Department of Primary Industries
Department of Regional NSW

Climate Change Research Strategy

Climate Vulnerability Assessment

Methodology Report

Vulnerability Assessment

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Acknowledgement of Country

The Department of Primary Industries acknowledges that it stands on Country which always was and always will be Aboriginal land. We acknowledge the Traditional Custodians of the land and waters, and we show our respect for Elders past, present and emerging. We are committed to providing places in which Aboriginal people are included socially, culturally and economically through thoughtful and collaborative approaches to our work.

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Contents

Acronyms

Acronym	Meaning (see glossary for further details)
AGDD	Accumulated growing degree days
AHP	Analytical hierarchy process
APSIM	‘Agricultural Production Systems sIMulator’
AWAP	Australian Water Availability Project
CP	Chill portions
CCIA	Climate Change in Australia
CCRS	Climate Change Research Strategy
CMEMS	Copernicus Marine Environment Monitoring Service
CMIP5	Coupled Model Intercomparison Project 5
NSW DPI	NSW Department of Primary Industries
GCM	Global climate model
GDD	Growing degree days
GEBCO	General Bathymetric Chart of the Oceans
HRZ	High rainfall zone
IPCC	Intergovernmental Panel on Climate Change
LLS	Local Land Services
MCA	Multi-criteria analysis
RCP	Representative concentration pathways
SST	Sea surface temperature
SILO	‘Scientific Information for Land Owners’
THI	Temperature humidity index
VA	Vulnerability assessment

Glossary

Term	Explanation
Adaptive capacity	Evaluates the ability of a system or community to respond to and cope with the challenges posed by climate change. This includes factors like technological capabilities, financial resources, governance structures, and human capacity. Higher adaptive capacity enhances resilience and reduces vulnerability.
Biosecurity risk	An organism that is an identified risk to the production of one or more commodities.
CCIA Application Ready Data	An ensemble of 8 statistically downscaled global climate models selected by CSIRO and the Bureau of Meteorology from the full set of CMIP5 models, as being those most appropriate for climate modelling in Australia.
Climate suitability	The extent to which climatic conditions satisfy the requirements of plant or animal growth without considering other limiting factors (Zhao et al., 2016). In the VA Project, this is quantified as a value between 0 and 1, inclusive.
Climate variable	An individual, measurable aspect of climate for which data have been recorded. For example, daily maximum temperature.
Climate vulnerability	Refers to the degree of susceptibility or sensitivity of a system, community, or region to the adverse effects of climate change. It is a multifaceted concept encompassing various dimensions that determine the potential for harm or disruption caused by climate-related factors. The three key components are exposure, sensitivity and adaptive capacity (see relevant definitions).
CMIP5	An archive of global climate models containing simulations from more than 40 global climate models. CMIP5 was developed during the 5th assessment cycle of the IPCC (2008-2013). Application-ready data from its successor, CMIP6, was not available in time for the VA Project.
Commodity	In this report, this term refers to a raw primary industry output which was studied by the Vulnerability Assessment Project; it includes broadacre and horticultural crops, pine trees, livestock and fish species, and pastures.

Term	Explanation
Delta downscaling	A technique used to resample data from a coarse-resolution global climate model at a finer spatial resolution by applying projected changes in mean climate from the model to historical climate data observed at a higher resolution.
Downscaling	The process by which coarse-resolution global climate model outputs are translated into finer resolution climate information, so that they better account for regional climatic influences. See ‘delta downscaling’, ‘dynamical downscaling’ and ‘statistical downscaling’.
Dynamical downscaling	A computationally intensive technique which involves running a climate model to simulate atmospheric and environmental conditions at fine resolution, using a global climate model to provide the large-scale boundary conditions.
Exposure	This assesses the extent to which a system or entity is subjected to climate change hazards such as rising temperatures, extreme weather events, sea-level rise, and altered precipitation patterns. Exposure helps identify the geographic and sectoral areas at risk.
GDA94	The Geocentric Datum of Australia (1994); a static coordinate reference for Australia that minimises distortion when depicting the 3-dimensional surface of the earth on a 2-dimensional plane.
Module	A standardised method used in the VA Project for transforming daily climate data into unitless climate suitability.
Node	A grouping of commodities and associated experts within the VA Project, based on the type of primary industry.
Phenophase	Key stages in an organism's life cycle, production cycle or management stages.
Radiative forcing	The change in the net vertical irradiance at the tropopause due to an internal or external change in the forcing of the climate system, such as a change in the atmospheric concentration of CO_2 or the output of the Sun.
Sensitivity	Measures the degree to which a system or community is affected by climate-related changes. It considers factors like the level of dependence on climate-sensitive resources, infrastructure, and socio-economic conditions. Highly sensitive systems are more likely to experience negative impacts.

Term	Explanation
SILO	‘Scientific Information for Land Owners’, a database of Australian climate data hosted by the Science and Technology Division of the Queensland Government's Department of Environment and Science.
Statistical downscaling	A downscaling technique in which observed relationships between local synoptic situations and the large-scale climate, as represented in a coarse-resolution global climate model, are used to build a statistical model used to infer local-scale changes from the large-scale changes generated by the global climate model.

1. Vulnerability Assessment Project

1.1. Climate Change Research Strategy

The primary industries sector in New South Wales operates a wide variety of production systems within diverse landscapes, all the while facing the challenges of a highly variable climate. Primary producers manage the daily impacts of climate variability as well as the complexities of droughts, floods, storms, bushfires, pests and diseases. To ensure the continued growth of NSW primary industries and to safeguard the future of regional communities and those that rely on their produce, it is vital that this $23.1 billion sector continues to build resilience and adaptability in response to changes in climate.

Supported by an investment of $29.2 million from the NSW Climate Change Fund, the Primary Industries Climate Change Research Strategy (CCRS) invested in project and program areas that could support the primary industries sector to adapt to climate change. The Vulnerability Assessment (VA) Project received $8 million and has been completed as one of 7 projects within the CCRS.

The Strategy encompassed 3 themes:

- Energy: providing innovative clean energy solutions including biomass alternatives and tackling rising electricity costs through efficiency and technology.
- Carbon Opportunities: by improving market access and better understanding the abatement opportunities available within agriculture.
- Climate Resilience: by testing technology and adaptation options and developing deep knowledge on the vulnerability of primary industries to climate change.

These themes will enable NSW primary industries to prepare for the challenges and opportunities which climate change presents. The results of this research are being used to inform government and industry bodies of opportunities for timely, industry-appropriate responses to climate change, and provide insights into navigating carbon and other emerging markets. The NSW Department of Primary Industries (NSW DPI) is using the results of the Strategy to inform forward work programs and policies to support the long-term sustainability of agriculture, forestry and fisheries in NSW.

This report describes the methodology used for the Vulnerability Assessment Project, which sat within the Climate Resilience theme of the CCRS.

1.2. Project Objectives

Primary producers in NSW are increasingly being impacted by climate change. Primary industries are critical to ensuring food security for Australia, and, thus, developing viable pathways to climate change adaptation for primary industries is becoming increasingly pressing.

There is a driving need for comprehensive information across the range of primary industries to inform effective policy and planning at a state and regional level. Integrative, cross-industry analysis of vulnerability to climate change across the primary sector can highlight future risks and opportunities and identify where an incremental or transformational adaptation might be necessary.

The Vulnerability Assessment Project is designed to respond to the following two objectives:

- To understand the vulnerability of primary industries in NSW to climate change and associated impacts.
- To provide evidence of the value of adaptation to reduce impacts on primary industries for NSW.

The first of these objectives can be understood to relate to 'climate suitability', generally regarding yield, for commodities, but also quality, which was studied separately; the second relates to 'climate adaptation'. They are both are underpinned by a need to provide better information and insights into the impacts of climate change across a range of primary industries. This will allow the identification of those industries most in need of adaptation strategies, and those industries where opportunities to be capitalised on may arise. A need also exists for a comparable approach across primary industries utilising shared resources, such as land and water, to assist in creating broad and connected planning and policy.

To achieve the project's objectives, the VA Project created a standardised framework for model development, spatial analysis and climate impact assessments. This framework was consistently applied across all commodities and biosecurity risks that were assessed by the project. The following sections of this document provide an in-depth explanation of the framework and the application of the framework throughout the VA Project.

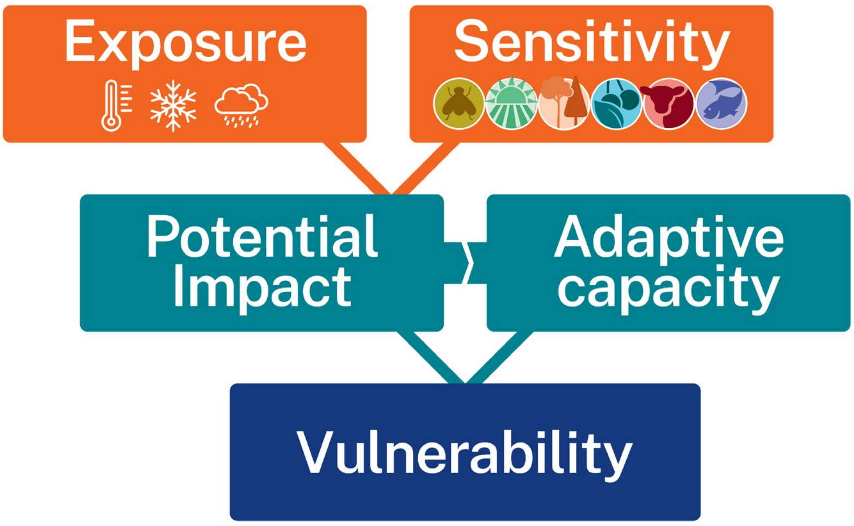

Figure 1: Components of a climate vulnerability assessment modified from a commonly used IPCC framework for assessing vulnerability to climate change (Ionescu et al., 2009)

A climate vulnerability assessment is used for assessing the potential impacts of climate change on an organism or system. The outline of such an assessment is shown in Figure 1. The exposure of a commodity or biosecurity risk to climate and the sensitivity of the organism to climate changes are combined to evaluate the potential impacts of those changes. By combining these aspects of climate and production, the vulnerability of the organism can be assessed.

The adoption of a consistent approach across multiple organisms or systems allows for comparisons to be made about their relative vulnerabilities to climate change, and about the interactions between them at different times of the year or at crucial stages of their growth or development. Combined with information and guidance from government and industry, the vulnerability assessment can help to identify priority areas for action and potential adaptations for alleviating climate change impacts. An important component of a vulnerability assessment is the selection of a suitability methodology which ensures this consistency. The VA Project has devised principles to underpin its methodology selection. These guiding principles are as follows:

- Consistency for comparability: the consistent application of a methodology that enables comparability between commodities and integration of biosecurity risks.
- Usability: a methodology that can be utilised in different areas of research, industry or government that produces results that can be readily applied to support planning and policy decision-making.
- Flexibility: a methodology whose components can be updated and expanded without significant additional resources, and which is responsive to feedback.
- Credibility: a credible methodology for policy and planning with the aim of supporting decision-making. Credible methods are those that have been peer-reviewed, effectively applied elsewhere and are targeted to the research questions and objectives.
- Scientific depth and detail: a methodology with sufficient scientific depth and detail to provide confidence in the results. This provides a foundation for planning and policy decision-making, integrating scientific knowledge and expertise.

1.3. Project Scope

1.3.1. Selection of commodities and biosecurity risks

The VA Project investigated a wide range of primary industry commodities and related biosecurity risks for which climate variables impose limiting factors on growing suitability and geographical extent. It settled on 28 commodities and 14 biosecurity risks, split across 6 broad industry categories, referred to as ‘nodes’ (see Table 1). The commodities were selected based on economic value to NSW, size of the industry in NSW or the commodity’s importance as an emerging or growing industry for NSW. Each node aimed to ensure that a mix of industries were selected. Consideration was given to including some emerging commodities and biosecurity risks that are expected to become more prominent, as well as to ensuring a geographical spread of assessed industries across the state. Alongside economic value and industry size, the availability of expert knowledge within NSW DPI was also a necessary for selection of a commodity or biosecurity risk for the VA Project. It was impractical to cover all primary industries in NSW, and additional commodities and biosecurity risks could be studied using the methods described in this report.

The inclusions in the biosecurity node were selected based on risk, not commodity. The biosecurity node selected a mixture of risks representing a range of pests and diseases relevant to the terrestrial commodities where these risks were deemed to be of considerable concern. The risks selected for the project were based on their presence as endemic to NSW, except for oriental fruit fly and stem rust, included as exotic species test cases, and serpentine leafminer, added after recent incursion led to it becoming established in NSW. With further resourcing, this approach could be expanded to cover other endemic risks to primary industries, including marine pests and other exotic species not yet detected in NSW or Australia.

Table 1: List of the primary industry commodities and biosecurity risks studied by the VA Project. Notes: (a) exotic biosecurity risks not yet found in NSW; (b) eradication ongoing in NSW; (c) biosecurity risk new to NSW (an incursion occurred during the VA Project); (d) biosecurity risk not currently found in NSW (most severe epidemic in Australia was in 1973). *results to be released in late 2024.

Horticulture & Viticulture	Broadacre Cropping	Forestry	Extensive Livestock	Marine Fisheries	Biosecurity Risks
▪ Almond ▪ Blueberry ▪ Cherry ▪ Citrus ▪ Macadamia ▪ Walnut ▪ Wine grapes	▪ Chickpea ▪ Dryland and irrigated wheat ▪ Dryland barley ▪ Dryland canola ▪ Irrigated cotton ▪ Irrigated lucerne ▪ Irrigated maize ▪ Irrigated rice ▪ Lupin	▪ Radiata pine	▪ Cattle ▪ Sheep ▪ High rainfall zone grazing systems ▪ Mixed cropping zone grazing systems ▪ Rangeland grazing systems	▪ Bonito ▪ Dolphinfish ▪ Kingfish ▪ Spanish mackerel ▪ Spotted mackerel	▪ Buffalo fly ▪ Oriental fruit fly(a) ▪ Parthenium weed(b) ▪ Queensland fruit fly ▪ Sclerotinia stem rot ▪ Serpentine leafminer(c) ▪ Serrated tussock ▪ Verticillium wilt ▪ Wheat stem rust(d) ▪ Wheat stripe rust ▪ Barber's pole worm* ▪ Biting midge* ▪ Blowfly* ▪ Cattle tick*

1.3.2. Selection of future greenhouse gas emissions scenarios

To assess the future climate suitability of the selected commodities and biosecurity risks, two scenarios were used which estimated the climate's response to sets of potential future greenhouse gas and aerosol emissions, and land-use scenarios, consistent with alternative future socio-economic assumptions (Collins *et al.,* 2013). These emissions scenarios, known as 'representative concentration pathways' (RCPs), describe possible futures in terms of radiative forcing, long-term atmospheric CO_2 levels and the trajectory of those levels over time, based on anthropogenic greenhouse gas emissions (van Vuuren *et al*., 2011). The two scenarios selected for the VA Project are:

- RCP4.5: an intermediate stabilisation pathway where radiative forcing is limited to approximately 4.5 Wm^{-2} in 2100, and emissions peak around 2040 before declining.
- RCP8.5: a high emissions pathway that leads to radiative forcing of greater than 8.5 Wm^{-2} in 2100, a 'worst-case scenario' pathway in which emissions continue to rise throughout the 21st century.

