DEPARTMENT OF PLANNING, INDUSTRY & ENVIRONMENT

Climate change impacts in the NSW and ACT Alpine region

Impacts on crop suitability

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Cover photo: Winter landscape in Kosciuszko National Park. John Spencer/DPIE

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ACT	Australian Capital Territory
APSIM	Agricultural Production Systems SIMulator
ANN	Annual
AWAP	Australian Water Availability Project
CAP	Catchment Action Plan
CC	CCCMA3.1
CGS	cropping growing season
CS	CSIRO-MK3.0
CMIP	Coupled Model Intercomparison Project
DD	deep drainage
DPIE	Department of Planning, Industry and Environment
EC	ECHAM5
EP	plant evaporation
ES	water evaporation
FTH	flowering to harvesting
GCM	Global Climate Model
MBE	mean bias error
MI	MIROC3.2
mm	millimetre
MM	Murray-Murrumbidgee state planning region
MRC	Murray–Riverina cropping region
NARCliM	NSW/ACT Regional Climate Modelling project
NSW	New South Wales
OEH	Office of Environment and Heritage
PAWC	plant available water capacity
PPD	Patched Point Data
PS	pre-sowing
RO	runoff

RCM	Regional Climate Model
SBC	secondary bias correction
SET	South East and Tablelands
SILO	Scientific Information for Land Owners climate database
SoilN	soil nitrogen
SoilWat	soil water
SRES	Special Report on Emissions Scenarios
STF	sowing to flowering
UNSW	University of New South Wales
WRF	Weather Research and Forecasting

Summary of findings

Impacts on crop suitability in the NSW and ACT Alpine region

1. This study investigated the impacts of climate change on four crops (wheat, barley, canola and lupin) across the Murray–Riverina cropping (MRC) region.
2. Results suggest that bias correction of simulated temperature and rainfall effectively removed biases in the climate models at an annual time scale; however, it did not remove biases at finer temporal scales such as the cropping season.
3. Results suggest that mean crop yield will slightly increase in the near future (2020 to 2039) and substantially increase in the far future (2060 to 2079) when compared to a baseline period (1990 to 2009).
4. The ensemble mean yield of 12 Global Climate Model/Regional Climate Model simulations for the four crops across the MRC region is projected to increase by 2–9% and 8–20% for the 2020 to 2039 and 2060 to 2079 periods, respectively, relative to 1990 to 2009.
5. The biases in climate variables could explain 72–76% of the variance in the crop yield biases and 80–87% of the variance in the crop phenological biases.
6. Small changes in seasonal radiation are projected for the near and far future periods. The ensemble means for projected change in growing season radiation were –0.13% in 2020 to 2039 and +0.22% in 2060 to 2079, relative to 1990 to 2009.
7. Strong seasonal warming trends are projected for the near and far future periods. Maximum temperature for the growing season was projected to moderately increase, 0.5°C in 2020 to 2039 and 1.7°C in 2060 to 2079, relative to 1990 to 2009.

1. Introduction

1.1 Background

The New South Wales (NSW) and Australian Capital Territory (ACT) Alpine region is located in the south-eastern corner of mainland Australia and is the highest mountain range in Australia. Though it comprises only about 0.16% of Australia in size, it is an important region for ecosystems, biodiversity, energy generation and winter tourism. It forms the southern end of the Great Dividing Range, covering a total area of 1.64 million hectares that extend over 500 kilometres. The highest peak, Mount Kosciuszko, rises to an altitude of 2228 metres.

This report is part of a larger project delivered by the NSW Department of Planning, Industry and Environment (DPIE) on the various impacts from climate change on the NSW and ACT Alpine region, hereafter referred to as the Alpine region. The full study region covers the Murray-Murrumbidgee region (MM), South East and Tablelands (SET) and the ACT, bordering the Victorian border in the south (Figure 1).

Within this study region, we analysed the Murray–Riverina cropping (MRC) region, which is located in southern New South Wales (Figure 2) and covers an area of 125,551 km^2 or 16% of the state, and around 35% of the NSW cropping area (Liu et al. 2014). There are 370 SILO (Scientific Information for Land Owners climate database) Patched Point Data (PPD) sites, which are relatively evenly distributed in the region (Figure 2). The region is characterised by a semi-arid climate with an average daily radiation of 18.0 megajoules per square metre, average annual minimum temperature of 9.3°C, maximum temperature of 22°C and annual rainfall of 495 millimetres over the entire region, with the 10th percentile of site rainfall being 312 millimetres and the 90th percentile being 677 millimetres.

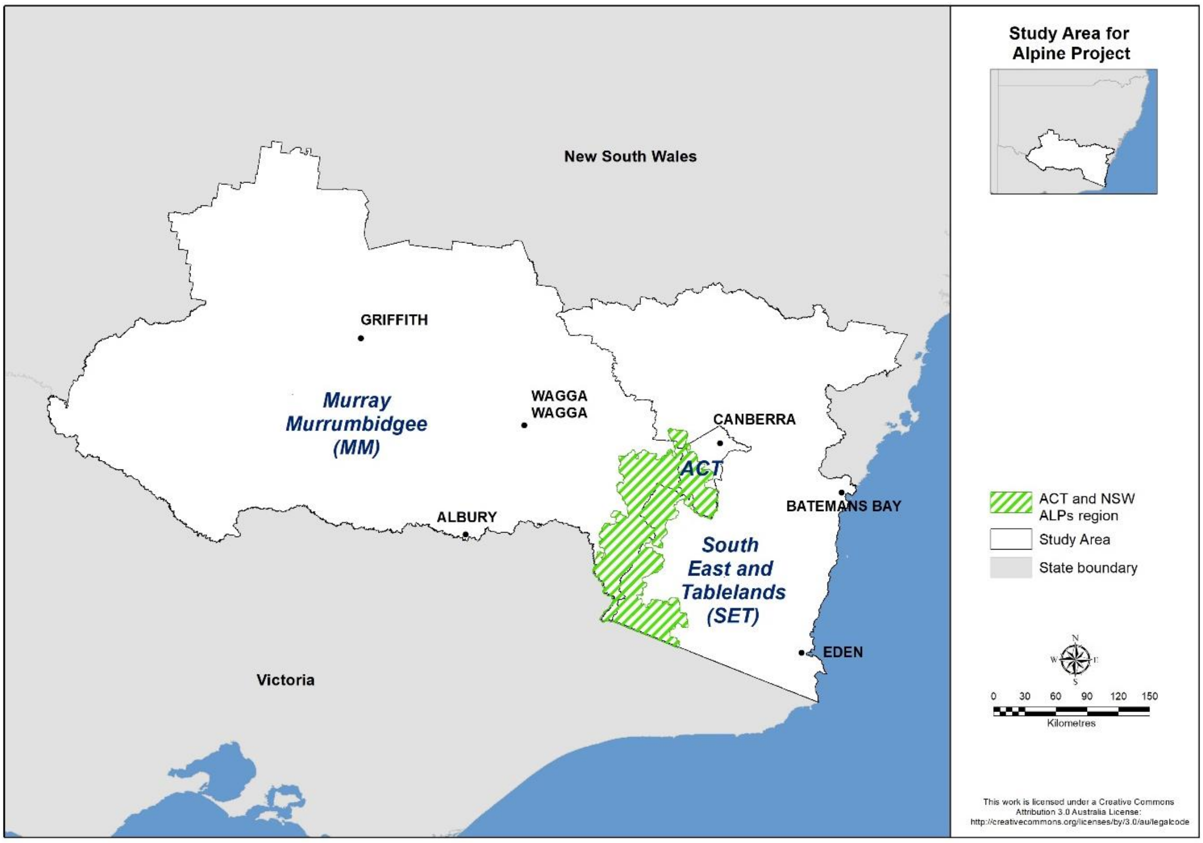

Figure 1 **The study area for the Alpine project, including the NSW and ACT Alpine region, Murray-Murrumbidgee region and South East and Tablelands**

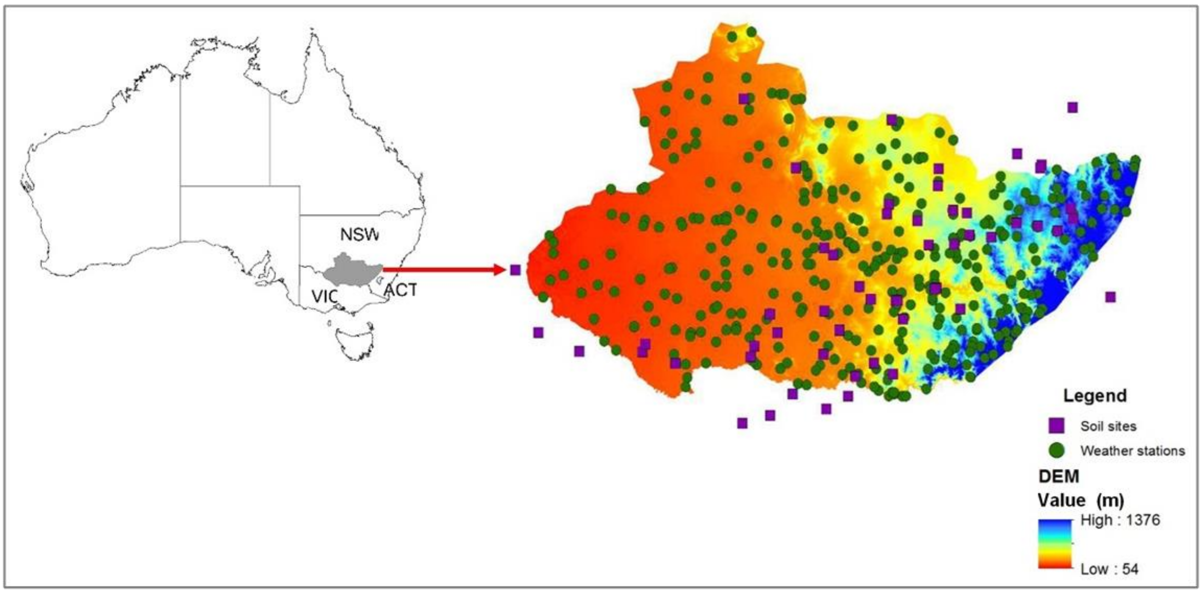

Figure 2 The Murray–Riverina cropping area and the distribution of weather stations (green dots) used in this study

The purple rectangles indicate soil sites used for the APSIM simulation, which also includes 13 soil sites outside the study area.

1.2 Objectives

Climate change has direct impacts on crop productivity, presenting challenges to food security worldwide (Ziska et al. 2012; Wheeler & Von Braun 2013; Tai et al. 2014; Lychuk et al. 2017). It has been estimated that climate change could decrease global wheat production by 37–52 and 54–103 megatonnes per year in the 2050s and 2090s, respectively (Balkovič et al. 2014). The Murray–Riverina region is an important NSW cropping region and it is anticipated that future climate change will impact significantly on the performance and profitability of farms. Understanding the regional impacts of climate change on crop yields is an essential step towards the development of key adaptive strategies to adapt to unavoidable climate change and mitigate the negative impacts on food security.

The downscaled 10 kilometre climate projections from the NARCliM project (Evans et al. 2014) have become available for the 1990 to 2009 baseline period, and the 2020 to 2039 and 2060 to 2079 periods. The improvement in simulation of wheat yields with increasing climate model resolution is largely due to an improvement in the simulation of growing season rainfall (Macadam et al. 2014), and a further study (Macadam et al. 2016) showed that downscaling to 10 kilometres, compared with 50 kilometres, was only beneficial when bias-corrected data were used. However, the bias-corrected NARCliM data has not been applied to the agricultural sector.

In this study, we used NARCliM simulations to drive a crop simulation model, the APSIM (Agricultural Production Systems SIMulator) model, to assess impacts of climate change on yields for four crops (wheat, barley, canola and lupin) and adaptation options related to nitrogen fertiliser application and stubble management. The objectives of the study were to:

- quantify the magnitude of climate change impacts on four crops
- assess whether adaptation options can mitigate the negative impacts of climate change.

Since this study is the first to generate crop yield projections from the NARCliM climate projections, meeting these objectives involved developing approaches to:

- assess the uncertainties in both NARCliM projections and the APSIM simulated outputs; these are critical for projection of wheat cropping modelling
- handle differences between the climate model output and the observed climate appropriately.

1.3 Outputs

Output	Details	Key users
Report	Crop suitability	Researchers
Maps	Maps of the annual and seasonal crop indices	Councils, NSW Rural Fire Service

2. Method

2.1 Source of data

Historical observed climate data

There are 370 climate observation sites with SILO PPD, which are relatively evenly distributed in the region (Figure 2). The site-specific observed climate variables (daily radiation, rainfall, minimum and maximum temperatures) for the 20-year 1990 to 2009 baseline period were downloaded from the SILO-patched point dataset. This period is chosen in order to compare the observational data with NARCliM baseline simulations.

