell in the region, for each of the 6 ensemble members. Aridity Index values > 2 all indicate very wet conditions. There is no meaningful difference past this value, so higher values were not presented. Horizontal grey bars represent the mean annual Aridity Index from selected regions across Australia — these provide an example of conditions the region may transition towards in the future. Coloured bars represent the projected global temperature increase expected in the future (following the RCP 8.5 scenario) which can be used to make decisions based on projected temperature change rather than time (for example, if the rate of warming rapidly increases, where temperature changes are experienced earlier, useful information can still be extracted from these figures by using the coloured boxes instead of the time-axis).

Figure 5: Violin plots of monthly Aridity Index for 20-year time periods from 2001 to 2100. Each violin represents monthly averages for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. In each violin panel the violins indicate the expected probability distribution of Aridity Index within each month across the growing year. The current period (2001–2030) is shadowed underneath the future time periods to highlight any differences expected into the future. Dots represent the mean monthly Aridity Index for each violin. If the violin shifts lower (higher) this indicates a change towards drier (wetter) conditions.

Figure 6: Distribution of seasonal Aridity Index (Winter, Spring, Summer, Autumn), presented as a probability distribution for each 20-year period. The shape of the curve is driven by the level of variability experienced within each 20-year period. Variability can occur spatially within the region, across years, or between ensemble members. Grey shapes represent the probability distribution of seasonal aridity for contrasting regions during 1997–2017. Differences in the shape of curves between the current and future periods indicate a change in the typical conditions. A shift to the left (right) indicates drier (wetter) conditions. Aridity Index values > 2 all indicate very wet conditions.

Figure 7: Mean annual Aridity Index accumulated from start of the growing season (July) to date of harvest, presented as a probability distribution for each 20-year period. Date of harvest refers to the date at which Growing Degree Days reach some example phenological thresholds (1000, 1500, 2000, 2500), chosen to reflect development time of different grape styles and varieties. Variability can occur spatially within the region, across years, or between ensemble members. A shift to the left (right) indicates drier (wetter) conditions. A missing time period indicates that the specific phenological threshold was not reached within the growing year (July–June).
Figure 1: Observed mean Excess Heat Factor (EHF) during heatwaves (as per Nairn and Fawcett (2013)), across all growing seasons from 1997–2017. EHF is an index that characterises heatwaves, high values indicate more intense heatwaves. The mean EHF is the mean value from all heatwaves that occurred from 1997–2017.

Figure 2: Change in mean EHF during heatwaves between the current (1997–2017) and historical (1961–1990) periods. Positive (negative) values indicate a trend towards more (less) intense heatwaves.

Figure 3: Projected mean EHF during heatwaves for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Increasing (decreasing) values indicate a trend towards more (less) intense heatwaves.

Figure 4: Time series of the number of days per growing year with temperatures greater than 30°C, 35°C, 40°C and 45°C. Bars indicate the number of days each threshold is exceeded per growing year. Values are averaged across all grid cells and the 6 ensemble members. Colours indicate each of the extreme threshold values. Generally increasing frequencies reflect a warming climate.

Figure 5: Time series of the number of days per growing year of high human heat stress. This is defined as days when daily maximum temperatures are >30°C and daily minimum humidity is >60%. These conditions cause severe risk of heat stress to humans (and potentially low productivity) to those working in exposed zones. Humans cannot work in high temperatures, high humidity environments without appropriate adaptive behaviours and equipment. Points are for each grid cell from each of the 6 ensemble members. Coloured bars represent the projected global temperature increase expected into the future (following the RCP 8.5 scenario) which can be used to make decisions based on projected temperature change rather than time.

Figure 6: Violins plots of high temperatures (°C) per growing year for 20-year time periods from 2001 to 2100. Colours indicate extreme threshold values (90th, 95th and 99th percentile) of temperature during each growing year. The 99th percentile value reflects the 4th hottest day each growing year; the 95th percentile is the 18th hottest day each growing year; and the 90th percentile is the 36th hottest day each growing year. Generally increasing values reflect a warming climate.

Figure 7: Distribution of daily minimum and maximum temperature during a heatwave.

Figure 8: Distribution of date of heatwave days.

Figure 9: Probability distributions of daily maximum temperatures and minimum overnight temperatures during heatwaves. Values of each curve indicate different time periods. The shape of the curve is driven by the level of variability experienced within each 20-year period. Variability can occur spatially within the region, across years, or between ensemble members. A shift to the right (left) indicates higher (lower) temperature heatwaves.
**Figure 1:** Observed mean frost risk days

Figure 1 shows the observed mean number of days at risk of frost during the growing season (October to April) over the period 1997-2017. Days at risk of frost are those with a daily minimum temperature $<2\,^\circ\text{C}$. High values indicate high frost risk.

**Figure 2:** Change in the mean number of days at risk of frost during the growing season (October to April) between the current (1997-2017) and historical (1961-1990) periods. Days at risk of frost are days with a minimum temperature $<2\,^\circ\text{C}$. High values indicate increased frost risk.

**Figure 3:** Projected mean number of days at risk of frost during the growing season (October to April) for 20-year time periods from 2021 to 2100. Each grid cell is the mean of the 6 ensemble members. Increasing values indicate a trend towards higher frost risk.

**Figure 4:** Violin plots of daily minimum temperature ($^\circ\text{C}$) for each month for 20-year periods from 2001 to 2100. Each violin represents daily data for each grid cell, for each of the 6 ensemble members, and for each growing year within the time period. The top violin in each set represents the daily minimum temperature for every January day in the period 2001-2020, for each grid cell in the region, for each of the 6 ensemble members. The current period (2001-2020) has been shadowed underneath future time periods to highlight any differences expected into the future. Dots represent the means for each violin. If the violin shifts lower (higher), this indicates a change towards colder (warmer) conditions.

**Figure 5:** Monthly average cumulative frost days for 20-year periods from 2001 to 2100. Values are a summary across all grid cells for all years with each 20-year period, for each of the 6 ensemble members. This reflects how frost risk varies across the year within each 20-year period. The current period (2001-2020) has been shadowed underneath future time periods to highlight any differences expected into the future.

**Figure 6:** Timeseries of accumulated frost intensity, which is the cumulative total of temperatures less than $2\,^\circ\text{C}$ over a growing season. This index characterises exposure to cold conditions. High values indicate cold winters/springs. Points are for each grid cell, averaged across the 6 ensemble members.

**Figure 7:** Time series of the number of days per growing year when temperature falls below selected thresholds ($<2\,^\circ\text{C}, <0\,^\circ\text{C}, <-2\,^\circ\text{C}$). Areas indicate the number of days temperatures fall below each threshold per growing year. Values are averaged across all grid cells and the 6 ensemble members. Fewer instances reflect a warming climate.