The VA Project considered these two scenarios to ensure the inclusion of a range of future climatic conditions. A low emissions scenario, RCP2.6, which represents the most efficient and effective mitigation scenario (keeping the global average temperature rise below 2°C), was not considered for the VA Project. This scenario is not consistent with projections based on current global policies. Another intermediate scenario, RCP6.0, was not considered because the scenario it describes falls within the range represented by RCP4.5 and RCP8.5. Additionally, projection data for RCP2.6 and RCP6.0 were not available for all global climate models (GCMs) contained within the climate dataset used by the VA Project (described below).

Greenhouse gas emissions have been tracking close to those described by RCP8.5 (Schwalm et al., 2020), and current estimates (United Nations Environment Programme, 2023) predict an increase in mean global temperature above pre-industrial levels of 2.5-2.9°C, consistent with RCP6.0 (1.4-3.1°C increase) and RCP8.5 (2.6-4.8°C increase) but mostly outside the range for RCP4.5 (1.1-2.6°C increase) (IPCC, 2013).

1.3.3. Selection of mid-century future time point

The decision was made to centre the study on 2050. This was driven by planning and policy relevance and by the need to base assessments on climatic trends that require decadal periods to discern. Timeframes earlier than 2050 would include data that effectively includes the present day and so would not provide strategic insight into potential change. Timeframes beyond 2050 were not selected as they would show stronger climate change trends compared with climate variability. Additionally, this timeframe would be less relevant to policy decision-making and industry strategic planning, which rarely extend beyond a 30-year time horizon. While the Bureau of Meteorology and others recommend using two future 30-year periods to consider both possible near-term climatic conditions and conditions further out from the present day, the VA Project determined to use just one future period. This decision was made in order that planning insights offered to policymakers would pertain to a foreseeable and relatable future, reducing the chance of dismissing any timeframe extending significantly beyond 2050 as irrelevant or inconsequential. However, given that the climate datasets used in the VA Project include other future periods, the modelling could be replicated for other periods of interest.

1.3.4. Selection and preparation of climate data

1.3.4.1. Terrestrial climate data

The VA Project sourced terrestrial[1] historical climate data from SILO[2], an Australian climate database constructed from observational data from the Australian Bureau of Meteorology (Jeffrey *et al.*, 2001), and used for historical calibration of models. The chosen historical baseline period was 1970-2019. This timeframe was selected to encompass the last 50 years of climate observations (as at early 2020). It also includes the 1981-2010 period adopted by the global climate models used in the VA Project (described below) to validate their future climate projections. A long historical baseline period also minimises the influence of natural variability on observed climate averages, while revealing long-term trends. The additional 10 years either side of 1981-2010 provide useful context for experts when applying their experience and knowledge of climate impacts on primary production commodities and biosecurity risks. The data were also aggregated by the VA Project from a spatial resolution of 0.05° to 0.2°, used to facilitate rapid model prototyping and development.

The future projection dataset used in the VA Project was the 'Climate Change in Australia (CCIA): Application Ready Data' (CSIRO and Bureau of Meteorology 2015): this dataset is an ensemble of 8 statistically downscaled global climate models (GCMs) for RCP4.5 and RCP8.5, for several future periods, at 0.05° spatial resolution. These GCMs were selected by CSIRO and the Bureau of Meteorology from the full set of CMIP5 GCMs as being those most appropriate for climate modelling in Australia. Their rationale for the selection of each model is listed in Table 2; use of these GCMs allowed the VA Project to consider most of the possible climate futures facing NSW. Following consultation and advice from the Bureau of Meteorology, and in line with common practice, the VA Project has focused on the 30 years spanning 2036-2065, centred on 2050.

The downscaled GCMs in the CCIA dataset are based on historical baseline climate data from the Bureau of Meteorology's Australian Water Availability Project (AWAP), using observational data for the 30 years spanning 1981-2010 on a 0.05° grid across NSW.

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[1] 'Terrestrial' refers to climate data associated with the land surface of the Earth.

[2] https://www.longpaddock.qld.gov.au/silo/

The VA Project identified the most important climate variables for assessing climate suitability for the selected commodities and biosecurity risks. They were temperature, rainfall, relative humidity and solar radiation, and these variables were included as the minimum, maximum or mean daily value, the mean monthly value or the mean value calculated across a phenophase or life cycle stage of interest. The mean temperature was calculated as the average of the minimum and maximum temperatures. Rainfall was included as the daily value or the cumulative sum over a given period. Several other derived climate variables, such as effective rainfall, were calculated from the above variables. Further information on the climate variables and the derived climate variables can be found in Section 2.3.3.

Table 2: Details of Climate Change in Australia's selected CMIP5 models and their notes on reasons for inclusion in the CCIA 'Application Ready Data' (adapted from the CCIA technical report (CSIRO and Bureau of Meteorology, 2015)).

Model	Institute	Atmosphere resolution (°) [km]	Ocean resolution (°)	Climate future	Notes
ACCESS1.0	CSIRO-BOM, Australia	1.9×1.2 [210×130]	1.0 x 1.0	Maximum consensus for many regions.	This model exhibited a high skill score for historical climate.
CESM1-CAM5	NSF-DOE-NCAR, USA	1.2×0.9 [130×100]	1.1 x 0.6	Hotter and wetter, or hotter and least drying.	This model was representative of a low change in an index of the Southern Annular Mode (per degree of global warming).
CNRM-CM5	CNRM-CERFACS, France	1.4×1.4 [155×155]	1.0 x 0.8	Hot/wet end of the range in southern Australia.	This model was representative of low warming/dry sea surface temperature (SST) modes described in Watterson (2012) (Sec. 3.6). It represents extreme El Niño in CMIP5 evaluations (see Cai *et al.*, 2014).
GFDL-ESM2M	NOAA, GFDL, USA	2.5×2.0 [275×220]	1.0 x 1.0	Hotter and drier.	This model represented the hot/dry SST mode described in Watterson (2012). It represents extreme El Niño in CMIP5 evaluations (see Cai *et al.*, 2014).
HadGEM2-CC	MOHC, UK	1.9×1.2 [210×130]	1.0 x 1.0	Maximum consensus for many regions.	This model has a good representation of extreme El Niño in CMIP5 evaluations (see Cai *et al.*, 2014).
CanESM2	CCCMA, Canada	2.8×2.8 [310×310]	1.4 x 0.9		This model was representative of the hot/wet SST modes described in Watterson (2012). It has a high skill score for historical climate and increases the diversity of climate futures represented (Knutti *et al.*, 2013). It represents extreme El Niño in CMIP5 evaluations (see Cai *et al.*, 2014).
MIROC5	JAMSTEC, Japan	1.4×1.4 [155×155]	1.6 x 1.4	Low warming, wetter.	This model represented a greater change in an index of the Southern Annular Mode (per degree of global warming). It represents extreme El Niño in CMIP5 evaluations (see Cai *et al.*, 2014).
NorESM1-M	NCC, Norway	2.5×1.9 [275×210]	1.1 x 0.6	Low warming, wettest.	This model was representative of the low warming/wet sea surface temperature mode described in Watterson (2012).

1.3.4.2. Marine data

Climate projection data for the marine environment was not available as part of CSIRO's 'Climate Change in Australia Application Ready Data'. To maximise compatibility with the terrestrial dataset, the VA Project prepared marine future climate projection data for RCP4.5 and RCP8.5 using 5 GCMs, which were selected according to two requirements:

- The GCM is included in the CCIA dataset for terrestrial climate variables.
- The GCM provides data for the 3 climate variables relevant to marine species habitat suitability.

Details of the 5 GCMs are given in Table 3; each model was downscaled to a spatial resolution of 0.05 degrees. The chosen 20-year future projection period centred on 2050, spanning 2040-2059, and the historical baseline period spanned 1993-2012. This historical baseline period was selected as data from satellite observations for a key variable of interest, ocean current strength, were not available before 1993, and thus, 20-year historical and future periods have been used for marine data. The VA Project's fisheries models used 3 marine climate variables: sea surface temperature, sea surface height and ocean current strength (also known as 'eddy kinetic energy'). Observed historical data for each variable were obtained from the Copernicus Marine Environment Monitoring Service[3] (CMEMS).

Table 3: Selected CMIP5 GCMs used to support projections of marine species habitat suitability off south-eastern Australia. Both RCP4.5 and 8.5 emission scenarios were used from each model.

Model	Institution	Native ocean resolution (°)
ACCESS1.0	CSIRO-BOM, Australia	1.0 × 1.0
CNRM-CM5	CNRM-CERFACS, France	1.0 × 0.8
GFDL-ESM2M	GFDL, NOAA, USA	1.0 × 1.0
HadGEM2-CC	MOHC, UK	1.0 × 1.0
MIROC5	JAMSTEC, Japan	1.6 × 1.4

The fisheries models also included two structural habitat variables to account for the influence of seascape topography on environmental suitability for harvested marine species: seafloor depth and an index of vertical seascape relief. These variables are static and remain fixed over durations much longer than the 30-year period used for historical analyses and future projections in the VA Project. The seascape topography data were obtained from the General Bathymetric Chart of the Oceans[4] (GEBCO) for 2020.

[3] https://marine.copernicus.eu

[4] https://www.gebco.net

1.3.4.3. Downscaling of marine GCM data

The coarse spatial resolution of GCM data (~1 degree) challenges its utility for projecting species' responses to climate change (Drenkard *et al.,* 2021), particularly in coastal marine environments where species distributions are structured at finer, kilometre-scale, spatial resolutions. Therefore, the widely used delta change factor method (see, for example, Morley *et al.,* 2018; Navarro-Racines *et al.,* 2020; von Hammerstein *et al.,* 2022), also known as 'delta downscaling' (CSIRO and Bureau of Meteorology, 2015) was used to downscale sea surface temperature, sea surface height and eddy kinetic energy data to a common 0.05-degree spatial resolution throughout the study region. Delta downscaling was selected as it has proven utility for providing high-resolution mean climatic conditions over decadal periods for climate impact studies (Navarro-Racines *et al.,* 2020). It also provides an element of model bias correction, since the high-resolution observational data contains empirical information on small-scale variations that are factored into the final product (Pourmokhtarian *et al.,* 2016). Delta downscaling is a relatively simple method compared to alternative downscaling techniques such as dynamical and statistical downscaling (Drenkard *et al.,* 2021) and is therefore well-suited for rapid climate change impact assessments of species.

The marine downscaling process involved 5 steps:

1. Remapping the curvilinear source GCM data to a global 1° rectilinear grid using the second-order conservative algorithm (remapcon2) in Climate Data Operators (Schulzweida, 2021).
2. Infilling missing data adjacent to the continental coast for datasets describing zonal (U) and meridional (V) flows using thin-plated splines interpolation in R (implemented in the *fields* package for R). This method has been shown to perform well for interpolating climate data (Jeffery *et al.,* 2001).
3. Calculating the difference (that is, delta value) between seasonally aggregated data for the period 2040 to 2059 and a modelled historical baseline period encompassing 1993 to 2012 for each climate variable, GCM and RCP scenario.
4. Disaggregating delta value matrices from their native model resolution (~1°) to the finer resolution of observed ocean data (that is, 0.05°) using bilinear interpolation.
5. Adding delta values to an observed seasonal climatology for each climate variable used in the VA climate suitability models, encompassing 1993-2012.

This method produced future ocean data downscaled to a common 0.05° resolution for 2040-2059, required to facilitate projections of species' habitat suitability under future emissions scenarios.

1.3.5. Selection of modelling approach

Climate suitability is defined as the extent to which climatic conditions satisfy the requirements of plant or animal growth without considering other limiting factors (Zhao *et al*., 2016). The most common methods for modelling climate suitability for Australian primary industries (Darbyshire *et al*. 2022) are biophysical process models, such as APSIM (Holzworth *et al*., 2014) and GrassGro (Moore and Herrmann, 2023), and correlative climate niche models, such as CLIMEX (Sutherst *et al*., 2007) and MaxEnt (Phillips *et al*., 2006). For several commodities and biosecurity risks assessed by the VA Project, including wheat, barley and Queensland fruit fly, such commodity- or species-specific models do exist. However, differences in model design and assumptions mean that cross-commodity comparisons are hampered: differences in outputs may be due to differences in the production model rather than meaningful impacts from climate change. Importantly, there are no existing, or no validated, biophysical process-based models for many of the commodities and biosecurity risks of interest to primary industries in NSW.

The VA Project required a modelling approach that could be consistently applied to all commodities and biosecurity risks to produce comparable outputs. To achieve the VA Project's objectives, a modelling approach called 'multi-criteria analysis' (MCA) was selected. MCA models allow information from various sources to be integrated to assess climate suitability, which can then be applied to historical data and future climate projections for NSW (Figure 2). The result is a spatial assessment of the climate suitability of each commodity or biosecurity risk.

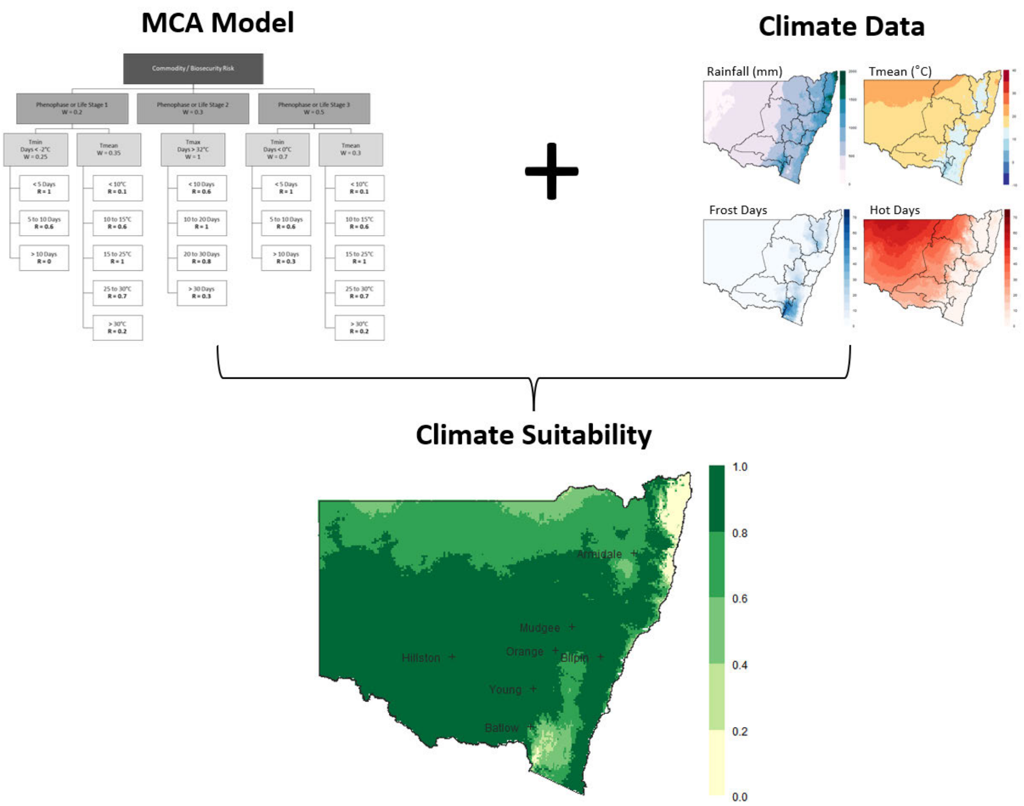

Figure 2: The VA Project developed MCA models of climate suitability for multiple commodities and biosecurity risks. The MCA model represents the sensitivity of a commodity or biosecurity risk to climate, while the climate data describes the spatial patterns of exposure to optimal or inadequate climatic conditions. Climate suitability is calculated across NSW by applying the MCA model to historical climate data and future climate projections.