NARCliM simulated climate data

NARCliM, simulations from four Coupled Model Intercomparison Project phase 3 (CMIP3) Global Climate Models (GCMs) were used to drive three Regional Climate Models (RCMs) to form a 12-member GCM/RCM ensemble (Evans et al. 2014). The four GCMs selected in NARCliM were CCCMA3.1, CSIRO-MK3.0, ECHAM5 and MIROC3.2, hereafter abbreviated to CC, CS, EC and MI, respectively. The GCM names are further followed by R1, R2 and R3, which denote the names of the three RCMs. For the future projections the Special Report on Emissions Scenarios (SRES) business-as-usual A2 scenario was used (IPCC 2000). The three selected RCMs are three physics scheme combinations of the Weather Research and Forecasting model (WRF). Each simulation consists of three 20-year runs for a baseline period (1990 to 2009) and near and far future periods (2020 to 2039 and 2060 to 2079). The four GCMs were chosen based on a number of criteria: i) adequate performance when simulating historic climate; ii) most independent; iii) cover the largest range of plausible future precipitation and temperature changes for Australia. The three RCMs correspond to three different physics scheme combinations of the WRF V3.3 model (Skamarock et al. 2008), which were also chosen for adequate skill and error independence, following a comprehensive analysis of 36 different combinations of physics parameterisations over eight significant East Coast Lows (ECLs) (Evans et al. 2012; Ji et al. 2014). For the selected three RCMs, the WRF Double Moment 5-class (WDM5) microphysics scheme and NOAH land surface scheme are used in all cases. Refer to Evans et al. (2014) for more details on each physics scheme.

We acknowledge that the results are model dependent (as all model studies are) but through the use of this carefully selected ensemble we have attempted to minimise this dependence. By using this model selection process, we have shown that it is possible to create relatively small ensembles that are able to reproduce the ensemble mean and variance from the large parent ensemble (i.e. the many GCMs) as well as minimise the overall error (Evans et al. 2013a).

Some initial evaluation of NARCliM simulations shows that they have strong skill in simulating the precipitation and temperature of Australia, with a small cold bias and overestimation of precipitation on the Great Dividing Range (Evans et al. 2013b; Ji et al. 2016). The differing responses of the different RCMs confirm the utility of considering model independence when choosing the RCMs. The RCM response to large-scale modes of variability also agrees well with observations (Fita et al. 2016). Through these evaluations we found that while there is a spread in model predictions, all models perform adequately with no single model performing the best for all variables and metrics. The use of the full ensemble provides a measure of robustness such that any result that is common through all models in the ensemble is considered to have higher confidence.

Soil data

There are 56 soil types registered in the APSoil database that are located in the region (Figure 2) and these were used to run APSIM. The most frequently occurring soil textures for the region were sandy clay and sandy loam above a clay layer, while the soil types range from sodosols (grey) to kandosols (red).

2.2 Simulation setup

Four winter crops, wheat (*Tritcum aestivum*), barley (*Hordeum vulgare*), canola (*Brassica napus*) and lupin (*Lupinus angustifolious*) were considered in the study.

We considered three levels of crop residue incorporation (0, 50% and 100%, denoted as RI0, RI50 and RI100, respectively). Crop residue incorporation is a farm management that incorporates harvested crop residue into soils by tillages. The procedure for executing crop RI were similar to those of Liu et al. (2014) and Liu et al. (2017). Under the APSIM Manager, we defined a variable to record the amount of crop residue at harvest time and calculated the appropriate amount of crop residue incorporated into the top 100 millimetres of soil for each treatment. Crop residue incorporation was executed two weeks after harvesting by disc tillage. The actual amount of crop residue incorporated by a single tillage depends on the amount of crop residue harvested. In this study, we implemented one additional tillage for RI50 and two additional tillages for RI100 to reflect actual residue incorporation.

The second option for farm management in the simulation was nitrogen fertiliser application; N-application hereafter. There were 12 levels of N-application, denoted as N1, N2, …, N12. The base N-application levels for wheat, barley, canola and lupin are 55, 65, 80 and 50 kilograms per hectare, respectively, which is denoted as N_{BS}. The amount of N applied for each treatment was calculated as

$$N_I = N_{BS}\left[1+\left(I-3\right)\times 0.4\right]. \qquad I=1, 2, 3, \ldots, 12 \qquad (1)$$

which gives the change N-rate of –80%, –40%, 0%, +40%, +80%, +120%, +160%, +200%, +240%, +280% and +320% over the base N-application. With the combination of all treatments (3 RI x 12 N-application = 36 treatments), future climate datasets (12 NARCliM x 3 time periods = 36 datasets), four crops and 370 sites, together with SILO baseline simulations, we have a total of 1,971,360 20-year simulations.

The APSIM has been widely validated for cropping system simulations under different environments worldwide, including this study region (Keating et al. 2003; Liu et al. 2016; O'Leary et al. 2016; Turpin et al. 2003). The APSIM version 7.7 (Holzworth et al. 2014) was used to evaluate the impact of climate change, crop RI and N-applications on the four broadacre crops for the MRC region in this study. The key APSIM modules that were used to represent the crops (wheat, barley, canola and lupin), were soil moisture (SoilWat/SWIM3), soil nitrogen (SoilN), surface organic matter (SurfaceOM) and crop management actions (Manager). Detailed descriptions of SWIM3, SurfaceOM and SoilN are also available elsewhere (Probert et al. 1998; Huth et al. 2014; Liu et al. 2014; Dietzel et al. 2015).

As large spatial variation in soil and climate including temperature, radiation and rainfall occurred across the MRC region, we developed a suitable sowing rule. To set a sowing rule that suited all soils and rainfall zones across the region, we considered the sowing as a function of soil water content, plant available water capacity (PAWC), recent rainfall and day of year. The relationship between the recent cumulative four-day rainfall and soil water content is illustrated in Figure 3, using different sowing days of year and PAWC. To assess the application of nitrogen across the region and climate effect on the cropping system without carrying over the cumulative effects, we reset the soil water and nitrogen to their respective initial levels on 1 February of each year. Without resetting, the residual N applied from previous years can affect crop growth for the current year and interact with climate and farming management.

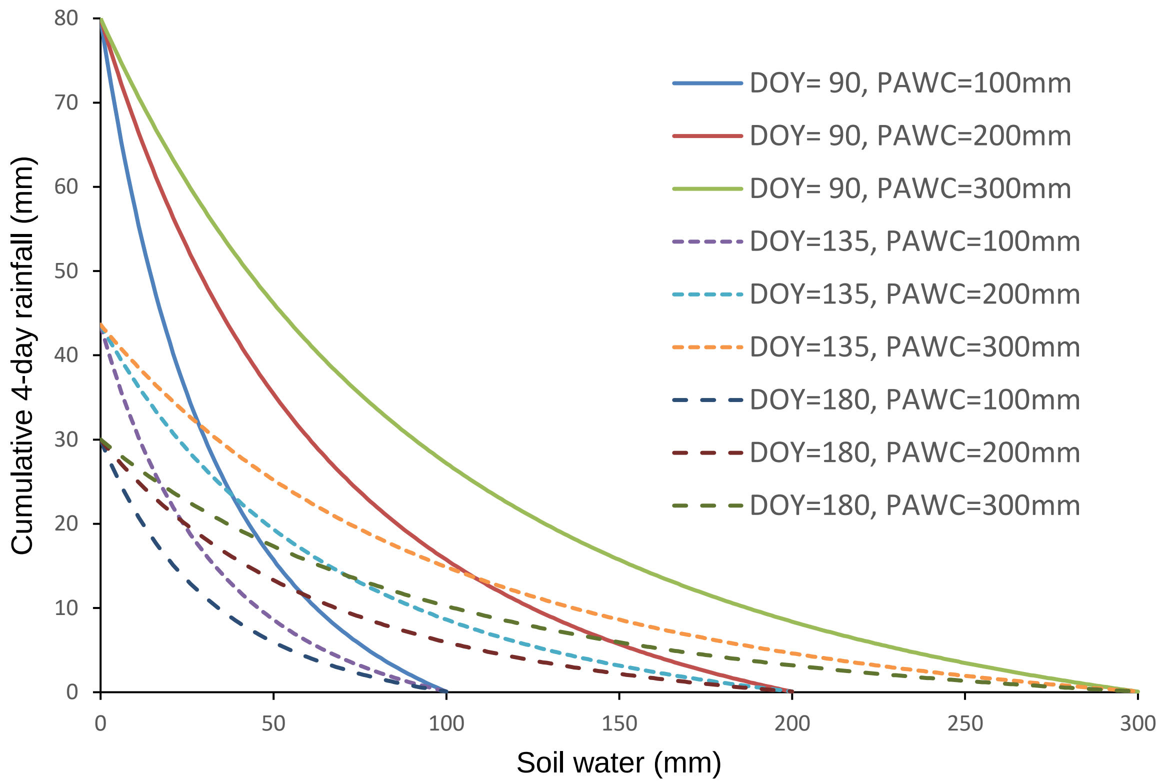

Figure 3 The relationship between the amount of cumulative four-day rainfall (mm) required for meeting the soil criteria and the soil water content at different days of year (DOY)

Sowing and soil types are characterised by plant available water capacity (PAWC).

Here, we used an innovative approach to determine sowing dates based on soil water content and cumulative rainfall. This approach allows crops to be sown in dry soils when there is a large amount of precipitation or sown in wet soils requiring no rainfall or a small amount of recent rainfall. In this way, the sowing rule suits a wide range of conditions for the study area.

2.3 Bias and secondary bias correction

We defined the biases in NARCliM climate variables as the differences between the RCM-simulated values (X_M) and their respective observed values (X_O). Similarly, the biases in APSIM outputs are the differences between the APSIM simulated outputs forced (i.e. applied) by RCMs (X_M) and those forced by observed climate (X_O). We defined mean bias error (MBE) as the differences in the mean over the 20-year period either in absolute terms (i.e. temperature in °C, runoff in mm) or in relative terms (i.e. rainfall, %) using the formula

$$MBE = \overline{X}_M - \overline{X}_O \text{ or } MBE(\%) = 100 \times \frac{\overline{X}_M - \overline{X}_O}{\overline{X}_O} \quad (2)$$

where $\overline{X}_M$ is the 20-year mean of NARCliM climate variables or the APSIM outputs forced by NARCliM climate, and $\overline{X}_O$ is the observed climate or the APSIM outputs forced by observations.

The bias correction applied in NARCliM resulted in more realistic daily temperature and rainfall than non bias-corrected outputs in many ways; however, no bias correction can fully eliminate all biases in climate model outputs (Piani et al. 2010). Due to this and the lack of bias-corrected solar radiation data available for the NARCliM simulations, we assessed both the remaining biases in the climate data and biases in APSIM outputs. We also removed the biases in APSIM simulated outputs, such as crop yield, by a 'secondary bias correction' (SBC) (Yang et al. 2016). We used the method proposed by Haerter et al. (2011) that can correct both the mean bias and biases in year-to-year variation as

$$X = \overline{X}_{O,bl} + \frac{S_{O,bl}}{S_{M,bl}}\left(X_M - \overline{X}_{M,bl}\right) \tag{3}$$

where the subscript *bl* denotes the baseline and *S* is the standard deviation. The data before SBC are hereafter denoted as NonSBC and after SBC as SBCMnSD.

2.4 Quality control

Input NARCliM data have passed a series of quality assurance/quality control checks. The APSIM model and methods used in this study have been widely used in other climate change impact studies. The SILO data and APSIM soil database are well-established.

This report has been reviewed by internal and external reviewers and followed the procedures set out in DPIE's Scientific Rigour Position Statement (OEH 2013). Two scientific papers have been published in academic journals: 'Propagation of biases in regional climate model simulations to biophysical modelling can complicate assessments of climate change impact in agricultural systems' has been published in the *International Journal of Climatology* (Liu et al. 2019) and 'Modelling and evaluating the impacts of climate change on three major crops in south-eastern Australia using regional climate model simulations' has been published in *Theoretical and Applied Climatology* (Wang et al. 2019).

Meetings were organised with external experts to evaluate the methodology and review the results of this study. The first meeting was held on 14 August 2017 at the University of New South Wales (UNSW) to elicit expert feedback on methodology and initial results. Project leader (Dr De Li Liu) introduced the method and presented the initial results to Professor Jason Evans (UNSW), Dr Nicholas Herold (UNSW), Dr Kathleen Beyer (NSW DPIE), Dr Fei Ji (NSW DPIE) and Dr Ian Macadam (NSW DPIE), who represent a broad range of expertise in regional climate modelling and its usage in assessing climate change impacts.