MCA models have many characteristics that make them ideal for modelling climate suitability for the VA Project, including:

- The ability to integrate multiple descriptors (i.e., climatic variables) of overarching climate suitability.
- The ability to incorporate a synthesis of research data and expert opinion.
- The ability to explicitly account for climatic risks to production.
- MCA model descriptions are transparent and easily understandable by industry experts.
- Climatic drivers of MCA model outputs are obvious compared with biophysical process models and niche-based models, in which model outputs may be opaque.
- When compared with sophisticated biophysical models, MCA models are straightforward to update with new knowledge or data. Biophysical models can take substantial time and resources to develop and modify.
- Multicriteria analysis is a well-developed and widely used modelling approach across a wide range of disciplines.

The ability of MCA models to incorporate potentially conflicting sources of information allows research data to be combined with expert knowledge into models in a transparent and easily understood manner (Caubel *et al*., 2015; Romeijn *et al*., 2016). The MCA models used in the VA Project were designed to capture the key climatic variables relating to the environmental requirements for a commodity to successfully contribute to industry, including survival, growth and reproduction, or for the growth and survival of a biosecurity risk. The MCA models take the form of hierarchical structures, wherein each MCA model element is assigned a weighting: an example of this structure is shown in Figure 4. This structure allows the influence of competing variables to be integrated into an overall climate suitability value on which to base decisions or analyses (Jankowski and Richard, 1994). Climate suitability can be derived at any level of the MCA model structure, facilitating the assessment of the role of specific climate variables in climate impacts.

1.3.5.1. Vulnerability Assessment Framework

The VA Project used an MCA modelling approach, which combines data from published research and expert knowledge. This approach is particularly useful when describing under-researched commodities or biosecurity risks. A key feature of the project is that all MCA models were developed consistently, and their climate impact assessments all used the same historical and future climate projection data, which enables a direct comparison of the results. This follows the guiding principles for the VA Project (Section1.2), providing a consistent, comparable approach across industries, maintaining a state-wide focus and transparent reporting and communications to address strategic industry planning and policy goals.

1.3.5.2. Considerations and limitations to climate suitability modelling

The MCA models developed by the VA Project have only been constructed to assess vulnerability to future climatic conditions. The models do not account for soils, topography or other biophysical parameters, although analysis of some seafloor data was included in the fisheries MCA models. Socio-economic factors such as proximity to infrastructure, workforce availability, or market access were also not included in the MCA models. Water demand was modelled separately to climate suitability for irrigated commodities, but no assessment of potential future water availability has been undertaken. All agricultural production MCA models assume that current 'best practice' management is employed.

The VA Project made assumptions relating to the spatial resolution of the GCMs included in the CCIA climate data. Specifically, the VA Project limited its modelling to the 0.05° spatial and 1-day temporal resolution of the CCIA dataset. In addition, future projections were not provided by the CCIA dataset for climate variables with high spatiotemporal variability, such as wind, snowfall and hail, and so these variables were excluded from our modelling. Relative humidity was only included in models as an average over periods of a month or longer.

Extreme weather events were also excluded from the climate suitability modelling. These events include intense rainfall episodes, heatwaves and cold snaps. The impact of complex climatic events was also unable to be modelled, including intense storms, cyclones and East Coast Lows, drought, floods and other phenomena such as bushfires. These events are a result of complex interactions between multiple climatic and environmental factors, often including a series of linked climatic events and conditions. Such factors are being researched (see, for example, Dowdy *et al.* (2019), Bruyère (2022), Donat *et al.* (2023) and Trascasa-Castro *et al.* (2023)).

In addition to the above exclusions, temporal sequences (for example, the number of consecutive days above a certain maximum temperature) were omitted from climate suitability modelling: future projections of climate variables derived by delta or statistical downscaling essentially retain historical daily patterns that cannot be meaningfully carried over into the future.

These MCA models primarily focused on the response of commodities and biosecurity risks to changes in average climatic conditions. However, in some situations, the exclusions mentioned above may limit the power of an MCA model to capture the actual effects of climate on agricultural production for a specific area. Future work that incorporates dynamically downscaled climate projection data could provide an improved capacity for describing such phenomena.

Additional assumptions and exclusions made for individual commodities and biosecurity risks will be detailed in upcoming reports.

2. VA Project Approach to MCA Modelling

A main objective of the VA Project methodology was to provide a flexible and consistent approach to describing the key elements of climate suitability.

The following principles were developed to help build the MCA models and to maintain consistency in the development of models across the VA Project:

- Develop the MCA model with a hierarchical structure around the key life cycle stages (also referred to as phenological phases, production phases or management stages; see Section 2.3.1 for further details).
- Select the most appropriate climate variables by considering what best aligns with the available knowledge of the commodity or biosecurity risk's climate suitability.
- Apply a modular approach to MCA model construction based on consistent methods for transforming climate data to climate suitability (see Section 2.3).
- Provide a standardised set of spatial outputs for all MCA models, with additional visualisations to support more detailed analyses.

The development of each MCA model was underpinned by applying available scientific knowledge when drafting the MCA model structure. During the literature review and MCA model-building phases, knowledge gaps often raised barriers to MCA model design. More evidence regarding key life cycle stages and climate variables was sometimes needed to allow their inclusion in the MCA model. In the absence of scientific knowledge, data exploration and expert knowledge were used to provide evidence and allow the draft MCA models to be revised.

The VA Project has benefited from effective and extensive internal collaboration across NSW DPI. Each commodity or biosecurity risk was assigned to an internal NSW DPI expert who collaborated with the core VA Project team to achieve broad cross-industry representation.

2.1. Key Steps

To apply the MCA model approach in the VA Project, several key steps were taken for each commodity and biosecurity risk (Figure 3). These steps show the iterative process of MCA model development, utilising considerable expert support and the integration of expert knowledge.

Literature Review

- Capture in the review 'What climate variables influence the commodity's growth or the biosecurity risk's survival?'
- Capture in the review 'How sensitive is the commodity or biosecurity risk to each climate variable identified?'

Draft MCA Model

- Determine the MCA model hierarchy of key life cycle stages and their dates
- Select the climate variables, categories and modules for each level in the MCA model
- Draft an MCA model for the commodity or biosecurity risk

Expert Review

- Seek feedback on the draft MCA model in a focus group meeting with 2-6 experts
- Ask the experts to weight the importance of the climate variables and phases using the AHP process
- Incorporate expert feedback into the MCA model

Historical Analysis

- Test and refine the MCA model using historical climate data
- Seek feedback on historical climate suitability across NSW and iterate analysis if further changes are required

Expert Review

- Prepare a report on the MCA model's historical output and seek expert feedback
- Seek expert endorsement of the MCA model and historical climate suitability

Future Projections

- Apply the MCA model to future climate projection data to produce future climate suitability outputs
- Assess the outputs and evaluate the future climate change impacts on the commodity or biosecurity risk

Impact Assessment

- Identify the key future climate vulnerabilities and opportunities
- Produce a Climate Impact Asssessment report for the commodity or biosecurity risk

Integration

- Integrate water demand and climate suitability outputs, where suitable
- Integrate biosecurity risk and commodity outputs, where suitable

Expert Review

- Present key findings from the Climate Impact Assessment to the experts
- Discuss key adaptation or management strategies

External Engagement

- Disseminate findings to industry and policymakers in a clear and concise way
- Engage with stakeholders to understand how adaptation or management strategies could mitigate future impacts of climate change

Figure 3: Key steps in the Vulnerability Assessment Project's framework process, developed to assess the potential impacts of future climate change on primary industries and biosecurity risks across NSW.

2.2. Literature Review

The literature review focused on capturing an overview of 'Which climate variables influence each commodity or biosecurity risk?' and 'How sensitive is the commodity or biosecurity risk to each climate variable identified?'.

The literature review was designed to extract the information needed to design and develop an MCA model. The 3 critical sections within the review were:

- **Describing the life stages or phenology**: the life stages, or phenophases, of the commodity or biosecurity risk were identified, and each stage's function was summarised.
- **Identifying the key climate variables**: the influencing climate variables (for example, daily rainfall, maximum daily temperature, or a combination of two variables, see Section 3.3.3) for each stage were identified. The review additionally captured what was known about optimal, sub-optimal or inadequate climatic conditions for the commodity's phases.
- **Identifying the knowledge gaps**: significant gaps in the literature were identified, and notes were taken of stages or variables where the required information could not be found.

After completing the literature review, the knowledge was transformed to create a draft (or 'working') MCA model for the commodity or biosecurity risk.

2.3. Building the MCA Model

The details of MCA model development are described in the following sections. An example of an MCA model is shown in Figure 4.

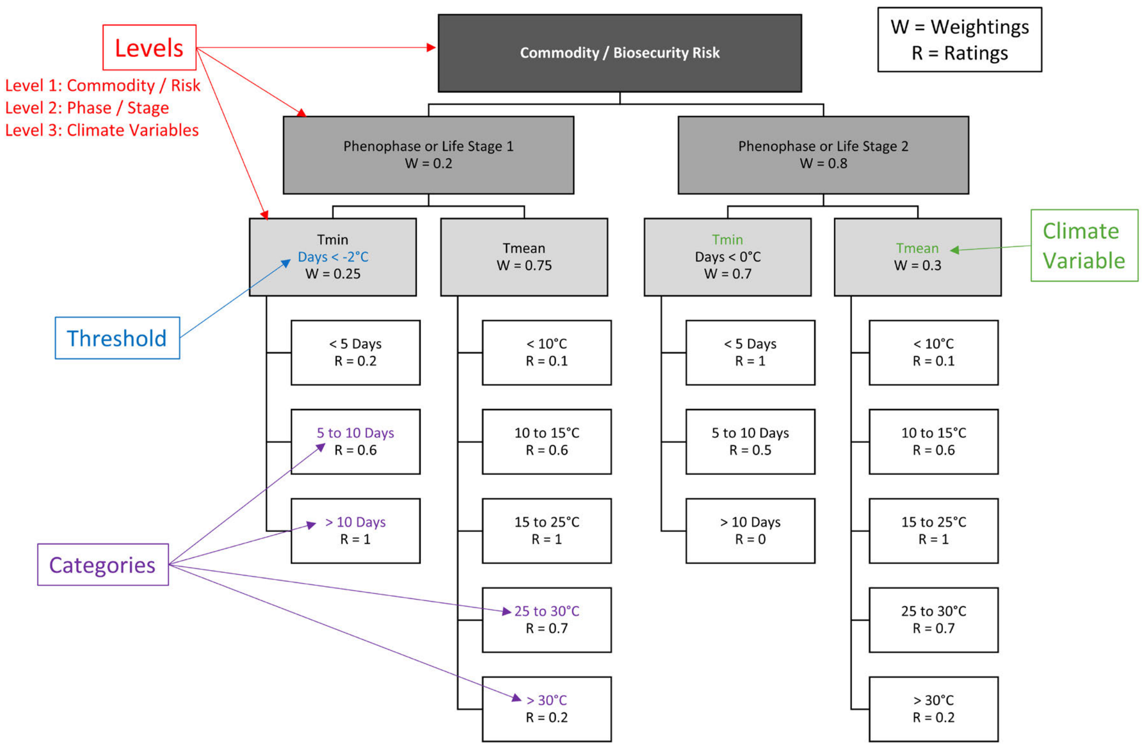

Figure 4: An example of a MCA model, showing the hierarchical structure and model components.

2.3.1. Developing the MCA model structure

The MCA models in the VA Project are comprised of a hierarchy of levels describing the commodity or biosecurity risk, its production and management phases and life cycle stages, together referred to as phenophases in this report. The model relates each phenophase to the climate variables that affect it. Construction of the MCA model structure and parameters involves determining those levels, the climate variables which influence each level, and the various parameters of those levels (categories, thresholds, ratings and weightings for the phenophases; see below).

2.3.1.1. MCA model levels

The knowledge captured by the literature review was used to develop the levels defining each MCA model's hierarchy. For most models, the levels were arranged as follows:

- The top level specified the commodity or biosecurity risk.
- The next level contains the phenophases identified as climate-sensitive by the literature review.
- The level below the phenophases contains modules which describe the effects of climate variables identified as important for each phenophase.

The phenophases for each MCA model are defined according to the production phases, life cycle stages or management stages of the commodity or biosecurity risk. These phenophases are specified by either fixed calendar dates or, in the case of dynamic phenology, thermal time thresholds. The duration of phenophases varies between species and between management systems (some life cycle stages lasting less than a week were combined into a single phenophase). After the phenophases were determined, the influence of climate on the commodity or biosecurity risk during each phase was taken from the literature and expert knowledge, and the specific climate variables to be used decided. The phenophases were assigned relative weightings, summing to 1, reflecting the importance of each phenophase to the overall success of the commodity or biosecurity risk. A focus group of experts assigned these weightings, and the procedure for developing weightings is described in Section 2.4.1.

In some cases, using life cycle stages and associated dates or thermal time triggers did not represent the organism's growth and survival very well. Examples of this arise for biosecurity pests, whose life cycle stages occur continuously and simultaneously. In these cases, the MCA models were run monthly or seasonally, with the phenophases assessed on these timescales by evaluating the MCA model using monthly or seasonal climate data.

- **Monthly**: monthly outputs capture the influence of climate in any given month on the individual phenophases. These MCA models simultaneously assess the climate suitability month by month for all life stages or production systems. Monthly data was used for biosecurity risks, where the life cycle stages can last from a few days to weeks. It is also appropriate for livestock production systems such as those used in the dairy industry, where calving can occur in any month of the year.

- **Seasonal**: seasonal outputs capture the influence of climate in any given season on the individual phases and allow capture of any potential changes in the seasonal dynamics. As with monthly MCA models, seasonal MCA models simultaneously assess climate suitability for all phenophases.

2.3.1.2. MCA model ratings

In the lowest level of the MCA models, modules are assigned to each phenophase which specify the set of climate variables affecting that phenophase. The modules for each phenophase are assigned relative weightings (summing to 1), reflecting the importance of each climate variable to the phase: the procedure for developing weightings is described in Section 2.4.1. The climate variables within each module are defined by well-defined ranges, or ‘categories’, of the climate variable. These categories describe the optimal, sub-optimal or inadequate conditions of the climate variable for the commodity (see Figure 6), using ‘ratings’ between 0 and 1 which are assigned to each category.

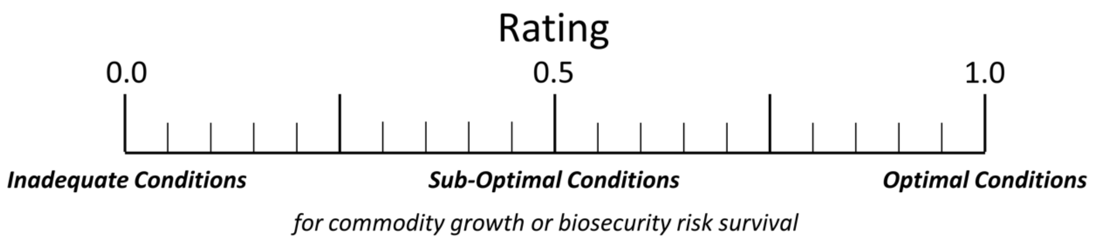

Figure 5: Rating system of MCA model where 0 = inadequate conditions, and 1 = optimal conditions.

2.3.2. Calculating climate suitability

The MCA models described are not designed to be yield-estimating models *per se*. Rather, they calculate climate suitability to demonstrate where a commodity or biosecurity risk is most likely to be found based on climatic conditions. Climate suitability is defined as the extent to which climatic conditions satisfy the requirements of plant or animal growth without considering other limiting factors (Zhao *et al*., 2016).

MCA model ratings define normalisation functions that describe key relationships between organisms and climate variables. These functions assign unitless climate suitability values between 0 and 1 to binned climate data (for example, temperature ranges). This results in a step function for each MCA model element that describes climatic conditions ranging from inadequate to optimal. An example of a climate suitability rating function for daily mean temperature is shown in Figure 8.

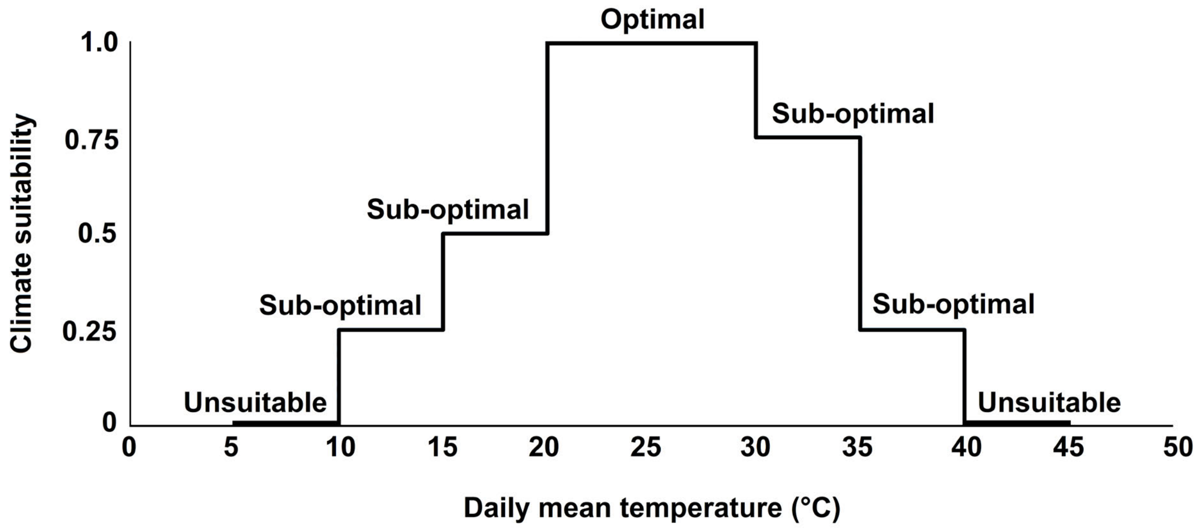

Figure 6: An example of a climate suitability rating function. Daily mean temperatures are transformed into values between 0 and 1 for each temperature range, which are 5°C wide in this example.

The influences of multiple aspects of climate on the organism (as reflected by these ratings) are then combined in a weighted linear combination to create a composite index of climate suitability (following Holzkämper *et al*. (2013) and Caubel *et al*. (2015)).

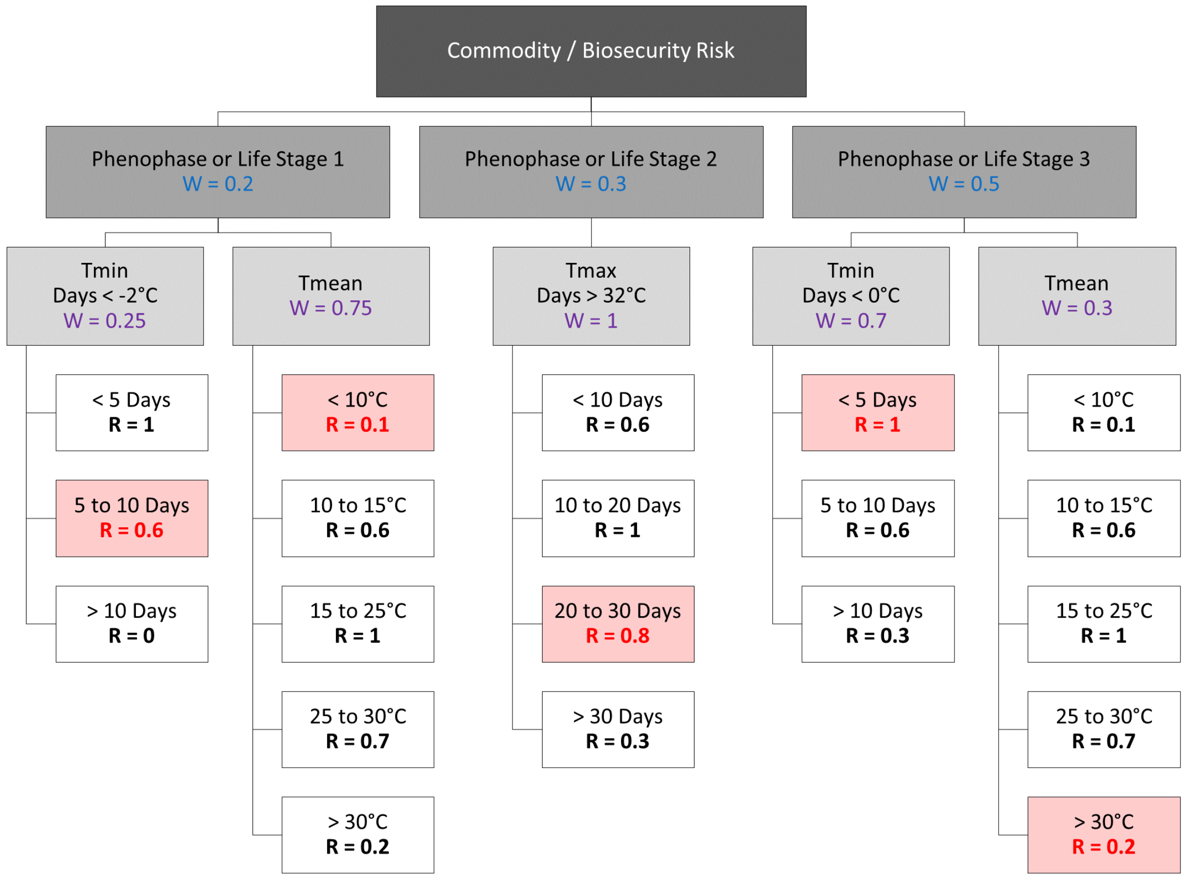

Figure 7: An example MCA model, the highlighted boxes are used in the example calculation of climate suitability within the main text.

Each pixel on the map of NSW falls within a category of each branch of the MCA model each day. An example of the climate suitability index calculation follows. Consider a pixel whose weather observations over one growing season fall into the boxes highlighted in pink in Figure 9. The calculation of the overall climate suitability for that pixel would be:

Phenophase 1 (1 January to 15 March, for example)
Tmin (Days < -2°C): 0.6 x 0.25 = 0.15
Tmean: 0.1 x 0.75 = 0.075
Phenophase 1 Suitability = 0.15 + 0.075 = 0.225 (Low Suitability)
Phenophase 1 Contribution to Overall = (0.15 + 0.075) x 0.2 = 0.045

Phenophase 2 (16 March to 22 April, for example)
Tmax (Days > 32°C): 0.8 x 1 = 0.8
Phenophase 2 Suitability = 0.8 (Very High Suitability)
Phenophase 2 Contribution to Overall = 0.8 x 0.3 = 0.24

Phenophase 3 (23 April to 1 June, for example)
Tmin (Days < 0°C): 1 x 0.7 = 0.7
Tmean: 0.2 x 0.3 = 0.06
Phenophase 3 Suitability = 0.7 + 0.06 = 0.76 (High Suitability)
Phenophase 3 Contribution = (0.7 + 0.06) x 0.5 = 0.38

Overall Pixel Value (climate suitability) = 0.045 + 0.24 + 0.38 = **0.665**

The spatial calculation of historical and future climate suitability from climate data using the finalised MCA models was implemented in R (R Core Team, 2023). Raster reclassification was used to transform climate data, according to the rating parameters defined in each MCA model, and the resulting rasters were aggregated by weighted linear combination, according to their assigned weightings in the MCA model. Most calculations were performed using the *raster*, *terra*, *sp* and *rgeos* R packages (Bivand *et al.,* 2017; Hijmans *et al.,* 2015; Hijmans *et al.,* 2022; Pebesma *et al.,* 2005), and figures were produced using the *ggplot2* and *rasterVis* packages (Lamigueiro *et al.,* 2022; Wickham *et al.,* 2016).

2.3.3. Climate variables

The most common climate variables used in the MCA models were minimum, maximum and mean daily temperature and rainfall. Daily relative humidity was also used in some MCA models. These variables appeared in the MCA models as the raw daily value, the mean monthly value or the mean value calculated across a phenophase or life cycle stage of interest. Mean temperature was calculated as the average of the minimum and maximum temperatures. Rainfall was included as the cumulative sum over a given period or as the daily value, depending on the commodity. Various other derived climate variables were included in some MCA models; details and definitions are given in Table 4.

Table 4: Terrestrial climate variables used in terrestrial MCA models, provided as part of the CCIA dataset. Data sources: Australian Water Availability Project (AWAP): CSIRO and Bureau of Meteorology (2015); ERA-Interim: Dee *et al*. (2011).

Variable	Description	Resolution	Units
Climate variables from the CCIA dataset			
Minimum temperature (T_{min})	The minimum daily temperature is derived via delta downscaling from the AWAP daily time series data.	0.05°	°C
Maximum temperature (T_{max})	The maximum daily temperature is derived via delta downscaling from the AWAP daily time series data.	0.05°	°C
Rainfall (Rain)	Total daily rainfall derived from the AWAP daily time series data via delta downscaling.	0.05°	mm
Relative humidity (RH)	Mean daily relative humidity derived from the ERA-Interim daily mean time series data via delta downscaling and averaging of hourly values. The ERA-Interim dataset provides data at the hourly resolution, and daily mean relative humidity is calculated as the average of this hourly data daily.	0.75° gridded data, bilinearly interpolated to 0.05°	%
Solar radiation (Rs_d)	Daily mean surface downwelling shortwave radiation derived from the ERA-Interim daily mean time series data via delta downscaling and averaging of hourly values. The ERA-Interim dataset provides data at the hourly resolution, and daily mean solar radiation is calculated as the daily sum of this hourly data.	0.75° gridded data, bilinearly interpolated to 0.05°	Wm^{-2}
Derived climate variables			
Effective rainfall	Effective Rainfall (*EffRain*) is the amount of daily rainfall that reaches the soil surface after interception by the crop/plant canopy (Brutsaert, 2010). For simplicity, rainfall interception was a fixed proportion (0.25) of rainfall, and heavy events (greater than 50mm rainfall in one day) were assumed to exceed the capacity of the soil to store water. Accordingly, *EffRain* was calculated from daily rainfall data using $$EffRain = 0.75 * \mathrm{Rain},$$ and then modified: values below 5mm were set to zero, values above 50mm were set to 50mm.	0.05°	mm day^{-1}
Potential evapotranspiration	Daily potential evapotranspiration (ET0d) involves the transfer of water vapour to the atmosphere from vegetated and unvegetated land surfaces. The simple model of Hargreaves and Samani (1982), which predicts ET0d from radiation and mean daily temperature, was extended by adding latitude and longitude in a simple regression approach to account for the impact of lower evaporation in the wetter, colder NSW coastal regions and advection in the drier western areas of NSW: $$\mathrm{ET0d} = 6.62872 + 0.00550 * \mathrm{R_{Sd}} * (\mathrm{T_{mean}} + 17.8) - 0.04047 * L + 0.01642 * b,$$	0.05°	mm day^{-1}

Variable	Description	Resolution	Units
	where R_{Sd} is daily incoming shortwave radiation measured at the ground (units for SILO data: MJ m^{-2} day^{-1}; units for CCIA data: W m^{-2} day^{-1} multiplied by a conversion factor of 0.0864, following FAO56), T_{mean} is mean daily temperature (°C), *b* is the latitude of the location (°N) in GDA94 (decimal degrees), and *L* is the longitude of the location (°E) of the location in GDA94 (decimal degrees).		
Chill portions	Chill portions measure chill accumulation in deciduous fruit trees, required for the plant to emerge from dormancy and begin the production of fruit. Chill portions were calculated based on the dynamic chill model developed by Erez *et al.* (1990) which has been shown to have consistent performance across various climates and is less likely to overestimate the impacts of warming climate on chill accumulation than less sophisticated models (Luedeling, 2012).	0.05°	unitless
Chill index (CI)	CI was used to describe the impact of cold climatic conditions on lambs. The chill index was calculated using the formula from Broster *et al.,* (2012): $\mathrm{CI} = (11.7 + 3.1 * V^{0.5})(40 - \mathrm{T_{mean}}) + 481 + (418 * (1 - e^{-0.04X}))$ where CI is potential heat loss (chill index), *V* is wind velocity (a constant value of 2.5km h^{-1} was used), T_{mean} is mean daily temperature (°C) and X is daily rainfall (mm).	0.05°	$kJm^{-2}h$
Temperature Humidity Index (THI)	THI measures the perceived temperature based on the combined effects of air temperature and relative humidity. THI was used to assess heat stress in livestock and was calculated using the formula from Moran (2005): $\mathrm{THI} = 0.8 * \mathrm{T_{max}} + \mathrm{RH} * (\mathrm{T_{max}} - 14.4) + 46.4,$ where T_{max} is the maximum daily temperature (°C) and RH is the mean daily relative humidity (%).	0.05°	unitless

2.3.3.1. Marine variables

The fisheries MCA models used 3 marine climate variables: sea surface temperature, sea surface height, and current strength (i.e., eddy kinetic energy). Historical observed data for these variables were obtained from the Copernicus Marine Environment Monitoring Service[5]. Some fisheries MCA models included a static structural habitat variable that remains fixed within historical analyses and future projections.