The second meeting was held on 12 December 2017 at UNSW to elicit further expert feedback on results. Project leader (Dr De Li Liu) presented the results of the analysis to Professor Jason Evans (UNSW), Anthony Coward (NSW DPIE), Dr Kathleen Beyer (NSW DPIE), Dr Cathy Waters (NSW DPI), Dr Fei Ji (NSW DPIE) and Dr Ian Macadam (NSW DPIE), who represent a broad range of expertise in regional climate modelling and climate change impacts.

2.5 Data storage and access

All output data were converted to raster format (ArcGIS ESRI grid) and supplied to the MCAS-S (Multi-Criteria Analysis Shell for Spatial Decision Support) datapacks for distribution and storage. All input data to the model and by-products are stored on hard disk drives. All data are in the NARCliM coordinate system. The extent of the datasets includes the MM region, ACT and SET with the boundary at top: –32.671254, left: 143.317445, right: 150.745676, and bottom: –37.505077.

3. Results

The observed and NARCliM simulated climate variables for the crop-growing season (from sowing to harvesting) are analysed for the baseline period (1990 to 2009), and a near future and far future period (2020 to 2039 and 2060 to 2079 respectively). The climate variables include radiation, rainfall, maximum and minimum temperature, which are required as input to APSIM. The biases for NARCliM simulated climate variables are expressed as mean bias errors (MBE) shown in box plots. Here, the biases were calculated for three stages of crop growth: pre-sowing (PS) from 1 February to sowing; sowing to flowering (STF); flowering to harvesting (FTH), as well as for the whole year. The PS is included in this analysis as our sowing rule is based on soil water at the sowing time.

To simplify the presentations, four treatments that include two contrasting residue incorporations (0% and 100%) and two N-applications (55 kg ha^{-1} and 165 kg ha^{-1}) were selected to illustrate the biases in soil water balance, crop phenology and crop yield. As biases were similar for each crop, we report bias results for a wheat cropping system only.

With the substantial biases in NARCliM simulated variables and the subsequent biases in APSIM outputs, biases in crop yield were removed prior to the impact assessment. This was followed by secondary bias correction and impact assessments for the four crops.

3.1 NARCliM simulated climate for cropping growing season for the baseline period

NARCliM simulated climate variables (radiation, rainfall, maximum temperature and minimum temperature) for the cropping growing season (CGS) were extracted and 20-year mean values for the baseline period were also calculated, which were compared with observations (SILO) for the same time period.

The spatial distributions of simulated radiation for the 12 NARCliM ensemble members and SILO are shown in Figure 4. All simulations overestimated radiation for CGS when compared with SILO, especially for the four R3 simulations. Over the region, the averaged difference between both R1 and R2 simulations and SILO observations ranged from +1.3 to +2.1 megajoules per square metre per day, and the difference between R3 simulations and observations ranged from +2.7 to +3.9 megajoules per square metre per day. However, the spatial distributions of observed SILO radiation were captured well by R1 and R2 simulations, i.e. higher values in the western region and lower values in the eastern region.

The patterns of bias-corrected RCM simulated CGS rainfall matched well with observations for all simulations (Figure 5); however, the three CC-driven simulations slightly overestimated observed rainfall, while other simulations produced much smaller amounts of CGS rainfall across the region.

The patterns of observed maximum and minimum temperatures for CGS are also well captured by all simulations (Figure 6 and Figure 7). The CC-forced and CS-forced simulations only overestimated maximum temperature by between 0.1 and 0.3°C, while the EC-forced and MI-forced simulations overestimated maximum temperature from 0.3 to 0.6°C. In contrast, most simulations underestimated minimum temperature for CGS except for the MI-R3 simulation, which slightly overestimated minimum temperature by about 0.1°C. The magnitude of overall overestimations in maximum temperature was approximately the same as overall underestimations in minimum temperature (Figure 6 and Figure 7).

The biases in climate variables are expected to affect the simulated results of crop models. In a semi-arid environment such as the Murray–Riverina cropping region, rainfall biases can significantly affect crop growth and crop yield.

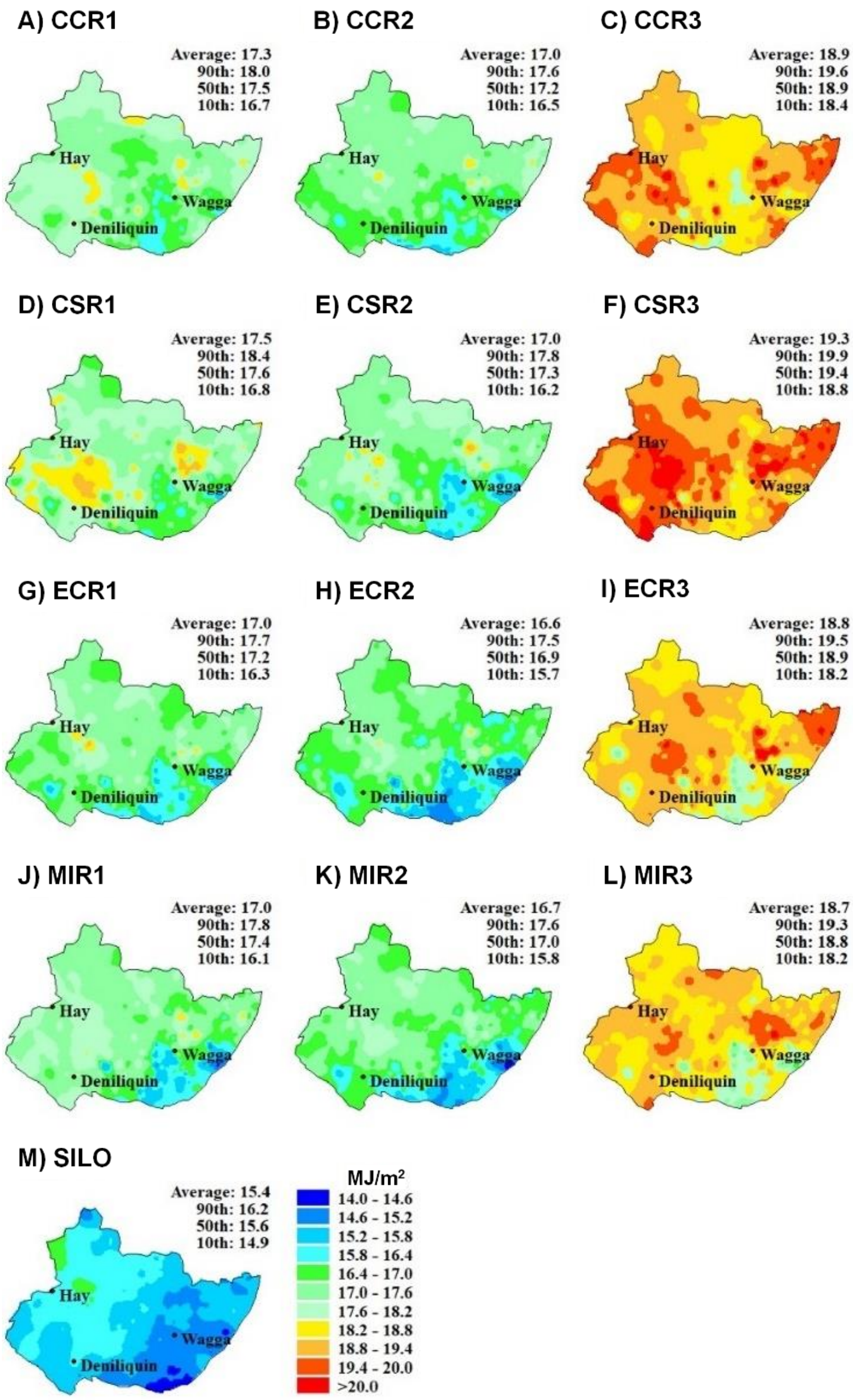

Figure 4 **Comparison of the 12 NARCliM RCMs simulated mean daily CGS radiation (MJ/m^2) (A–L), with SILO data (M), across the Murray–Riverina cropping region, for the 1990 to 2009 baseline period**

Here and in the following three figures, the four GCMs: CCCMA3.1, CSIRO-Mk3.0, ECHAM5 and MIROC3.2, are abbreviated to CC, CS, EC and MI, respectively, followed by R1, R2 and R3, which denote the RCMs.

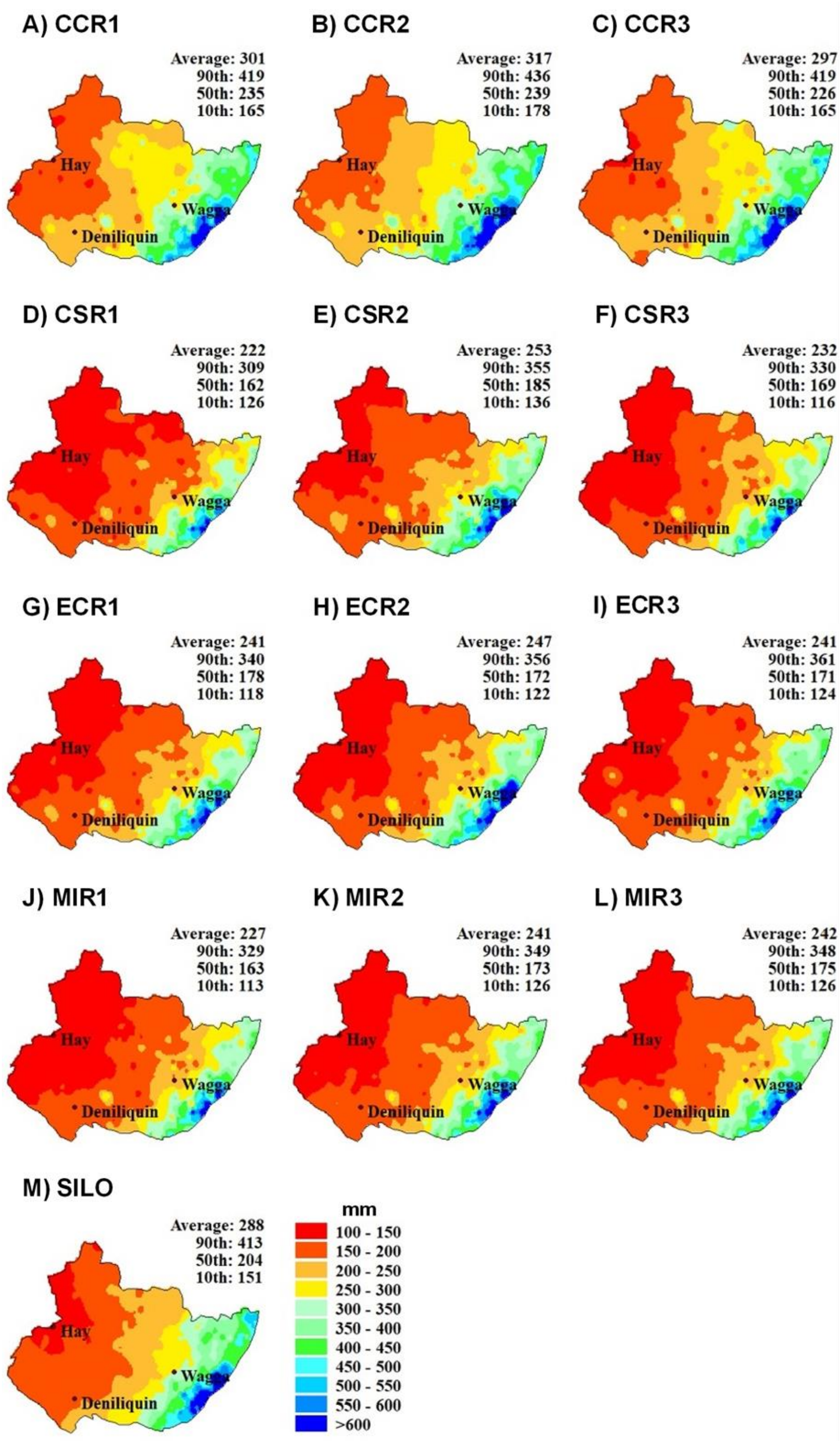

Figure 5 **Comparison of the 12 NARCliM RCMs simulated total CGS rainfall (mm) (A–L), with SILO data (M), across the Murray–Riverina cropping region, for the 1990 to 2009 baseline period**

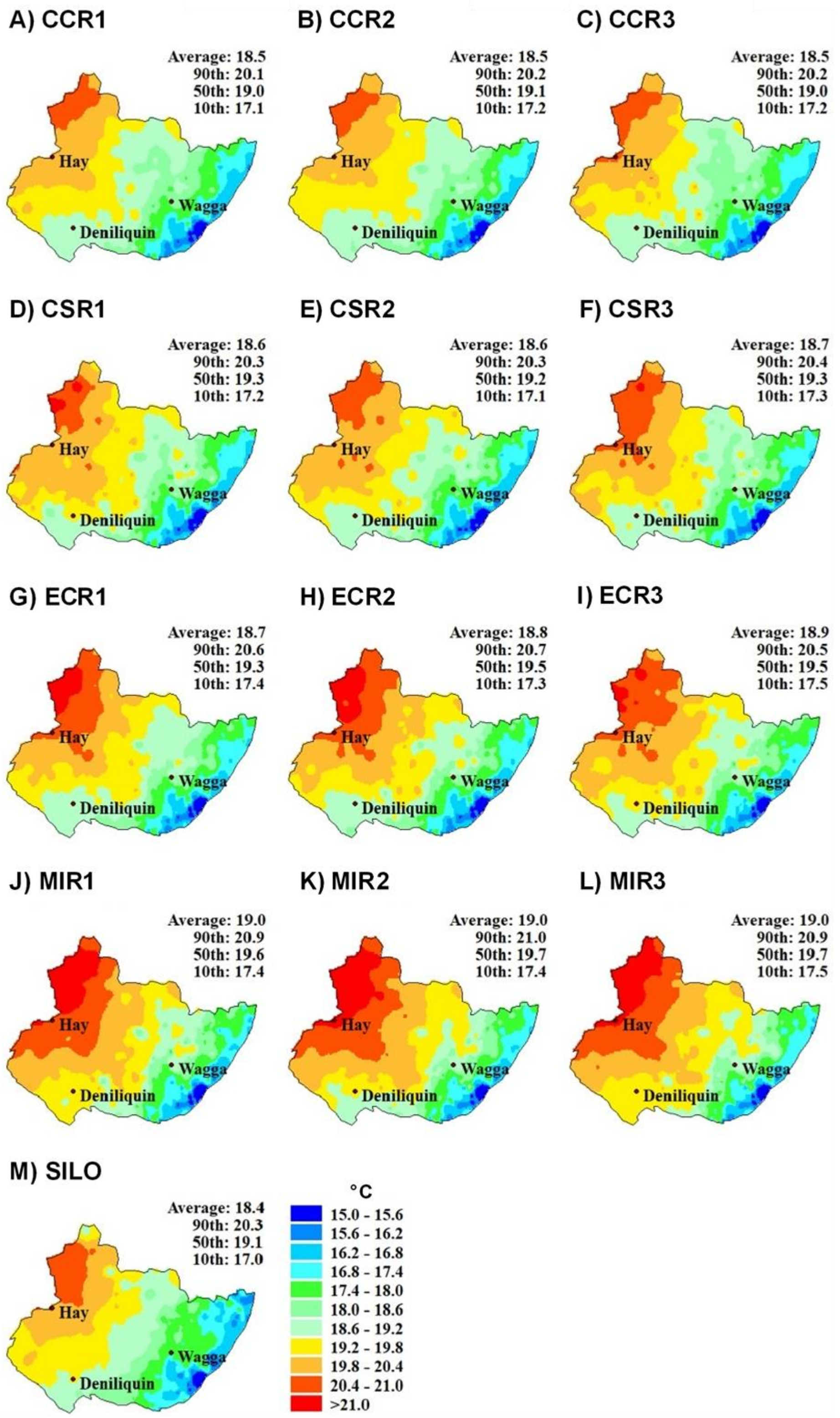

Figure 6 **Comparison of the 12 NARCliM RCMs simulated mean CGS maximum temperature (°C) (A–L), with SILO data (M), across the Murray–Riverina cropping region, for the 1990 to 2009 baseline period**

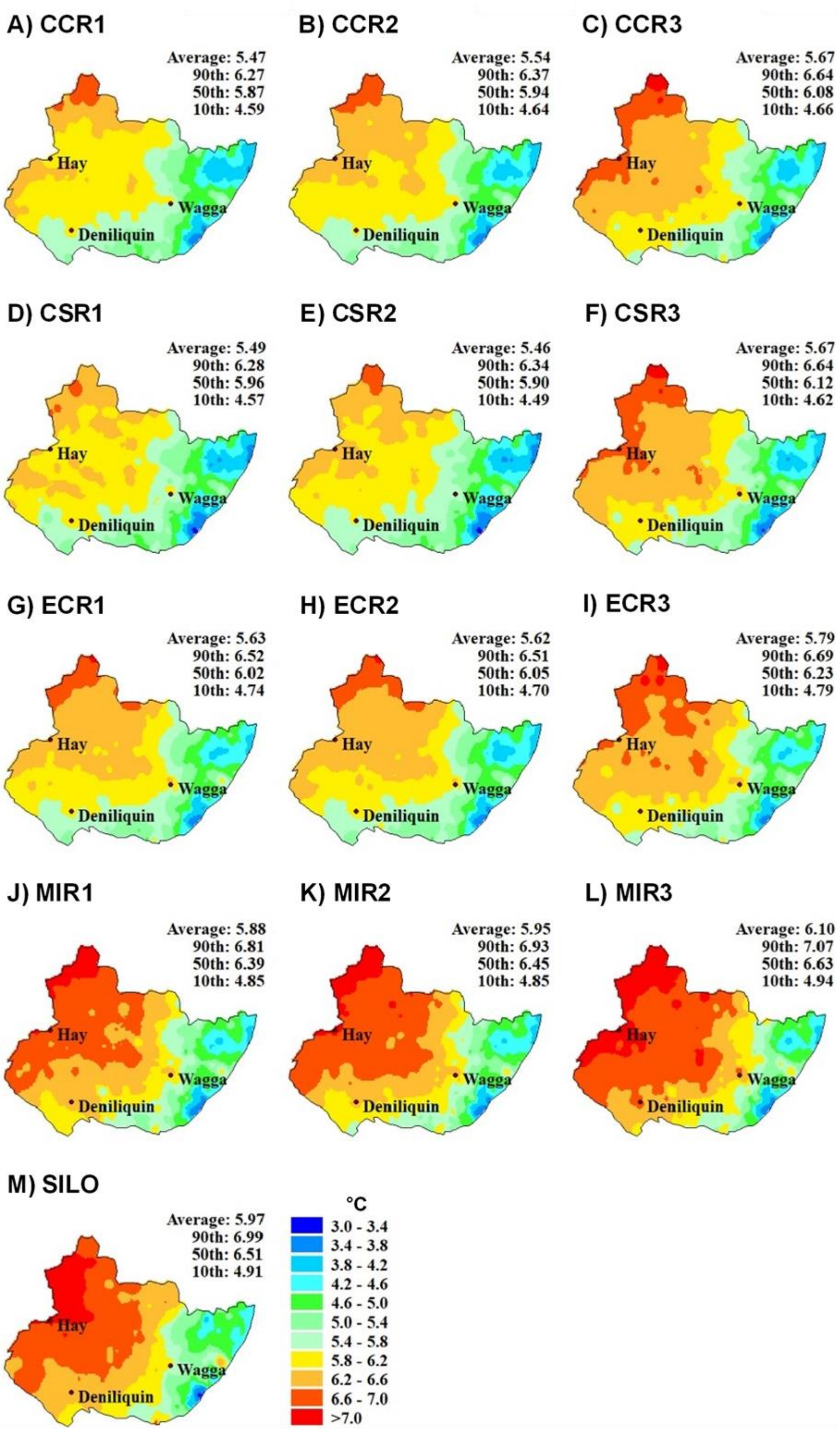

Figure 7 Comparison of the 12 NARCliM RCMs simulated mean CGS minimum temperature (°C) (A–L), with SILO data (M), across the Murray–Riverina cropping region, for the 1990 to 2009 baseline period

3.2 Future climate projections

We used box plots to summarise the changes across the 12 RCM combinations. Figure 8 shows the distribution of changes in mean radiation, maximum, minimum and mean temperature, and rainfall, for the growing season and non-growing season for each simulation over 370 sites in 2020 to 2039 and 2060 to 2079. Changes are relative to the 1990 to 2009 baseline period. In the text, 1990 to 2009, 2020 to 2039 and 2060 to 2079 are abbreviated to 2000s, 2030s and 2070s respectively. Changes in intra-seasonal variance (intra-SD) for the climate variables are also calculated.

Small changes in seasonal radiation are projected for the near and far future periods for each simulation (Figure 8A); for example, the ensemble means for projected change in growing season radiation were –0.13% in the 2030s and +0.22% in the 2070s relative to the 2000s over the region. Similarly, non-growing season radiation was projected to decrease (–0.53%) in 2020 to 2039 and –0.51% in 2060 to 2079 (Figure 8A)

For the two future time periods, a strong seasonal warming trend was observed for all RCM simulations (Figure 8B); in particular, maximum temperature for the growing season was projected to moderately increase (+0.5°C and +1.7°C) across all 12 simulations in 2020 to 2039 and 2060 to 2079, respectively. Increases in maximum temperature for the non-growing season are projected to increase +0.7°C and +2.2°C for 2030s and 2070s, respectively (Figure 8B). A similar warming trend was found in minimum temperature with a larger increase from December to March (Figure 8C).

Overall, the changes in mean temperature were similar to those for the minimum and maximum temperature (Figure 8D). Decreasing growing season rainfall was observed for some of the 12 simulations (e.g. CS-R1, CS-R2, and CS-R3) (Figure 8E) and, on average across all simulations, growing seasonal rainfall was projected to decrease (–3.8% and –2.4% for 2020 to 2039 and 2060 to 2079 respectively). It may be worthwhile to note that the increased rainfall occurred in the non-growing season (+5.8% and +13% for 2030s and 2070s, respectively). While this may have no immediate benefit to crop yields, this rainfall may provide useful levels of soil moisture to aid crop establishment.

The variance of future growing season radiation changed little, relative to the 1990 to 2009 baseline period (Figure 8F); however, the change in the variance of non-growing season radiation varied greatly among RCMs for both future time periods. Almost all RCMs projected increased intra-seasonal variances of temperature (Figure 8G, H and I). In contrast, there was a large difference in change of intra-seasonal rainfall variability for the RCMs (Figure 8J).

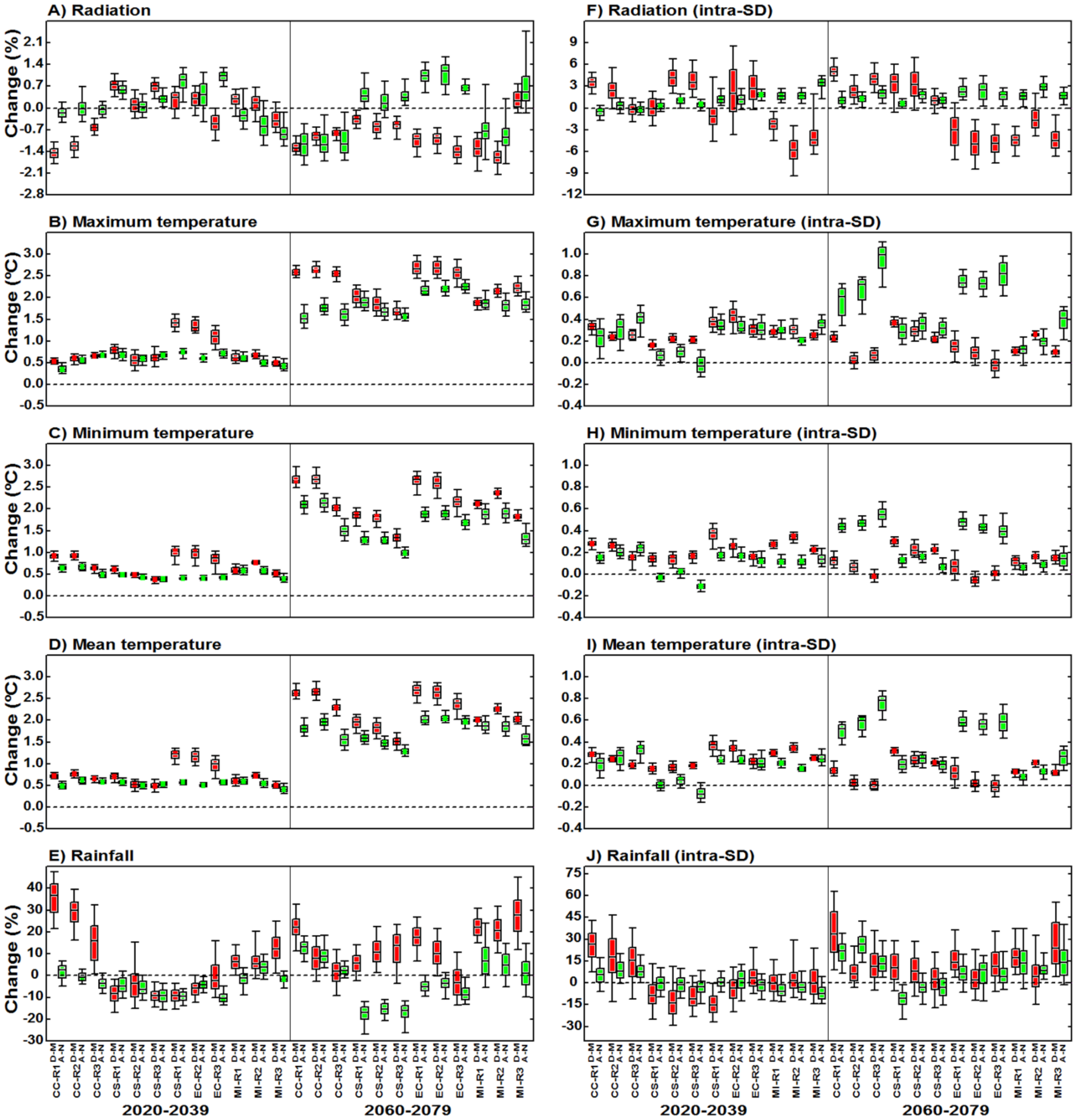

Figure 8 **Projected changes in mean radiation (%), maximum, minimum and mean temperature (°C), and rainfall (%) in the growing season (green = April through November (A–N)) and non-growing season (red = December through March (D–M)) (A–E), and intra-seasonal standard deviations (intra-SD) of same (F–J)**

Box plots show the distribution of mean changes and intra-SD in the period 2020 to 2039 and 2060 to 2079 relative to 1990 to 2009 for each of the 12 RCMs across the MRC region. Box plots show the 10, 25, 50, 75, and 90 percentiles, calculated from the 370 sites.