[5] https://marine.copernicus.eu

Table 5: Marine variables used in fisheries MCA models.

Variable	Description	Resolution	Units
Dynamic Variables			
Sea surface temperature	Daily global sea surface temperature reprocessed (level 4) from Operational SST and Ice Analysis system (CMEMS product #010_011)	0.05°	°C
Sea surface height	Daily gridded sea surface height (level 4) from the Sea Level Thematic Assembly Centre (CMEMS product #008_047)	0.25°	m
Current strength	Daily eddy kinetic energy computed from zonal and meridional velocity components from the Sea Level Thematic Assembly Centre (CMEMS product #008_047)	0.25°	m^2s^{-2}
Fixed variables			
Bathymetry	Seafloor depth from the GEBCO (GEBCO_2020) global bathymetric dataset.	0.004°	m
Vertical relief	The index of vertical seascape relief utilised in the marine MCA models was derived from the GEBCO (GEBCO_2020) global bathymetric dataset as follows: $\text{Vertical relief} = 100 \times \frac{SD_{pixel}}{Median_{extent}}$ where SD_{pixel} is the standard deviation of groups of pixels aggregated by bilinear interpolation from a gridded resolution of ~0.004° (the native resolution of the GEBCO_2020 dataset) to 0.05° (the common resolution of variables used to create spatial predictions in the VA Project). $Median_{extent}$ is the median bathymetric value calculated nearshore of the continental shelf-break throughout the study extent.	0.004°	unitless

2.3.4. Modules and functions

The VA Project strongly emphasised a modular approach to MCA model development. This provides standardisation and consistency across the modelled commodities and biosecurity risks. The modules and functions used in MCA models are described in Table 6.

A set of modules was developed to provide these standardised methods for transforming climatic data into MCA model ratings. These modules typically perform two functions:

- Calculate a summary statistic, such as the sum or mean, across a period of interest.
- Apply a climate suitability step function to produce ratings between 0 and 1.

Table 6: Description of modules and functions used by the MCA models.

Module	Explanation
Standard ratings	*Standard Rating* variables use summary statistics calculated across a period of interest, such as average temperatures or cumulative sums of rainfall. The climate suitability step function is applied to return a single rating per year of data. For MCA models replicated monthly or seasonally, this summary is performed individually for each month or season.
Proportional ratings	*Proportional Rating* variables calculate ratings based on the proportion of time spent in each category. The climate suitability step function is applied to each daily value, and the result is averaged. This approach smooths out discontinuities resulting from applying a piecewise step function. Proportional Ratings were typically used to define optimal conditions for growth.
Threshold ratings	*Threshold Rating* variables use the time a variable spends above or below a threshold to produce a rating. Threshold ratings were typically used to define conditions that negatively affected growth (for example, the number of days over 42°C in a phenophase).
Matrices	*Matrices* capture the interaction between two variables across phases, most commonly mean temperature and rainfall. Matrices are defined by pairwise categories of their two variables and act like a two-dimensional *Standard Rating*.
Functions	**Explanation**
Lurking variables	*Lurking Variables* are only activated if the temperature or rain threshold is reached or exceeded. Activating a lurking variable sets the climate suitability to zero for the entire year, month or phenophase.
Damage penalty	*Damage Penalties* can ascribe cumulative, multiplicative penalties on total climate suitability due to heat or cold. These penalties are applied to the overall climate suitability calculated by the MCA model and followed the approach of Lilley *et al.* (2015) and Bell *et al.* (2016). For example, an MCA model might define mild (–2°C, say) and moderate (–4°C, say) frost damage penalties, with each occurrence incurring a penalty of, say, 0.1 and 0.2, respectively. Then, two mild and one moderate frosts in a single phenophase would reduce the maximum possible climate suitability to (1 – 0.1) * (1 – 0.1) * (1 – 0.2) = 0.648.

2.3.5. MCA model extensions

Extensions to the standard MCA framework described above were included for some commodity models in the VA Project. These were:

- dynamic phenology,
- thermal time,
- germination triggers,
- commodity quality and
- extensions related to water requirements.

The specific modules used for each commodity and biosecurity risk model will be described in upcoming reports.

2.3.5.1. Dynamic phenology

Dynamic phenology was implemented for several crops within the cropping node. In this extension, the start and end dates of phenophases were determined by thermal time thresholds (see below) or a mixture of specified dates and thermal time thresholds.

Therefore, the start and end dates of each phenophase were driven by the thermal environment and varied spatially within a given year and from year to year at one place, rather than being fixed across the whole state, as for the standard MCA models. The date when these thermal time targets are achieved defines the date when phenophases change and, therefore, the periods over which climate variables of temperature and rainfall are assessed. No allowance for vernalisation or photoperiod was made.

2.3.5.2. Thermal time

Elapsed thermal time is the accumulated growing degree days (AGDD). The accumulation of AGDD begins each year when the crop starts to grow at the 'day of germination' identified by the corresponding 'sowing rule' (see explanation below for germination triggers). AGDD is calculated as

$$AGDD = \sum_{d=0}^{n} GDD_d, \tag{1}$$

where GDD_d is the thermal time accumulated on the d^{th} day after growth started. GDD_d is calculated as follows:

$$GDD_d = \begin{cases} \left(\dfrac{Tc + Tmin_d}{2}\right) - Tb & \text{if } Tmax_d > Tc \\ max\left\{\left(\dfrac{(Tmax_d + Tmin_d)}{2}\right) - Tb, 0\right\} & \text{otherwise,} \end{cases} \tag{2}$$

where $Tmax_d$ (°C) is the maximum temperature on the d^{th} day, $Tmin_d$ (°C) is the minimum temperature on the d^{th} day, Tb (°C) is the base temperature below which growth ceases, and Tc (°C) is the ceiling temperature above which growth ceases. These coefficients are specified by each MCA model which uses this extension.

2.3.5.3. Germination triggers

Following sowing, thermal crop time begins to accumulate when sufficient rainfall is received by the fallow seeds. The rainfall threshold adopted by the VA Project requires that at least 15mm of rain be received in any consecutive 14-day period within the 56-day germination window, which immediately follows the end of the fallow period. The crop commences to grow, and thermal time accumulates, from the last day of the first 14-day period in which the rainfall threshold is met. If the threshold is not met during the germination window, germination fails and the overall suitability rating for that year becomes 0.

2.3.5.4. Water stress index

For rain-fed crops, water stress in each phenophase is estimated by the ratio between effective rainfall (EffRain) during that phenophase plus carry-over (CO) from the previous phenophase and the total crop evapotranspiration (ETc) during that phenophase:

$$\text{Water stress} = \frac{\text{EffRain} + \text{CO}}{\text{ETc}}. \quad (3)$$

2.3.5.5. Carry-over of rainfall

Carry-over of rainfall between phenophases was included in some cropping MCA models. Rain is carried over into subsequent phases using the following rules:

- 15% of fallow rainfall is carried over into the 1st growth phase,
- 15% of fallow rainfall is carried over into the 2nd growth phase,
- 30% of effective rainfall falling during a crop growth phase is carried over to the subsequent phase.

For models which use this extension, the start and end dates of the commodity's fallow period must be specified.

2.3.5.6. Quality

Quality MCA models were developed for some horticulture and cropping commodities (Table 6). This extension was designed as a complementary system to assess climate impacts on the quality of commodities. This is particularly important for high-value crops, for which the crop quality can significantly affect profitability as yield.

Table 7: Commodities for which quality MCA models were developed.

Horticulture quality		Cropping quality	
• Almond	• Macadamia	• Rice	• Barley
• Blueberry	• Walnut	• Cotton	• Canola
• Cherry	• Wine	• Wheat	
• Citrus			

The quality MCA model extension captures changes in climatic conditions that influence individual quality issues. However, it was found that information about climatic variables impact on quality has not been well studied. The published research focused primarily on climate impacts on yield without considering quality as an outcome. For these reasons, some of the biggest quality issues impacting horticulture and cropping remain poorly understood.

The framework developed for the VA Project uses grey literature, data exploration and expert elicitation to fill this knowledge gap. In some cases, these knowledge sources facilitated the development of quality extensions for MCA models. Including quality impacts in the vulnerability assessment has highlighted potential future climate risks to commodities that may have been overlooked if the focus remained on commodity yield. This extension could be applied to other commodities with further investigation, providing a greater understanding of the climatic variables influencing quality issues.

2.3.5.7. Irrigation water requirements

Irrigation water requirements for fully irrigated crops were calculated as the difference between crop evapotranspiration and total effective rainfall (calculated as described in Table 3). The resulting values also provide estimates of the relative change in irrigation water requirements.

Total soil water use, either transpired by the crop or evaporated from the soil surface, crop evapotranspiration (ETc), during a growing season (one annual crop cycle), is calculated by the FAO56 crop coefficient method according to

$$ETc = \sum_{p=1}^{n} Kc_p \sum_{d=t_1}^{t_2} ET_{0d} \tag{4}$$

where ET_{0d} is the reference evapotranspiration (mm day^{-1}) for the dth day of the pth phenophase, Kc_p is the crop coefficient ascribed to the pth phenophase and t_1 and t_2 are the first and last days of the year of each phenophase, respectively. Published Kc_p values were used for each crop.

For broadacre cropping MCA models, the number of phenophases and the first and last days of each phenophase will vary between MCA models and is be specified for each commodity. To estimate water demand or water stress during individual phenophases, *ETc* is be summed over that phenophase.

For the horticulture MCA models which operated on a monthly timescale, a crop coefficient value was assigned to each month, rather than to each phenophase.

Reference evapotranspiration on the dth day of the year, ET_{0d}, was estimated from daily weather data across NSW using a simple parametric model given (see Table 4).

The water requirements of irrigated crops, calculated over a production year, were taken to be the difference between crop evapotranspiration and the sum of the total effective rainfall and any initial water added at the time of sowing.

2.4. Expert Engagement

The VA Project involved 113 NSW DPI experts and a further 77 external experts. Their association with the project ensured thorough peer review and validation of the MCA models, as detailed below. The break-down of these numbers by node is shown in Figure 8.

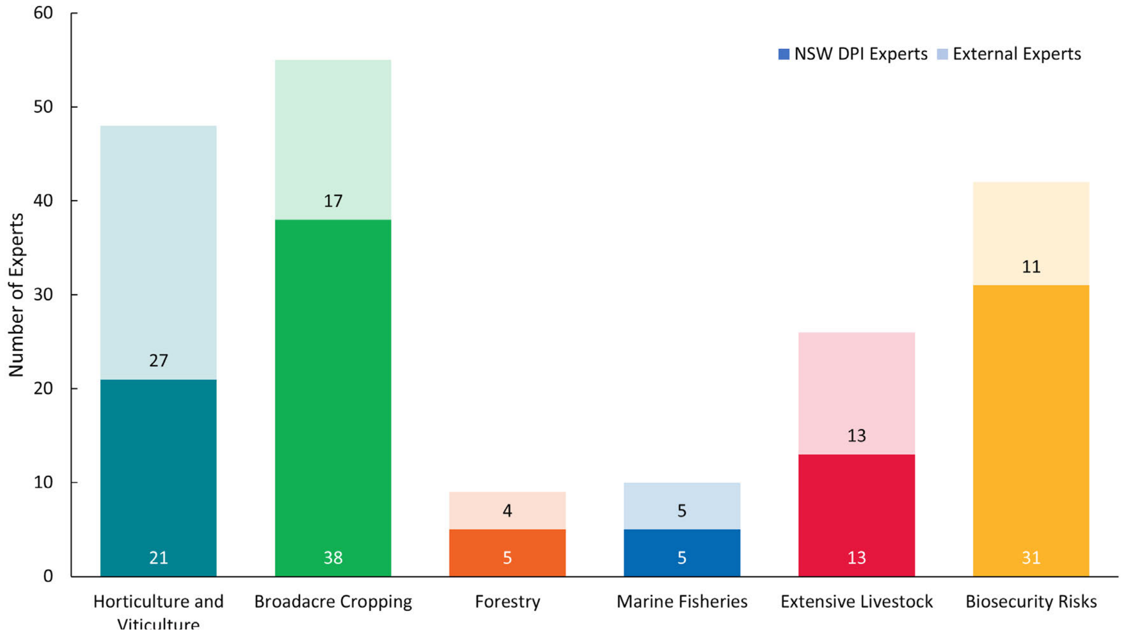

Figure 8: Experts were used to peer review the MCA models across the 6 VA Project nodes, from within NSW DPI staff and externally.

2.4.1. Focus groups

In the VA Project, a focus group of experts was convened to serve two important purposes. The first is to review the draft MCA models and utilise their expert knowledge, ensuring that the contents of the MCA models reflect both published knowledge and lived experiences. Experts were selected to provide input based on their perspectives as individuals familiar with the published literature or as people who could bring their on-the-ground experiences to the project.

The second purpose was to complete the weighting process: the climate variables were reviewed through pairwise comparisons to determine their relative importance in the overall climate suitability of each commodity or biosecurity risk. In this process, known as an 'analytical hierarchy process' (AHP) (Saaty, 1980), experts were asked to draw on their expertise and knowledge to make qualitative judgements on the influence of different variables on the commodity or biosecurity risk of interest. The final weightings derived through the AHP reflected the consensus reached by each focus group.

The overall mix of experts consisted of:

- Expertise that spans a broad (ideally state-wide) geographical range.
- Expertise that spans all phases of the commodity or biosecurity risk.
- In-depth knowledge of the biological responses to weather and climate and knowledge of the industry over time (usually people who have been involved in the industry intensively over many years).
- *In situ* experience: people who have worked on the ground extensively, having seen how the commodity or biosecurity risk develops and is managed in real-world conditions.

Experts included academics, consultants, industry representatives, government staff from NSW and other government agencies in Australia or abroad. The goal was to have a good balance of perspectives to validate and enhance confidence in the MCA models. Furthermore, the experts' experience assisted in filling the knowledge gaps that could not be addressed using the scientific literature alone. The VA Project oversaw 45 focus groups, mainly via online video conferencing due to the COVID-19 pandemic. A breakdown of the sectors represented by these experts is shown in Figure 9.