3.3 Biases for NARCliM simulated climate variables

Biases in climate variables for each of the 12 RCM simulations were calculated by comparing NARCliM simulated climate with SILO observed climate for the 1990 to 2009 baseline period. Figure 9 shows the mean bias error (MBE) for the climate variables (radiation, minimum, maximum and mean temperature, rainfall) and their intra-SD, as well as rainfall probability and rain intensity. As intra-SD measures the variability of daily sequences, a negative or positive intra-SD bias means the daily sequence of RCMs exhibits a larger or smaller daily variation than observed daily sequences, respectively.

It is important to quantify intra-SD because crop development and growth are sensitive to range of diurnal temperature variation, which is quantified by daily minimum and maximum temperature, and also because rainfall distribution in the season can greatly affect crop growth. As a crop has different sensitivities to bias in different crop stages, we calculated the bias for annual and three cropping periods: pre-sowing (PS) from 1 February to sowing, sowing to flowering (STF), and flowering to harvesting (FTH).

Small annual biases in both magnitude and the variations over the 370 sites were found across all RCMs for all variables, except for both mean and intra-SD of radiation (Figure 9A&B). This largely reflects large biases in radiation that are due to no observed radiation for bias correction of simulated radiation. In addition, the annual biases in intra-SD of rainfall and rain intensity were also quite large, with significantly lower values when compared to observations for all RCMs (Figure 9K and 9L).

In the three cropping periods (PS, STF and FTH), almost all RCM simulations overestimated radiation (Figure 9A). Radiation MBE exhibited an increased trend of MBEs from PS to FTH. Biases for R3 simulations were larger than those for R1 and R2 simulations; however, the intra-SD of bias in radiation for the STF period had negative MBEs, largely positive (Figure 9G) before flowering (PS & STF), indicating that the daily sequences of the NARCliM simulated radiation didn’t match the SILO-radiations. It is worth noting that NARCliM simulated radiation was not bias-corrected, but a large proportion of radiation in SILO was calculated (i.e. not actual observed).

Unlike the consistent biases in radiation, the temperature MBE varied considerably between RCMs and growing periods (Figure 9B–D). The most distinct feature was that the bias had a reciprocal low–high pattern between periods, i.e. one higher companied with another lower, suggesting some different biases in different seasons. For example, downscaling of some GCMs (CC-, CS- and EC) produced higher minimum temperature (T_{min}) in the PS period, but lower in another two phenological stages (STF and FTH) (Figure 9C).

In comparison between climate variables, RCMs gave a higher maximum temperature (T_{max}) in one period and often showed a lower T_{min} for the same period. For example, CC-R1 had a median MBE of +0.7°C for T_{max} in the period of FTH (Figure 9B), but –0.5°C for T_{min} in that period (Figure 9C). However, the magnitude of MBEs was not the same for T_{min} and T_{max}; the MBEs for daily mean temperature (T_{mean}) were still large and maintained a similar pattern to T_{max} or T_{min}. Generally, more negative T_{mean} MBEs for the STF period were found for CC-, CS- and EC-forced RCMs, but more positive T_{mean} MBEs were found for MI-forced RCMs for this important phenological period (Figure 9D). This may lead to biases in the phenological development as temperature is a primary factor controlling crop phenology. The intra-SD MBEs for temperatures varied considerably, suggesting a mismatched distribution of NARCliM simulated daily temperature sequences with observations (Figure 9H–J).

The rainfall simulated by the CC-forced RCMs had lower bias than other RCM simulations, showing a narrow MBE interquartile from –10% to +30% (Figure 9E). A second group of RCM simulations forced by the CS and EC GCMs, produced significantly higher rainfall than observed in the PS period, but lower rainfall for the crop growing periods (STF and FTH), exhibiting a wide MBE interquartile from –40% to +50% across RCMs. The third group of simulations forced by the MI GCM gave over 90% of sites with positive MBEs in the PS period and negative MBEs in the STF period. Generally, a similar seasonal bias pattern, i.e. a positive MBE in one period companied with a negative in another period, was found in rainfall bias, suggesting imperfect matching between seasonal bias-corrected NARCliM rainfall and observation. The intra-SD MBE for rainfall in the growing season was mostly negative, suggesting smaller variations in daily rainfall than observations (Figure 9K).

In the semi-arid environment of our study area, rainfall characters such as the frequency of rainfall events and rain intensity are important because they can alter rainfall water partitioning in soil water balance and availability of moisture for crop growth. Thus, in addition to analysis of rainfall MBE, we further explored the rain-event characters. Figure 9F and 9L exhibit an obvious contrasting pattern between rainfall probability and rainfall intensity, demonstrating that RCMs tended to produce a higher rainfall probability (Figure 9F) and lower rainfall intensity than observations (Figure 9L). This indicates that all RCMs simulated more frequent but less intensive rainfall when compared with SILO data.

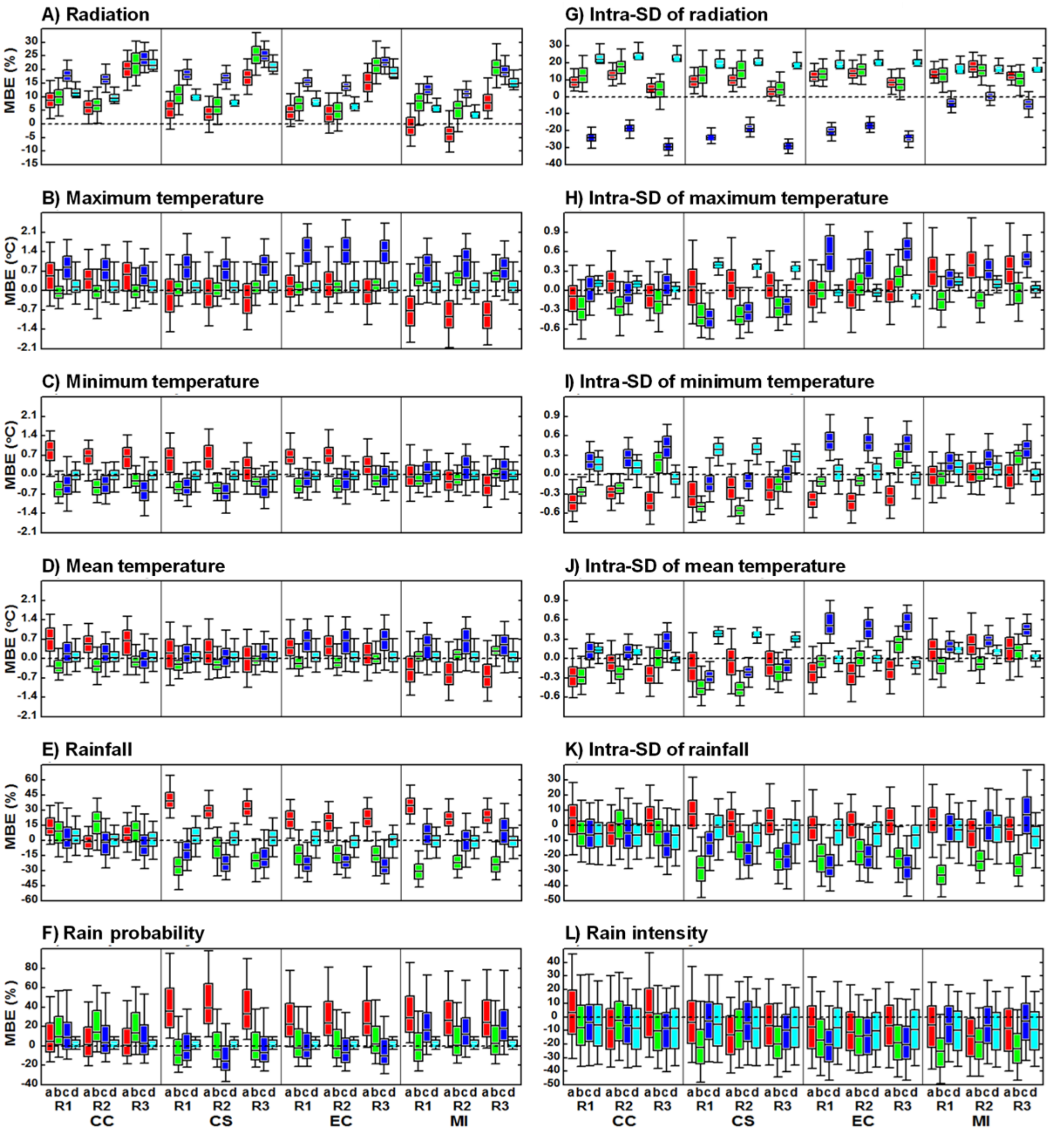

Figure 9 **Mean bias error (MBE) in NARCliM simulated climate variables radiation (%), maximum, minimum & mean temperature (°C), and rainfall (%) (A–E), and their intra-SD (G–K), along with MBEs in rain probability (%) (F) and rain intensity (%) (L), for PS (red, a), STF (light green, b), FTH (dark blue, c) and annual (cyan, d)**

Box plots show the 10, 25, 50, 75 and 90 percentiles, calculated from the 370 sites.

Biases for APSIM simulations forced by NARCliM data

It is important to understand the consequences of RCM biases for the APSIM outputs. Here we do not assess the uncertainty of APSIM simulations, but we use the same settings of APSIM for observed climate and RCM simulated climate. The underlying hypothesis is that if the climate variables simulated by RCMs were realistic and perfectly matched the observed climate, the outputs of a biophysical model forced by the observed and RCMs projected climate should be identical. The differences in APSIM outputs between RCM simulated climate and observed climate is considered as the biases that are derived from the differences between the two climates. We compared the biases in a wide range of APSIM outputs through the difference between the outputs forced by RCMs simulated climate and observed climate (SILO).

Biases in APSIM simulated soil water balance, crop phenology and production are shown in Figure 10. Most RCMs resulted in a positive MBE in soil water at sowing (SWS) at most sites, due to their produced higher pre-sowing rainfall; however, biases in runoff (RO) (Figure 10B) and deep drainage (DD) (Figure 10C) were negative at the majority of sites. Similarly, biases in soil water evaporation (ES) were positive at all sites. In addition, across around 75% of sites, plant transpiration (EP) biases were higher when APSIM simulation were forced by the CC-forced RCMs and lower than observations for the remaining nine RCM simulations (Figure 10E). These results were highly correlated with the biases in the rainfall simulations; for example, the CC-forced RCMs that produced positive EP are the RCMs that had positive rainfall biases, while the other three GCM-forced RCMs resulted in negative EP MBE largely due to their negative rainfall biases. Moreover, because plant N uptake follows water uptake, the biases in APSIM simulated N uses (NU) exhibited a similar pattern to EP biases (Figure 10F).

Importantly, there is a clear interaction between biases in APSIM outputs and farming management practice; for example, the crop residue incorporation (RI) considerably reduced the range of the SWS bias (Figure 10A), deep drainage bias (Figure 10C) and plant transpiration bias (Figure 10E) at RI0 but increased the magnitude of the negative RO MBE in RI100 (Figure 10B). Similarly, a larger bias in EP and NU were simulated at a higher N-application than lower N-application (Figure 10E & 10F). The study reveals that farm management practice may interact with the climate biases and consequently interact with biophysical modelled outputs such as biomass and crop yields.