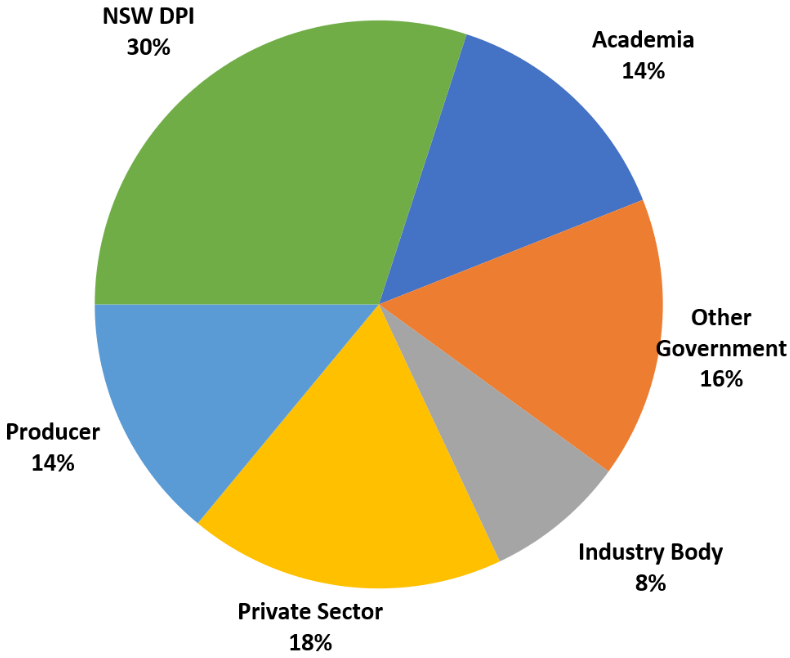

Figure 9: The peer-review processed, used to develop MCA models in the Vulnerability Project, engaged with experts from a wide variety of sectors.

Whilst these focus group meetings contain a subjective component, the rationale for each expert's response was always sought and articulated throughout the group's engagement. These rationales would usually draw on data and real-world observations and be noted by the meeting facilitators along with confidence levels based on these discussions.

The experts helped to inform changes in the MCA models, which were made directly on the day of each meeting. This allowed collaborators to see how the model would work based on their decisions, and the rapid feedback allowed them to make quick assessments of the model validity. Where needed, further changes were then completed following a supplementary investigation. Transcripts of the meetings were saved and distributed. This ensured that all decisions could be cross-checked and confirmed if necessary.

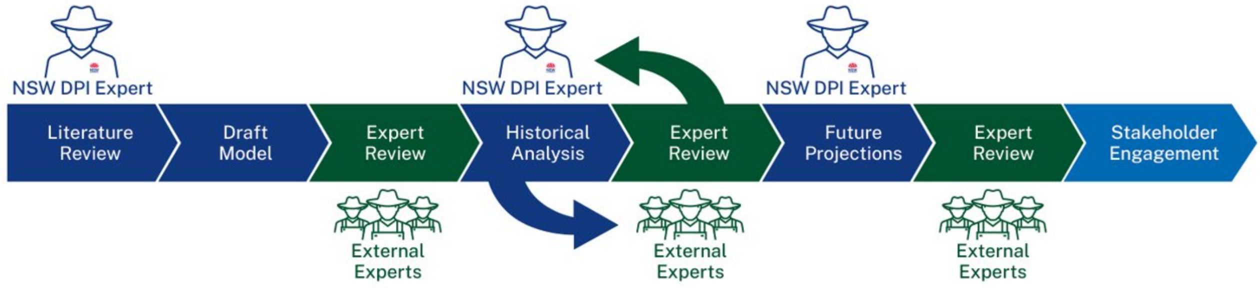

Figure 10: The Vulnerability Assessment Project framework contained a sequence of peer-review elements, where internal NSW DPI staff and external experts had input into the MCA modelling process.

2.4.2. The analytical hierarchy process

During the focus group meetings, the experts considered the criteria at each level in the MCA model for their commodity or biosecurity risk. A series of pairwise comparisons were made, using the analytical hierarchy process (AHP), to determine the weighting for each criterion within the model. The outcome of these comparisons were relative weightings for the phenophases identified as climate sensitive as well as the important climate variables for each phenophase.

The AHP is a well-tested, systematic method which allows a blend of research and expert knowledge to determine the weightings in the MCA model (Saaty, 1980). The weightings reflect the relative importance of each criterion in the MCA model, so that criteria with higher weightings have more influence on the model.

To facilitate the AHP, a dedicated calculator application was built for use at focus group meetings. The calculator implemented the pairwise comparison calculation of Saaty (1980) in the *shiny* package in R.

2.4.3. Verification of historical climate suitability

After being assessed by the relevant experts, each MCA model was run using the SILO historical climate data for the years 1970-2019 to produce a series of spatial analyses showing the historical climate suitability. The historical climate suitability shown in these spatial analyses underwent a rigorous assessment by focus group members before the MCA models were further fine-tuned. A report containing the historical climate suitability outputs, in the form of boxplots, timeseries and maps and a summary of any changes proposed was sent to the focus group experts to seek further comments on the MCA model and to confirm whether these outputs were consistent with their expert knowledge and experience.

After consideration by these experts, any further changes deemed necessary were made and the SILO data reprocessed using the refined MCA model. New historical climate suitability outputs were then produced and re-assessed. This process could occur several times until the experts were satisfied with the resulting historical climate suitability.

2.4.4. Peer-review by Deakin University

The MCA model was finalised once the focus group experts confirmed and agreed on the historical climate suitability results. Of the 42 MCA models developed, 25 were sent out for external peer review by technical experts at Deakin University's Centre for Regional and Rural Futures. The Deakin University review process assessed whether:

- MCA model structure and weightings were clear and reasonable.
- Feasible climate variables were employed, and a range of conditions considered.
- Historical conditions were represented with enough consideration for future climate possibilities.
- MCA models captured and responded to ratings outside the historical range.
- Identified representative sites for the modelled commodities demonstrated sufficient state-wide coverage.

The reviewers typically requested clarification or additional information in the following areas:

- Rationale for the hierarchy structure for the MCA model.
- Calculation of variables like temperature-humidity index and solar radiation.
- MCA model assumptions and exclusions.

The external peer review process improved the VA Project's approach, especially regarding MCA models' transparency, and was valuable for maintaining consistency across all MCA models.

3. Standardised Impact Assessment Reporting

After the evaluation of an MCA model against historical climatic conditions, the model was applied to projected future climate data to produce future climate suitability outputs for each commodity and biosecurity risk. These outputs allow for assessing future climate change impacts on the commodities at each level of the MCA models.

3.1. Climate Impact Assessment

A Climate Impact Assessment report was completed for each commodity or biosecurity risk to ensure a thorough evaluation of the future projection outputs at all levels of its MCA model. A detailed assessment of climate suitability was undertaken on key phenophases and climate variables, especially those that exhibited large positive or negative change. Due to the MCA models' size and extensive outputs, not all phenophases were assessed in detail, particularly if there was negligible change or if the change occurred in regions deemed irrelevant to that commodity or biosecurity risk. Quality, water demand and the cropping MCA model extensions were also assessed to understand the possible impact of future climate on those aspects of commodity production.

In addition to the MCA model output, NSW DPI experts completed a series of post-assessment questions to evaluate whether climate suitability would lead to the expansion or contraction of the industry, identify what drove the change in climate suitability and what the implications of that change might be to the industry.

3.2. Cartography of Future Projections

One of the VA Project's objectives was to provide government and industries with a state-wide overview of future exposure and sensitivity to climate change across the primary industries sector. The main medium identified to provide this information was through mapping products. Considerable time went into developing maps that present the complex model output in a concise, unambiguous and accessible manner. This section details the various maps produced by the VA Project.

The climate suitability map series present the mean suitability for historical data over 30 years of observations (1981 to 2010). For future projections, the mean suitability for 30 years (2036 to 2065) was first calculated for each of the 8 GCMs, and the median of the 8 GCMs was then taken to produce ensemble future projection climate suitability maps for the two RCP scenarios, RCP4.5 and RCP8.5. This process is summarised in Figure 11. Details of the various maps produced by the VA Project are provided in Section 3.4.

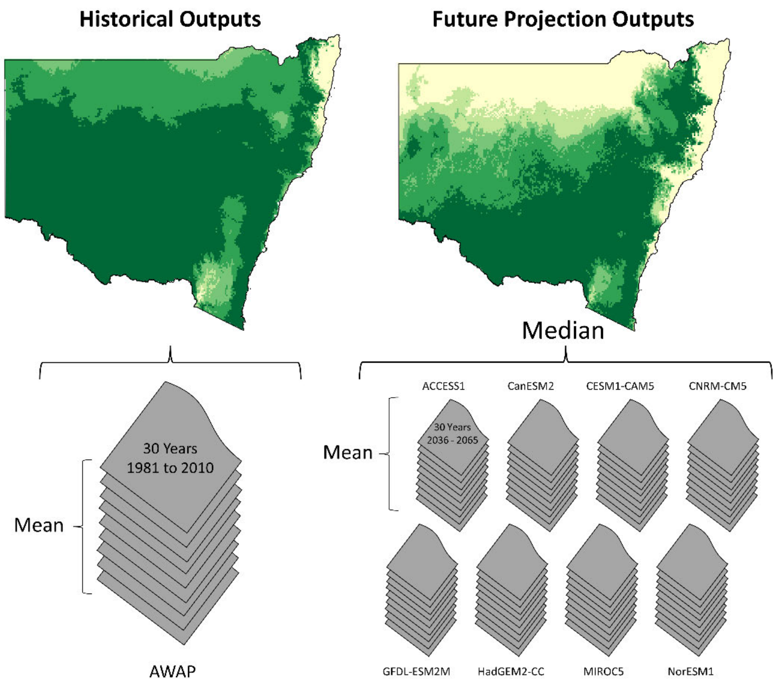

Figure 11: Climate suitability map products were created by the Vulnerability Assessment Project using historical and future projection climate data. The main results present the mean climate suitability over each year of the data sets, and the median climate suitability for the ensemble of global climate models.

3.3. Accounting for Uncertainties

The climate suitability MCA models and associated impact assessments produced by the VA Project are subject to uncertainties that must be acknowledged and addressed to avoid producing misleading results and to reduce misinterpretation. The sources of uncertainty in this project can be grouped into several categories, outlined below, along with ways of accounting for them.

3.3.1. Sources of uncertainty

3.3.1.1. Model limitations

One of the primary sources of uncertainty lies in the development of the MCA models used to model the response of commodities and biosecurity risks to climate change. Building these MCA models involves assigning ratings to different factors affecting an organism's tolerance to environmental changes and weighting them according to their relative importance. These ratings and weightings were often based on expert opinion, which may have been influenced by biases, recent personal experience or limited knowledge. In addition, the MCA model approach is relatively simplistic and does not capture all the complex interactions and feedback pathways between organisms and their environment. This introduces uncertainties in the predicted impacts derived from the MCA model outputs.

3.3.1.2. Future climate uncertainty

Another source of uncertainty lies in the disagreement between GCMs. Each GCM uses different assumptions and approximations to represent the very complex processes involved in the Earth's climate system, leading to variations in the predicted outcomes. For instance, significant differences exist in how the GCMs simulate rainfall, a critical variable in some MCA models. To address this uncertainty, the VA Project utilised future climate projection data from an ensemble of GCMs to capture a range of possible future outcomes. The VA Project has used the recommended the ensemble of GCMs considered suitable for climate modelling in Australia (CSIRO and Bureau of Meteorology, 2015). However, even this curated set of GCMs contains projections of individual future climates for NSW which vary in character and translate, via the MCA models, into differences in commodity and biosecurity risk climate suitabilities. The extent of these differences is expressed in confidence statements and maps which accompany climate suitabilities reported by the VA Project.

3.3.1.3. Spatiotemporal data resolution

The MCA modelling used a single daily value of each climate variable, ascribed to a grid of 0.05° (approximately 5km by 5km). This resolution cannot capture the complex climatic variations over small spatial and temporal scales. This limitation could lead to inaccuracies in predicted outcomes, particularly for systems highly sensitive to small environmental changes.

3.3.1.4. Downscaling uncertainty

The GCMs in the CCIA ensemble had been downscaled to a 0.05° grid using a simple statistical method incorporating local climate data (CSIRO and Bureau of Meteorology, 2015). This process introduces uncertainty and produces outputs suitable for analysis of central tendencies but less useful for analysis of variability or extremes.

3.3.2. Minimising effects of model limitations

Limitations and uncertainties associated with the modelling and impact assessment process have been addressed in the following ways, categorised here by the source of uncertainty.

- Climate suitability maps have been presented using a categorical scale. This prevents the outputs from being interpreted as containing fine-scale differences in climate suitability, which the MCA model cannot resolve.
- The change in climate suitability maps included a 'negligible' category, represented by values between –0.1 and 0.1. Use of this category prevents the identification of areas as experiencing change not supported by the MCA model outputs.
- A gap analysis was conducted to identify where MCA models were poorly supported by published research.

By adopting these practices, the VA Project sought to minimise misunderstandings and the potential for misuse of the model outputs.

3.3.3. Addressing uncertainty in climate data

Limitations and uncertainties associated with the CCIA climate data set have been addressed in the following ways, categorised here by the source of uncertainty.

3.3.3.1. Disagreement between GCMs

- The ensemble of 8 GCMs used in the VA Project represents a broad range of plausible future climates for NSW.
- Climate suitability was presented as the median response to these 8 GCMs, with a corresponding confidence map illustrating the level of agreement between the GCMs.

3.3.3.2. Downscaling and spatiotemporal resolution uncertainty

- Climate variables considered unreliable on the stated spatial and temporal scales were avoided. Data use was restricted to appropriate temporal scales; for example, no direct analysis of consecutive days of extreme daily climatic conditions was included, nor analysis of event sequences.
- Maps of changes in climate suitability included a category of 'negligible' change which was employed to indicate where confidence was low. This prevents overreliance on highly uncertain results.

- Site-level data was reported as the median of a small spatial region around a given location rather than the value at a single geographical point.

3.3.3.3. General future greenhouse gas emission uncertainty

- Given the wide range of potential anthropogenic greenhouse gas emissions between now and 2050, two greenhouse gas emission scenarios, RCP4.5 and RCP8.5, were analysed to study future climates arising from intermediate and high emissions.

3.4. Explanation of Mapping Colour Schemes

As climate suitability does not have a well-established or commonly known colour scheme like temperature anomalies or rainfall, a stakeholder survey was conducted to assess the ability of participants to understand and interpret climate suitability maps. The survey presented maps produced from MCA models' spatial outputs, in various proposed colour schemes, with the aims of:

- Assessing whether participants associate 'higher climate suitability' with darker or lighter colours.
- Assessing whether participants associate 'positive change in climate suitability' with darker or lighter colours and/or warmer or cooler tones.
- Assessing the ability of different cohorts of participants to understand maps of climate suitability and change in climate suitability.
- Assessing the effectiveness of including a colour bar in assisting in the interpretation of climate suitability and change in climate suitability.

To produce the final colour schemes for the VA Project, the results of the survey, along with accessibility considerations, were used to produce a series of complementary colour schemes. These were modified from ColorBrewer[6] and CARTOColors[7] palettes to create palettes for 'Climate Suitability', 'Change in Climate Suitability', 'Water Demand,' and 'Frequency' maps.

The presentation of all maps produced by the VA Project is done using 'map panels', in which carefully selected maps are always shown together. These are the historical climate suitability map and 3 maps for each of the two RCP scenarios: median climate suitability, change in climate suitability and confidence in change in climate suitability. Together, these maps provide historical context for the commodity or biosecurity risk as well as allowing for comparison between the two emissions scenarios.