For MI-RCMs, approximately 75% of sites had a sowing date (SD) later than that resulting from observed climate, while other GCM-based RCMs exhibited more negative SD biases (Figure 10G). The numbers of days from sowing to flowering (DTF) and crop duration (CD) simulated by APSIM forced by CC-, CS- and EC-RCMs were longer (positive MBE) at most sites but those forced by MI-based RCMs were shorter (negative MBE), relative to that forced by observed climate (Figure 10H & 10J). It is not surprising that the differences in crop phenological biases were consistent with the biases in NARCliM simulated temperature, i.e. the MI-RCMs that produced a faster development (negative positive DTF and CD MBE) in crop development are the RCMs that had positive T_{mean} biases in this phenological period (Figure 9D).

Similarly, the three CC-RCMs showed positive biomass bias in more than 75% of sites, largely resulting from the positive rainfall MBEs; however, the positive biomass biases forced by CC-RCMs are not large for wheat yield, due to the difference in the rainfall biases from the positive rainfall biases in the STF period to the negative rainfall biases in the FTH period produced by these RCMs (Figure 9E). Simplistically, the crop used CO_2 and water to form photosynthetic product (biomass). The nine RCM (CS, EC & MI) forced simulations exhibited negative biases in both wheat biomass and wheat yield in most sites, corresponding to the pattern of the biases in rainfall and ultimately plant transpiration (Figure 10).

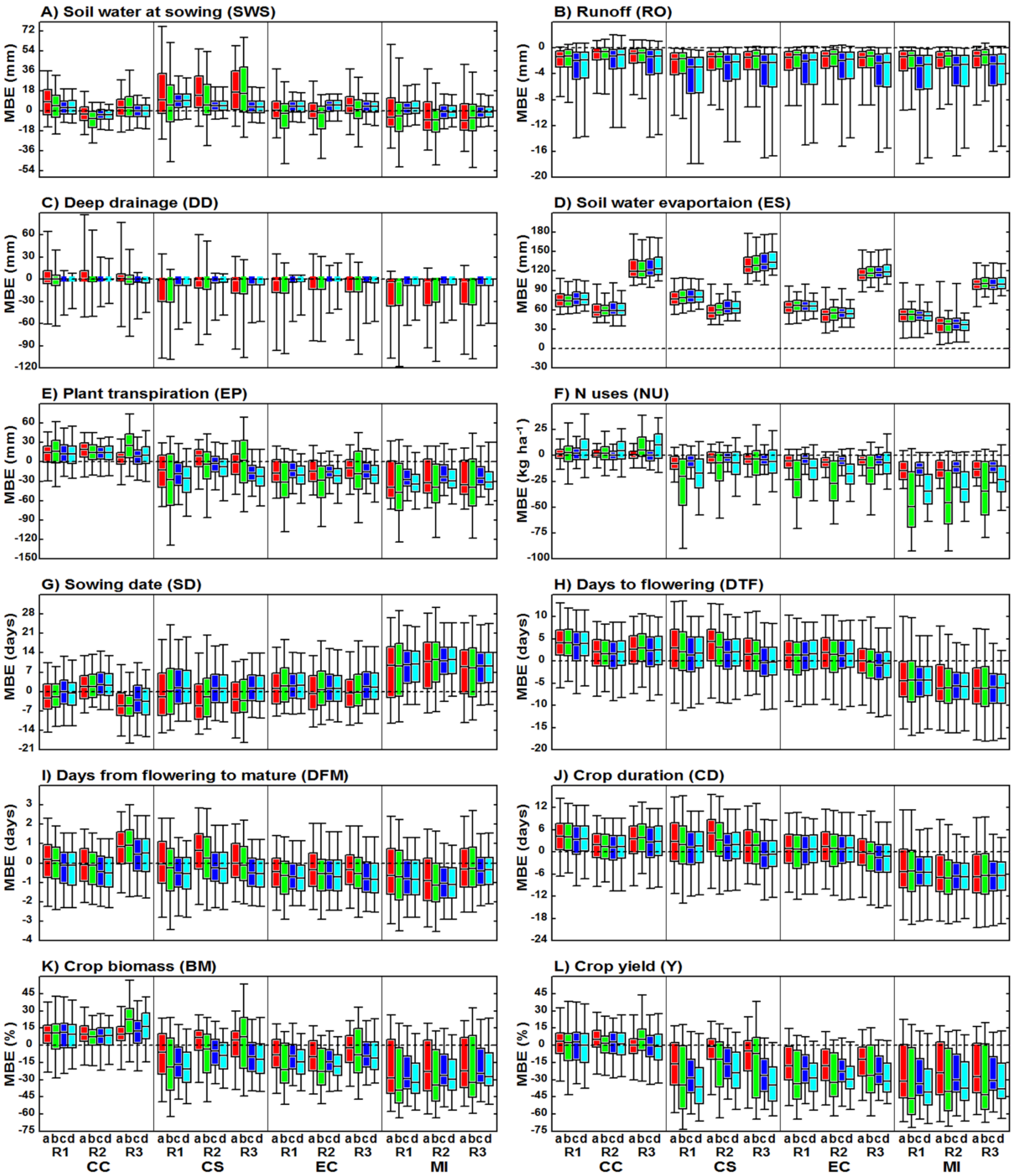

Figure 10 **Biases in APSIM simulated soil variables (A–E), N-uses (F) and plant variables (G–L) under the four management treatments (a, red: 0% residue incorporation (RI) by 50 kgN ha^{-1}; b, green: 0% of RI by 165 kgN ha^{-1}; c, blue: 1000% of RI by 50 kgN ha^{-1}; d, cyan: 100% of RI by 165 kgN ha^{-1})**

Box plots show the 10, 25, 50, 75 and 90 percentiles, calculated from the 370 sites.

Secondary bias correction

We used a simple secondary bias correction (SBC) method to correct the biases in RCM-driven crop yields (Yang et al. 2014). The distributions of rainfed crop yield for the 1990 to 2009 baseline period are shown in Figure 11. For all cases, using NonSBC outputs produced a high skewness of yield distributions relative to those forced by SILO observations when simulated wheat yield was lower than approximately 2200 kilograms per hectare; however, when projected yields were more than 3000 kilograms per hectare, a low skewness of yield distribution was shown (Figure 11a&b). Similar results were found for canola and lupin crops (Figure 11c–f). Applying the simple SBC resulted in yield distributions largely consistent with those forced by historical observations (Figure 11b,d&f).

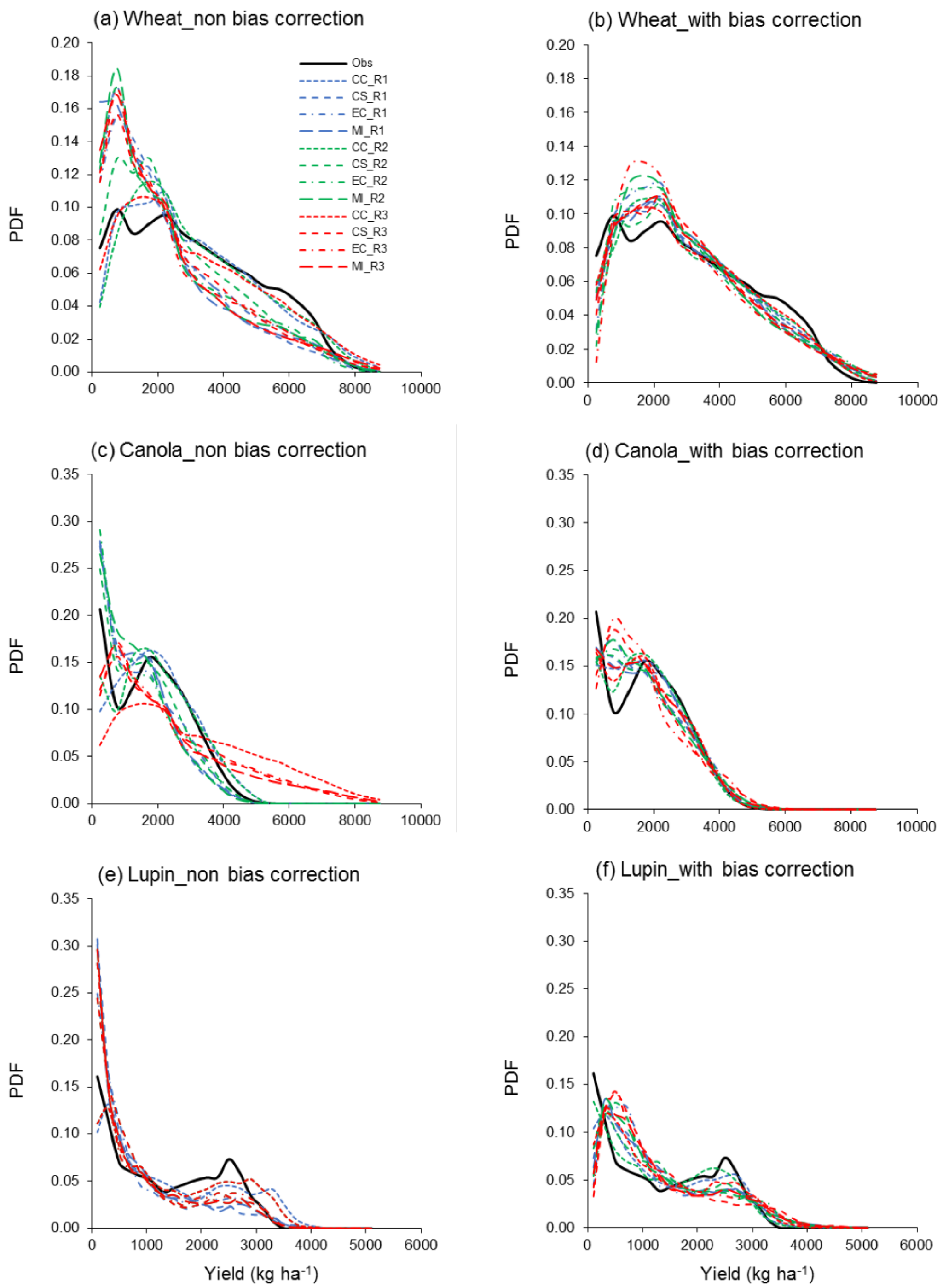

Figure 11 **Probability distribution functions of APSIM-simulated yields for the 1990 to 2009 baseline period, driven by historical observed climate data (black line) and 12 RCMs climate data with NonSBC (a,c,e) and SBCMnSD (b,d,f) values**

SBC yield largely eliminated the distributional discrepancies against the yield driven by observed climate.

Impact of climate change on crops

The bias-corrected yields were to assess future climate change impacts on crop yield for the 2020 to 2039 and 2060 to 2079 projection periods. To simplify the presentation of results, only four N-applications (N1, N3, N6 and N9) are illustrated here. The change in future simulated crop yields varied across the sites. Overall, the ensemble mean of yield for four crops across the MRC region (A2 emissions scenario) was projected to increase for both future time periods compared to the reference period (Figure 12 to Figure 15). The magnitude of increase in crop yields was larger in the far future as a result of the high carbon dioxide (CO_2) concentration compensating some negative effects of climate change. Crop responses to elevated CO_2 is through increase in efficiency of radiation and water use.

Figure 12 shows the mean changes in wheat yield for the 12 RCM ensemble at RI0 and RI100 and different N-applications in the 2030s and 2070s over the study area. The results show more significant increases in wheat yield for the 2070s in the western region than the eastern region (Figure 12). When residue was completely removed, and nitrogen application was at a very low level (N1), wheat yield was projected to increase by +2.6% and +10.5% in the 2030s and 2070s, respectively (Figure 12). Such increases likely resulted from the elevated CO_2 concentration that over-performed the low N-application in the current environment; however, the change in yield increased with increasing rate of nitrogen application in most cases, particularly when 100% residue incorporation was considered (Figure 12). This is likely due to RI increasing soil porosity and soil water availability for crop uses, and the interaction of high N and evaluated CO_2 concentration. The largest increase of +24.9 % for wheat yield was projected in the 2070s with high amounts of N and 100% RI (Figure 12).

Figure 13 shows the changes in barley yield of the RCM ensemble mean at RI0 and RI100 and different N-applications in the 2030s and 2070s over the study area. Similarly, results showed more significant increases in barley yield in the 2070s in the western portion of the area than those in east (Figure 13). There was a strong N response to the future yield increase. When residue was completely removed, barley yield was projected to increase by +0.8% at N1 to +8.5% at N9 in the 2030s and by +3.2% at N1 to +19.8% in the 2070s (Figure 13). It is interesting to note the significant effect of residue incorporation and also its interaction with N-application. With N-applications of N1, N3, N6 and N9, the difference in barley yield change was +2.6% (from 0.8–3.4%), +3.1% (1.99–5.04%), +1.0% (4.9–5.9%) and –2.2% (8.5–6.3%) from complete residue removal to 100% RI, respectively for the 2030s. However, in the far future higher yield changes are expected +9.7%, +15.3%, +9.6% and +2.9% for N1, N3, N6 and N9, respectively. Again, the effectiveness of N interaction with RI is likely the interaction of elevated CO_2 concentrations.