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[6] https://colorbrewer2.org/

[7] https://carto.com/carto-colors/

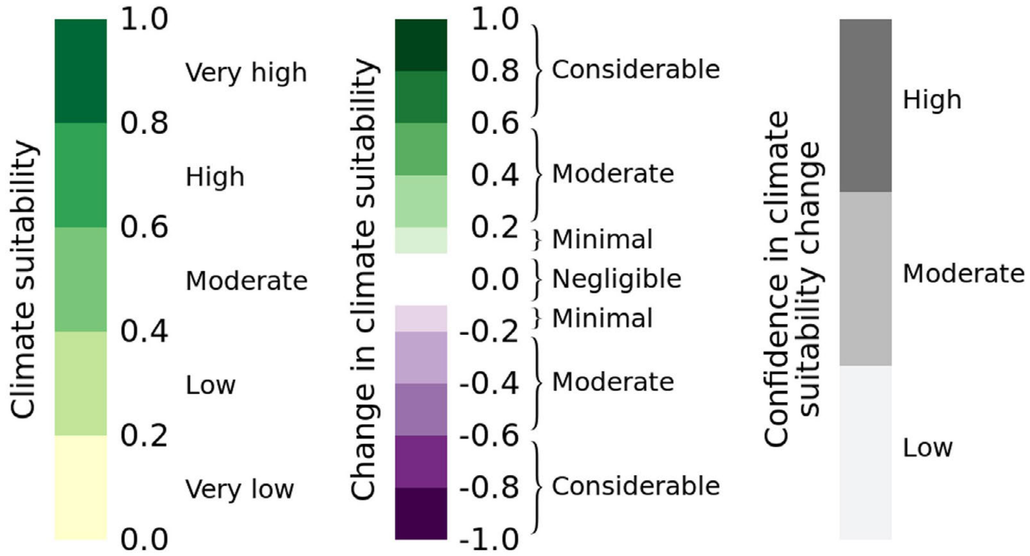

Figure 12: The Vulnerability Assessment Project adopted standardised language for categories of climate suitability, change in climate suitability and confidence in that change. This language allows for a consistent comparison of results across all commodities and biosecurity risks.

Considered and consistent language has been adopted by the VA Project to describe the results shown in these maps. The same descriptions of suitability, change and confidence are used across all commodities and biosecurity risks, along with consistently applied categories for each type of map: these are summarised in Figure 12. The adoption of standardised language across the VA Project assisted 53 collaborators to complete project reporting for their commodities or biosecurity risks and ensured that this reporting would be consistent and comparable across nodes.

3.4.1. Climate suitability maps

The climate suitability panels show the output of the MCA models and are presented as a unitless index, ranging between 0 and 1. Climate suitability maps use a light yellow to dark green colour scheme with 5 categories (see, for example, Figure 13 A), B i) and C i)): light yellow at the low end of the colour scheme (values from 0 to 0.2, corresponding to very low suitability) and darker greens at the high end of the colour scheme (values from 0.8 to 1.0, corresponding to very high suitability). Growing region polygons and key growing sites are displayed on the maps to highlight areas where the commodity is currently produced and where the biosecurity risks are found or the host commodities.

3.4.2. Change in climate suitability maps

The change in climate suitability panels show the change between a commodity or biosecurity risks' historic climate suitability and its future projected climate suitability (for both RCP4.5 and RCP8.5). Change in climate suitability uses a purple-white-green colour scheme (see, for example, Figure 13 B ii) and C ii)) with 11 categories: 5 shades of purple for negative change, a white category for negligible change and 5 shades of green for positive change. Positive change, where the future climate is more suitable for the commodity or biosecurity risk, is shown in shades of green. Negative change, where the future climate is less suitable, is shown in shades of purple. Darker shades of green or purple show greater changes (values closer to −1 or 1), and lighter shades of green or purple represent smaller changes in climate suitability. Negligible change (values between −0.1 and 0.1) is represented by white.

3.4.3. Confidence in change maps

Confidence in the MCA models' predictions of changing climate suitability was assessed using the ratio of the absolute value of median change across the 8 GCMs to the standard deviation of climate suitability across the 8 GCMs. This ratio expresses the level of agreement of the MCA model outputs between the different GCMs. It provides a statistical assessment of the likelihood that the median change is greater than that expected due to random chance. Higher ratios reflect greater confidence that all 8 GCMs agree on the extent of change in climate suitability.

Modifications were made to the resulting confidence in two cases where the calculated confidence category was unrealistic:

- Areas of negligible change (non-zero median change with absolute value less than 0.1), low standard deviation (less than 0.1) and low confidence were modified to moderate confidence: this occurs when all GCMs agree on negligible change but disagree on the direction (positive or negative) of that small change.
- Areas associated with no change (median change less than 0.01) and zero standard deviation (that is, agreement across all GCMs) were set to high confidence.

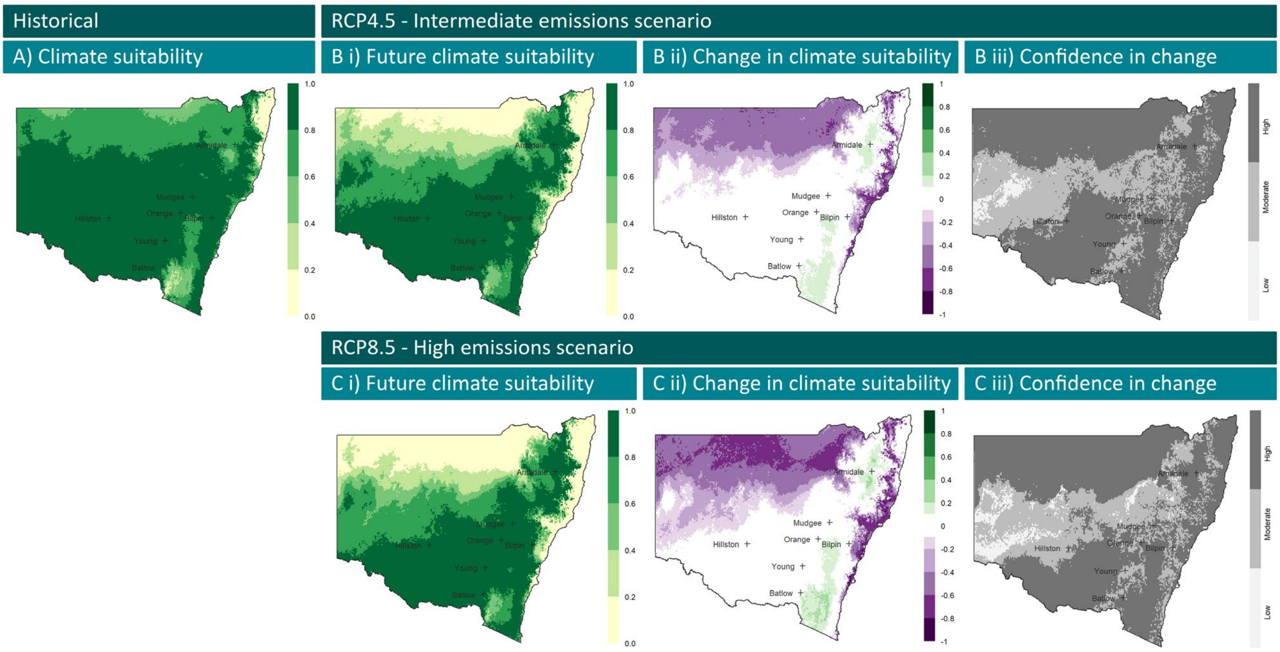

Figure 13: Example of a climate suitability panel, comprised of 7 maps. A) shows mean historic climate suitability for 1981-2010; B) and C) shows future climate suitability for 2036-2065 for the intermediate (RCP4.5) and high (RCP8.5) emissions scenarios, respectively; i) shows the mean future climate suitability, ii) shows the median change in climate suitability between the historical and future time periods, and iii) shows the confidence in those changes, reflecting the level of agreement between the 8 GCMs. The colours and standardised language used by the Vulnerability Assessment Project to describe these maps are explained in Figure 12.

Confidence maps (see, for example, Figure 13 B iii) and C iii)) are included in the climate suitability panels using 3 categories: low (ratio less than 1), moderate (ratio between 1 and 2) and high (ratio greater than 2). The confidence in change map uses a 3-part greyscale colour scheme, with the lightest grey representing low confidence and the darkest grey representing the highest confidence.

3.4.4. Water demand maps

Water demand maps use a pale yellow to burgundy colour scheme to show the water required by the commodity (see, for example, Figure 14 A), B i) and C i)), with 2 ML Ha^{-1}-wide categories. Darker shades of burgundy represent higher water demand, where larger amounts of water are required for optimal production of a commodity, and lighter shades of yellow and orange represent lower water requirements for optimal growth.

Change in water demand maps use a brown-to-teal colour scheme with 11 categories showing absolute change. Increased demand (positive values), where a crop will require more irrigation in the future, is shown in shades of brown. Decreased demand (negative values), where a crop will require less water in the future, is shown in shades of teal; this is a rare occurrence in the VA Project outputs. Darker shades indicate greater changes, whilst lighter shades represent smaller changes (see, for example, Figure 14 B ii) and C ii)). Negligible change (values between −0.5 and 0.5 ML/Ha) is represented by white. Confidence in the change in water demand was calculated in the same manner as climate suitability.

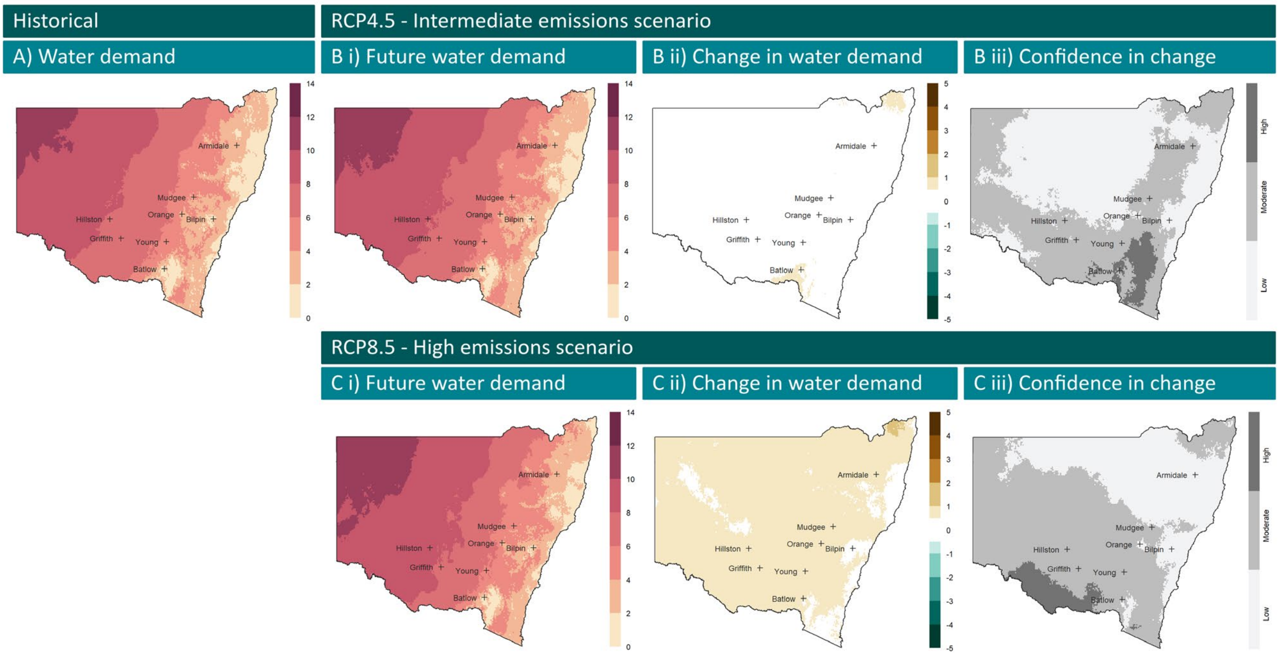

Figure 14: Example of a water demand panel, comprised of 7 maps. A) shows mean historic water demand for 1981-2010; B) and C) shows future climate suitability for 2036-2065 for the intermediate (RCP4.5) and high (RCP8.5) emissions scenarios, respectively; i) shows the mean future water demand, ii) shows the median change in water demand between the historical and future time periods, and iii) shows the confidence in those changes, reflecting the level of agreement between the 8 global climate models.

3.4.5. Frequency maps

For many primary industries commodities, it is important to understand how often or likely it is that something occurs. Examples of this include the frequency of germination in cropping and the frequency of the growing degree days being completed for some fruit crops (allowing fruit maturation to occur). Frequency maps were calculated for the 30 years of historical and future projection climate data, showing the proportion of those years that a given event occurred or that the climate suitability threshold was met or exceeded.

Frequency maps were also used to show the number of months each year in which conditions were optimal for biosecurity risk growth and survival. ‘Frequency of optimal months’ maps were calculated as the number of months per year during which the biosecurity risk's climate suitability was 0.6 or greater, averaged over the 30 years of historical and future projection climate data. The order of operations in this calculation was repeated for each RCP scenario:

- For each GCM, calculate the mean number of months per year for which climate suitability was greater than or equal to 0.6.
- Take the median across the GCMs to calculate the frequency of optimal months and median change.
- Calculate confidence as the ratio of the median change to the standard deviation across the 8 GCMs.

Frequency maps use an orange colour scheme, with lighter and darker shades of orange representing lower and higher frequencies, respectively (see, for example, Figure 15 A), B i) and C i) and Figure 16 A), B i) and C i)). ‘Change in frequency’ maps use an orange-to-purple colour scheme, with purple shades representing negative changes (drops) in frequency and orange shades representing positive changes (increases) in frequency. Darker shades of purple and orange indicate greater changes, whilst lighter shades represent smaller changes (see, for example, Figure 15 B ii) and C ii) and Figure 16 B ii) and C ii)). Negligible change (values between −0.1 and 0.1) is represented by white; for monthly frequency change maps, negligible change means −1, 0 or 1 months.

Confidence in change of frequency maps was calculated in the same manner as for climate suitability, except that the thresholds for negligible change and low standard deviation were set to 0.5 to account for the increased range of variation in the number of months of high suitability.