For canola, there was strong agreement among all the treatments with respect to pronounced projected increases in yield (Figure 14). The simulated canola yield increased due to increased CO_2 concentrations in the A2 emissions scenario. N-application and RI had limited contributions to yield increase in each time period; for example, canola yields only increased from +34.7% to +39.4% for the 2070s when N was increased from 16 kilograms per hectare (N1) to 272 kilograms per hectare (N9) at 100% RI (Figure 14D & P).

In addition, it is not surprising that simulated lupin yield had no response to nitrogen increase due to its nature of N fixation, although average yield was expected to increase by +4.6% to +29.9% across the study area (Figure 15).

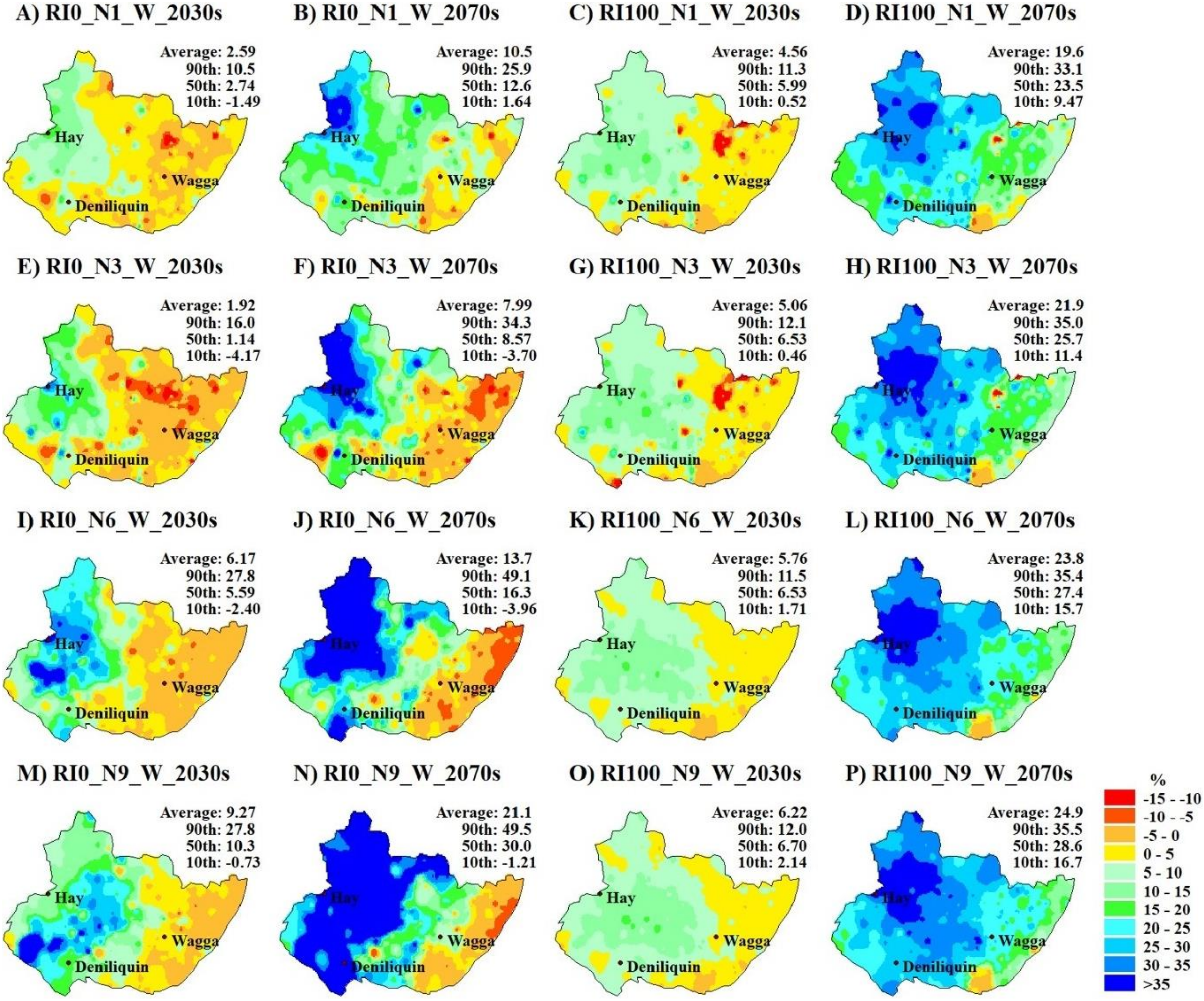

Figure 12 **Impact of climate change on wheat (W) at two contrasting residue incorporations (RI0: 0%; RI100: 100%) and for N-application (N1, N2, N6 and N9) in the 2030s and 2070s over the Murray–Riverina cropping region**

Here and in the following three figures, 2030s and 2070s refers to the 2020 to 2039 and 2060 to 2079 periods, respectively.

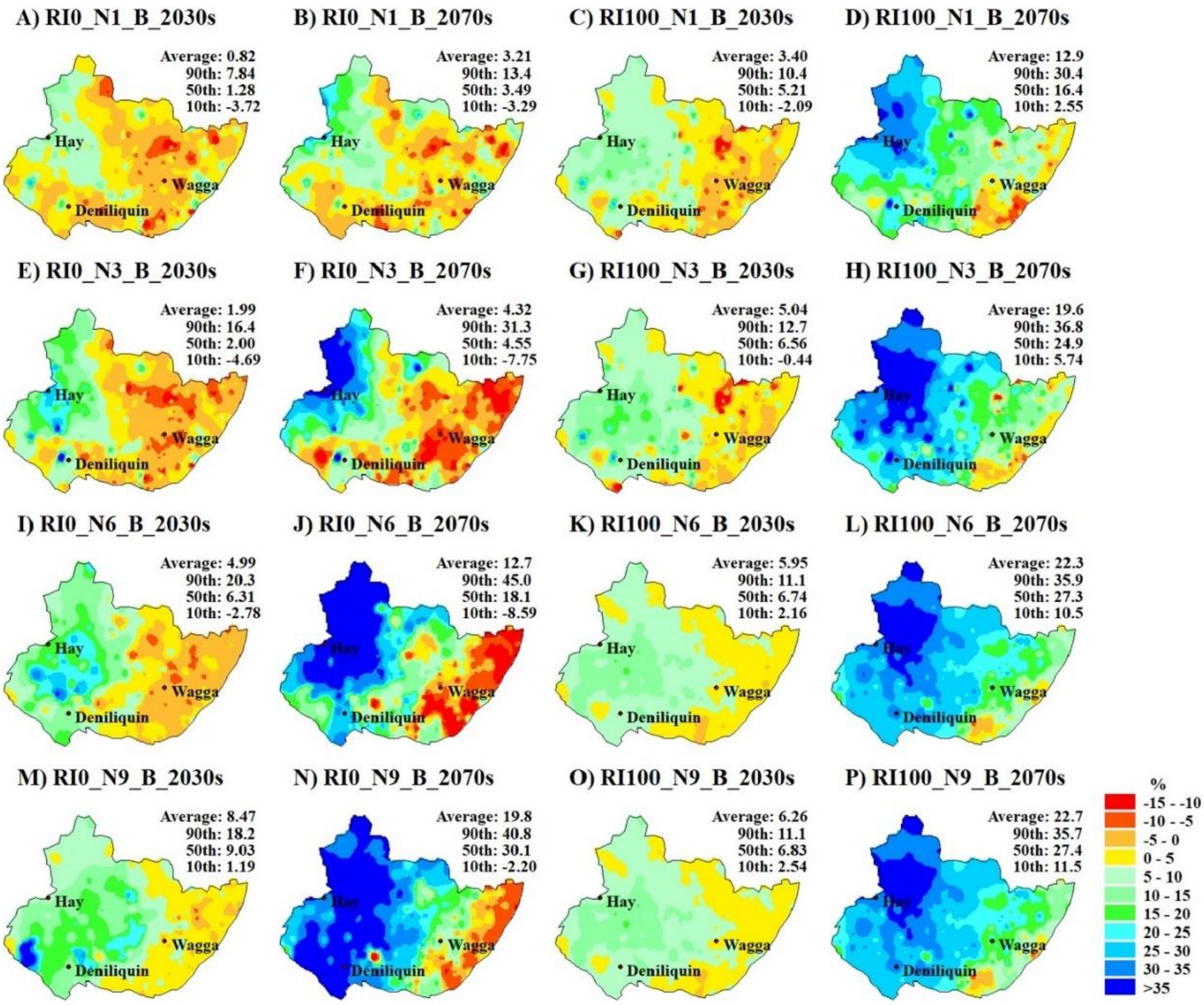

Figure 13 **Impact of climate change on barley at two contrasting residue incorporations (RI0: 0%; RI100: 100%) and for N-application (N1, N2, N6 and N9) in the 2030s and 2070s over the Murray–Riverina cropping region**

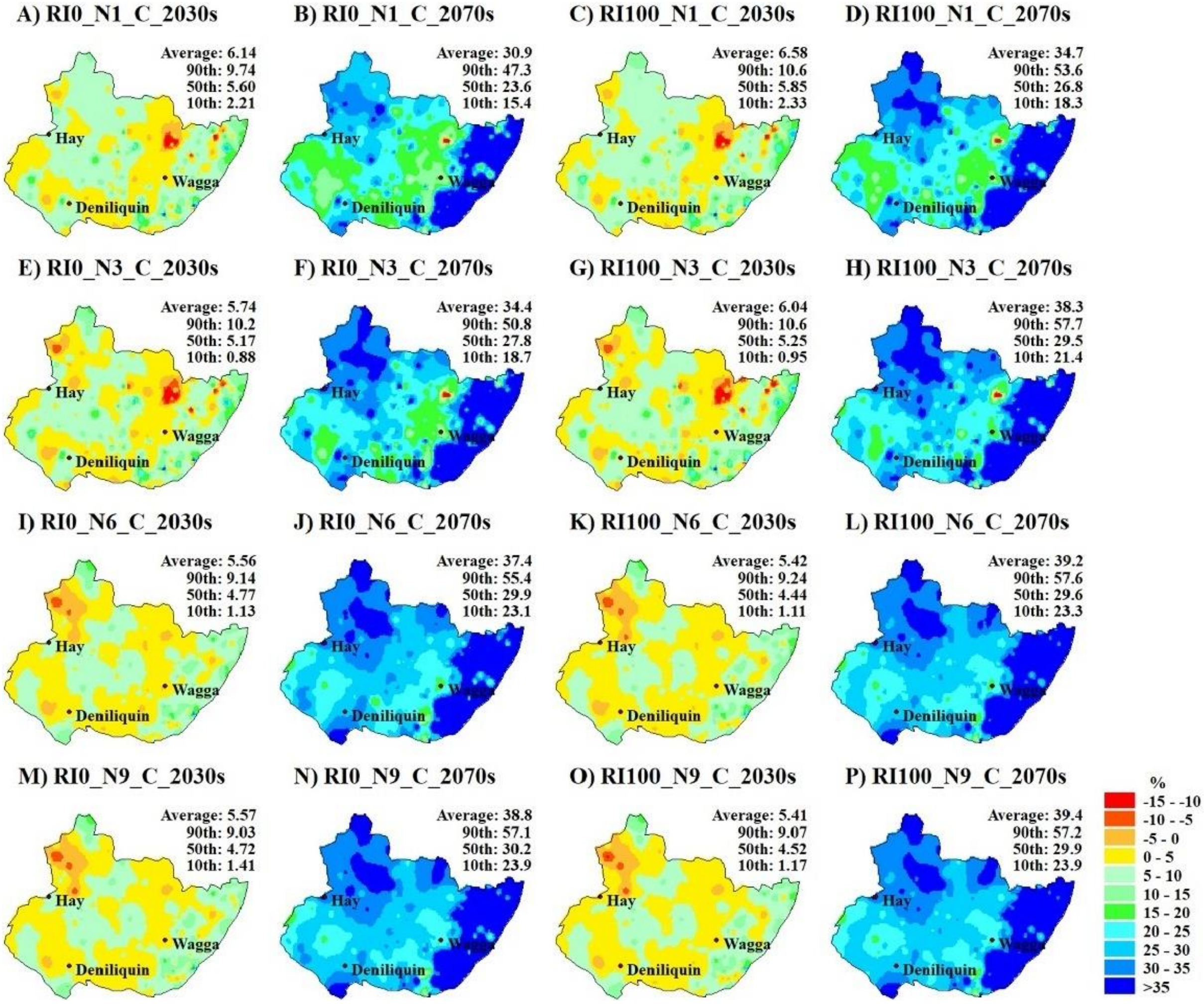

Figure 14 **Impact of climate change on canola at two contrasting residue incorporations (RI0: 0%; RI100: 100%) and for N-application (N1, N2, N6 and N9) in the 2030s and 2070s over the Murray–Riverina cropping region**