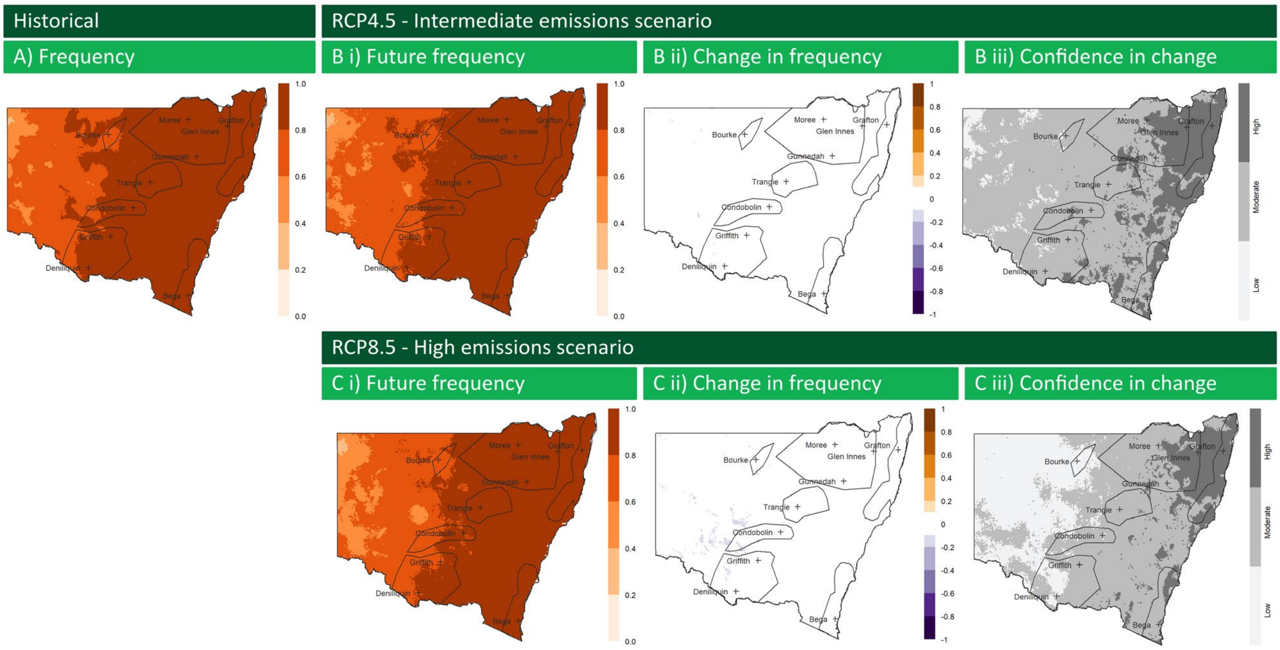

Figure 15: Example of a frequency panel for crop germination, comprised of 7 maps. A) shows mean historic germination frequency for 1981-2010; B) and C) shows future germination frequency for 2036-2065 for the intermediate (RCP4.5) and high (RCP8.5) emissions scenarios, respectively; i) shows the mean future germination frequency, ii) shows the median change in germination frequency between the historical and future time periods, and iii) shows the confidence in those changes, reflecting the level of agreement between the 8 global climate models. Black outlines show the current commodity growing regions.

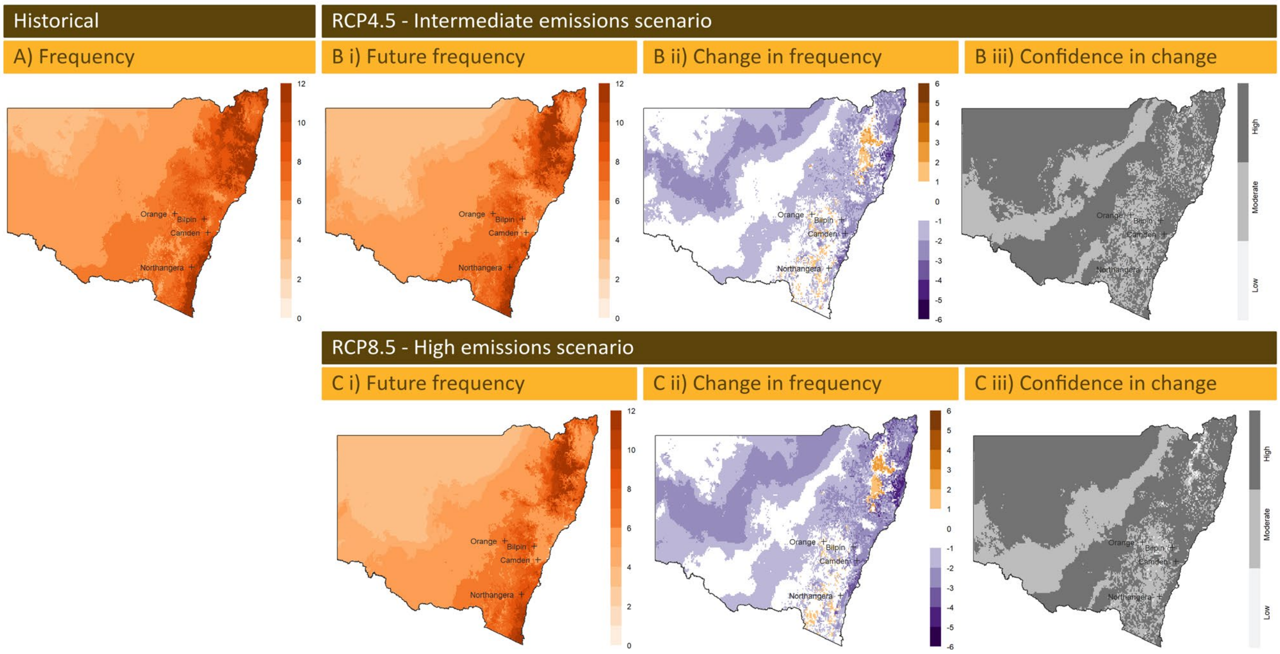

Figure 16: Example of a frequency panel for optimal months for a biosecurity risk. Optimal months were defined as having a climate suitability of greater than 0.6. The panel is comprised of 7 maps. A) shows mean historic frequency for 1981-2010; B) and C) shows future frequency for 2036-2065 for the intermediate (RCP4.5) and high (RCP8.5) emissions scenarios, respectively; i) shows the mean future frequency, ii) shows the median change in frequency between the historical and future time periods, and iii) shows the confidence in those changes, reflecting the level of agreement between the 8 global climate models.

3.5. Site Data

Site-level data were extracted from the MCA model outputs to obtain a clearer local picture of climate suitability, water demand, suitability change and confidence outputs for regions of interest to each commodity. These were for key production locations for commodities or areas of concern for the biosecurity risks.

The coordinates of these locations were specified, and values extracted from pixels within a 0.1° (~10km) radius around each location to provide site-level data. The median of these values was provided as the value for that site. Pixels within this radius falling outside the NSW state boundary or off the coastline were excluded from this analysis.

Site-level data was also used to create annual calendar plots for biosecurity risks, and phenological calendar plots for horticulture and cropping commodities. Historical and median RCP4.5 and RCP8.5 calendars for each site allow for a visual comparison of changes in climate suitability, frequency of optimal months and dynamic phenology to be made. An example of a calendar plot for a biosecurity risk is shown in Figure 13.

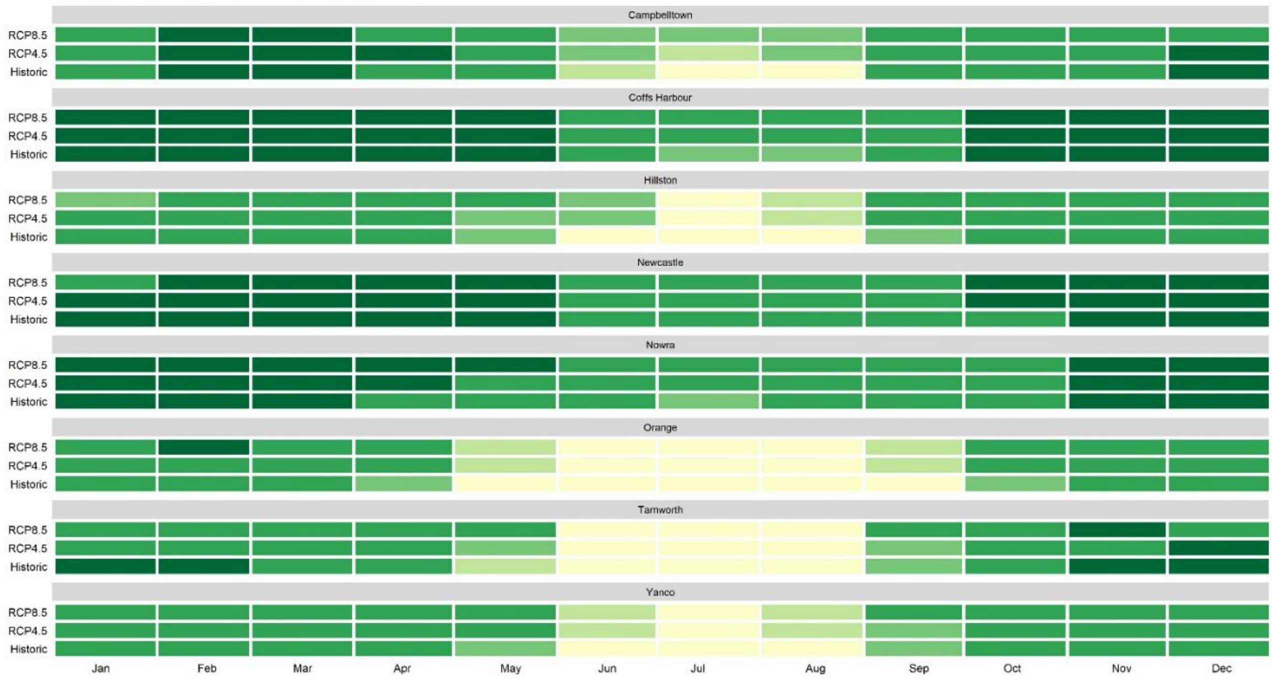

Figure 13: Calendar plot for biosecurity risk. The calendar plot is divided into sections for each representative region for host commodities. Columns represent months of the year, and rows for each region show the climate suitability for the historical and future emissions scenarios. In this example, note that, during winter, the period of very low climate suitability (yellow bars) in several of the regions becomes broader under the future emissions scenarios.

Calendar plots for the biosecurity risks highlighted the climate suitability for each month for each life cycle phase of a biosecurity risk. By analysing monthly climate data using the biosecurity risk MCA models, these calendar plots provide a visual representation of the change in climate suitability across the year. Note that the number of optimal months in these plots for the key locations can differ slightly from the values provided in the ‘frequency of optimal months' maps, particularly when future climate projections are associated with low confidence. This is because suitability categories are determined by the median suitability rather than considering a suitability threshold and then calculating the median.

3.6. Gap Analysis

The VA Project conducted state-wide climate impact assessments across many primary industries to identify the climate vulnerabilities facing each sector in NSW. The new data generated by this project will help identify the climate vulnerabilities, adaptation priorities and opportunities for each industry.

However, many knowledge gaps were identified during the development and validation of the individual MCA models. These knowledge gaps were barriers to developing the MCA models, sometimes leading to the exclusion of key climate criteria for commodities or biosecurity risks because there was no data to justify their inclusion in the MCA model. It increased the difficulty in validating the historical MCA model output.

External experts were heavily relied on to address knowledge gaps. Their knowledge and experience were used to inform the development and validation of criteria within the MCA models. Gap analyses were conducted to capture where 'expert knowledge' was used to inform criteria within the MCA models. The approach visually identified the knowledge source used for each MCA model and was consistently used across all MCA models in the VA Project. At the end of the gap analysis, a list of research priorities was generated to assist in directing future research and project development.

3.6.1. Knowledge categories

Data sources were categorised according to their level of confidence as follows:

- 'Published data' have been peer-reviewed and published, including peer-reviewed journal articles and industry reports. This category is regarded as the most reliable source of information and is the preferred source for thresholds, ranges and ratings.
- 'Data exploration' includes modelling or datasets, including data from unpublished field trials or monitoring experiments or models such as APSIM[8], used to identify values, thresholds and ratings.
- 'Expert experience' derives the variables, thresholds and ratings from individuals' experience, observations, and judgment during focus group meetings. This is usually used when no suitable published data or exploration options exist. It includes widely used 'rules of thumb'.
- 'Modified published literature or data' are published data modified by focus group experts or through data exploration. Common reasons for changing or modifying the

[8] https://www.apsim.info/

literature and data include studies conducted on a similar variety, crop or species, studies conducted outside of NSW or Australia, where conditions may be slightly different, or laboratory studies requiring adjustments to reflect the differences between laboratory and real-world conditions.

- ‘Modified data exploration’ are field trials or monitoring results that have been modified or adjusted by experts, usually to address known issues, limitations or biases in the model or dataset. Modified data exploration may also occur when the dataset covers a similar variety, crop or species or when the dataset is based on data collected outside of NSW or Australia.
- ‘Modified literature and data’ are literature and data sources that are used to develop the draft MCA model and then modified or combined through the experts' discussion during a focus group meeting. This category will often apply when complex literature and data exploration combinations have been used to provide a basis for thresholds and values.

4. Ending the VA Process

4.1. Final expert review

4.1.1. Focus group review of projections

The key aspects of the lifecycle of the commodity or biosecurity risk that may be impacted by a future negative change in climate suitability were identified during the Impact Assessment process. These key findings were presented to the focus group experts, and a discussion about the key adaptation strategies was facilitated in these meetings. The objectives of this engagement were to:

- Seek the focus groups’ input on the impact assessment findings, specifically which findings are most pertinent for communication to industry and government.
- Identify adaptation priorities for industry members.

The discussions captured in these meetings were used to develop the communication narrative and associated documentation for the MCA model.

4.1.2. Industry and government briefings prior to general release

Prior to the general release of the Summary Report, which contains key results for each commodity a series of industry and government briefings were held. These briefings continued the collaborative approach taken to develop the MCA models and have provided the VA team and the relevant industry/government bodies an opportunity to share their knowledge and become familiar with the project and the findings.

The VA team communicated the following in these meetings:

- The rationale for the project and an overview of the methodology

- The combined use of published literature and expert elicitation in MCA model development
- The change in climate suitability for the commodity/biosecurity risk and the opportunities or risks this presents
- The adaptation options proposed by experts to reduce industry vulnerabilities
- The on-going research and development priorities

The sessions allowed industry and government stakeholders to provide feedback about the findings or the adaptation options already being considered or developed for that commodity. In addition, it allowed for the knowledge and experience of these bodies to inform project reporting and identify future research priorities and collaboration opportunities. Lastly, it has helped the VA team to refine the communication messages and narratives further and identify issues for resolution.

4.1.3. Public release

The primary objective was to promote the findings of the VA Project with the long-term goal of reducing the climate impacts and increasing the resilience of primary industries in NSW. The release of the results and supporting documentation will enable NSW DPI to contribute these findings into the completion of State and National Climate Risk Assessment programs in the near future. Early consultation has shown a strong interest in the results.

Effective communication was achieved by:

- Consulting with industry and government to understand their needs.
- Collaborating with industry and government to develop and review research findings.
- Development of clear, engaging and easily interpretable outputs and collateral.

In summary, this collateral was produced for use across various audiences to support the communication activities, including:

- Reports – summarising findings for commodities and biosecurity risks, including maps, adaptation priorities.
- Website content – incorporating maps, fact sheets, infographics, commodity and biosecurity risk summaries, adaptation priorities, case studies industries and adaptations in action.
- Briefings – industry and government prior to release to increase familiarity and garner feedback.
- Presentations – for NSW DPI staff to share with stakeholders internally, online and across government.

The dissemination of results was staged to deliver understanding, acceptance and engagement across the industry and government and achieve the overarching communication goal of ensuring the utilisation of the project findings.

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Primary Industries Climate Change Research Strategy

Climate Vulnerability Assessment

Methodology Report

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