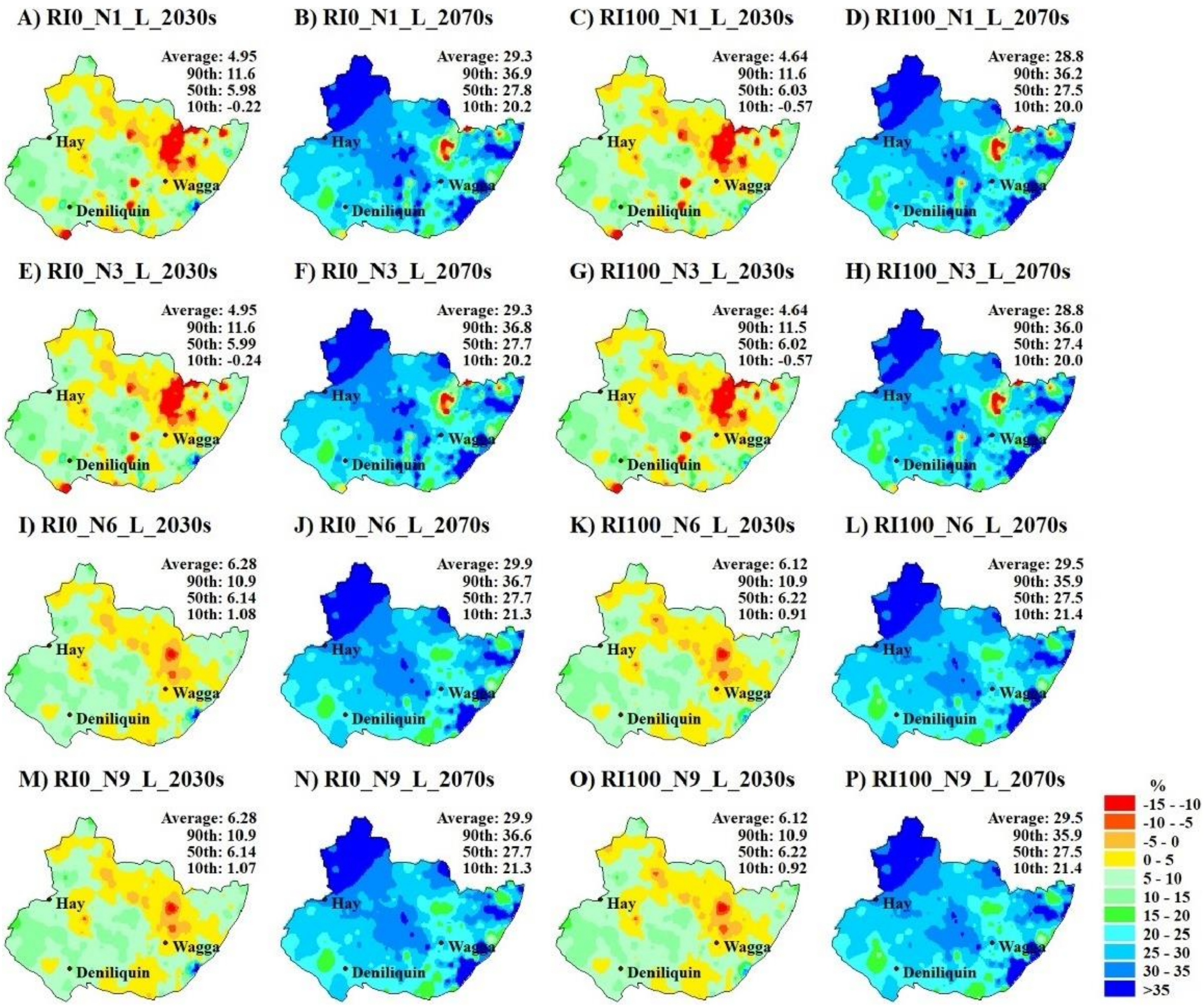

Figure 15 **Impact of climate change on lupin at two contrasting residue incorporations (RI0: 0%; RI100: 100%) and for N-application (N1, N2, N6 and N9) in the 2030s and 2070s over the Murray–Riverina cropping region**

4. Discussion

4.1 Key findings

NARCliM simulated climate

Although the bias correction (BC) of NARCliM simulated temperature and rainfall effectively removed bias at an annual time scale (Evans et al. 2017), it did not remove biases at finer temporal scales such as cropping season. We show that a positive bias in one phenological period for a given variable such as temperature or rainfall was often associated with a negative bias in a different period. Therefore, we suggest that BC should be done at finer temporal scales, i.e. seasonally or monthly, which could be useful for simulation of crop growth.

APSIM modelling responses to RCM biases

The biases in climate variables could explain 72–76% of the variance in the crop yield biases and 80–87% of the variance in the crop phenological biases. The climate biases were the cause of biases in the biophysical modelling outputs. Figure 16 shows the trajectories of the biases in crop yields through a schematic representation of bias source in APSIM crop yield. This tracks the sequence of climate biases and soil water balance biases that leads to less water available to the crop.

The results indicate the climate biases can interact with the projected climate change, which can result in confounding contributions to biophysical modelling outputs that increase uncertainties about effects of climate change and farm management factors. For example, simulated lower rainfall intensity associated with higher rainfall probability than observed climate, can be found in the largest proportion of sites. Low intensity, frequent rainfall makes the soil surface wetter and results in greater soil water distribution in shallow layers. This characteristic rainfall pattern can reduce water availability for plant use because a wetter soil surface can contribute more soil water evaporation, resulting in less water available for plant uptake. Our results showed that the responses of the wheat cropping system to this type of rainfall are typically positive biases in soil evaporation across almost all sites, which consequently lead to less water available for plant transpiration and ultimately lower yield. In addition, we found that the majority of sites had negative biases in both runoff and deep drainage. This highlighted that rainfall characteristics were as important as the total amount of rainfall in agricultural systems. Improved downscaling outputs are prerequisites for realistically assessing climate change impacts in agricultural systems.

Functions of secondary bias correction

Applying a simple SBC resulted in yield distributions largely consistent with those forced by historical observations. Importantly, the bias correction can effectively remove the uncertainties. The simple SBC method applied on the modelled yield outputs could result in RCM-driven crop yields being consistent with the PDF of observation-driven crop yields. After the SBC was applied to correct some of the biases in APSIM simulated yield, the parameters associated with the impact assessment became more meaningful, i.e. regaining positive atmospheric CO_2 effect on future crop production and diminishing the false collinearity between changes in climate variables and farm management practices.

However, SBC used in the study corrects the mean and variance under the assumption that the APSIM responses of climate biases in the baseline period are the same as in the future periods. As crop models are implemented with many linear and non-linear functions, the response of crop models to climate biases may interact with the changes in environmental conditions such as elevated future atmospheric CO_2. Such possible interacting responses of climate biases cannot be corrected by SBC. Thus, preference should be given to using improved climate projections that can result in small biases in biophysical modelled outputs.

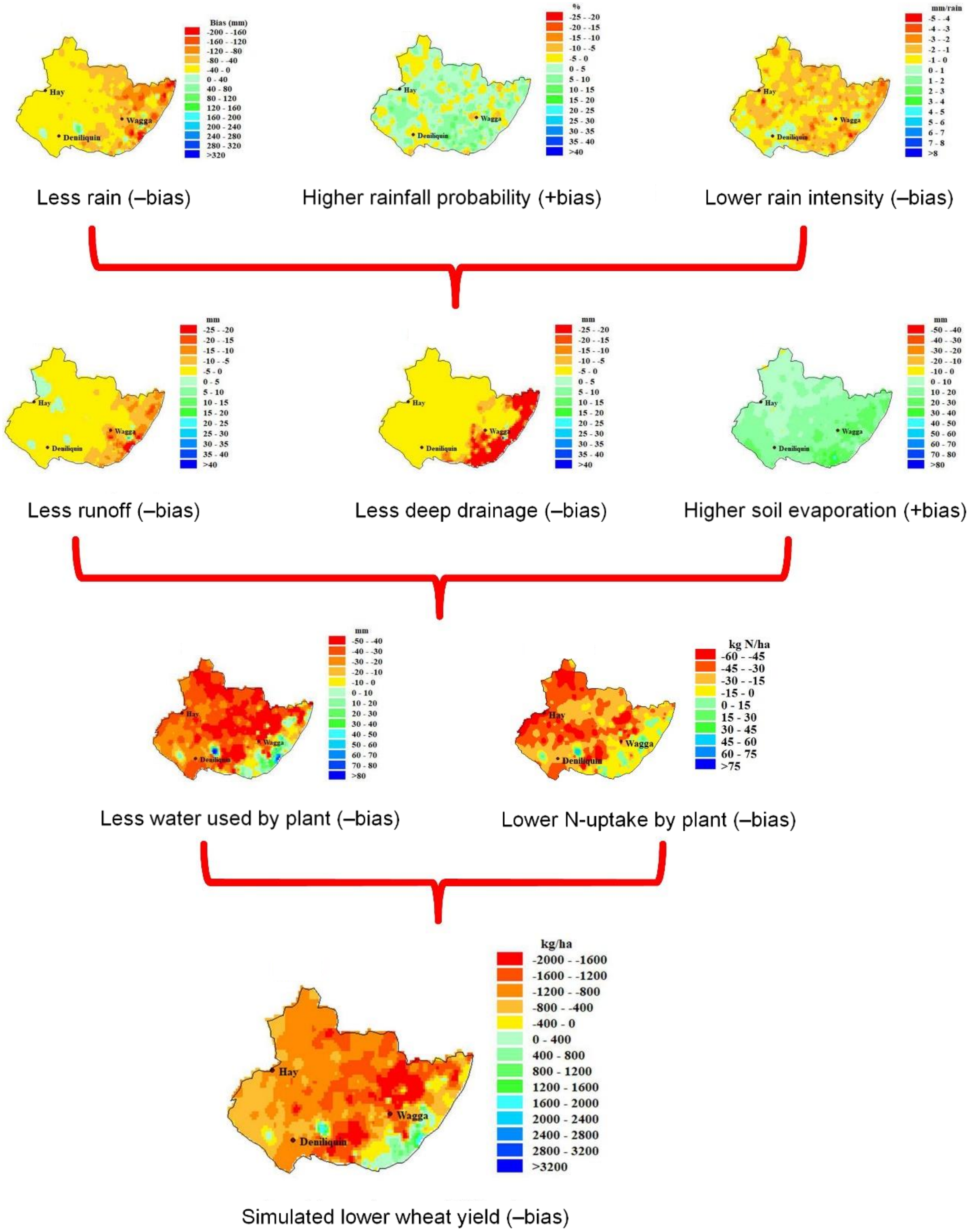

Figure 16 **Schematic representation of the cause of biases in APSIM crop yield that track back to the subsequence of climate biases on soil water balance biases that lead to less plant water uptake, using the GCM MIROC3.2 as an example**

Impacts of climate change on major crops in the MRC region

The bias-corrected yields were used to assess future changes in crop yields for the 2030s and 2070s. The simulated change in future crop yields varied across the study area. Overall, the ensemble mean yield for four crops across the Murray–Riverina cropping region corresponding to the A2 emissions scenario was projected to increase for both future time periods compared to the reference period. The magnitude of increase in crop yields was significant in the far future as a result of the higher CO_2 concentration compensating for some negative effects of climate change, such as shortening development due to increased temperature.

4.2 Limitations and further research

Uncertainties in the study include uncertainty of the GCMs and CO_2 emissions scenarios, the dynamical downscaling procedure and the bias correction of climate data based on an annual scale that resulted in retention of biases on a seasonal scale. Further, biophysical models contribute to uncertainties in the assessments. Therefore, care is needed in assessing each source of uncertainty and possible elimination of such biases is warranted.

5. Conclusion

This study provided a comprehensive assessment of biases in NARCliM simulations at different cropping growth stages. Substantial biases were identified in NARCliM simulated climate for crop growing season, largely due to the NARCliM bias correction not accounting for different biases in different seasons. The biases in rainfall characteristics were generally positive in rainfall probability and negative in rainfall intensity, which resulted in APSIM simulated negative biases for most of the study area in runoff and deep drainage and positive biases in soil evaporation (due to wetter soil surface as a consequence of small and frequent rains). Consequently, biases in soil water balance and water availability resulted in less plant transpiration and less N uptake. Ultimately, those biases together with biases in crop phenology led to biases in crop yields.

The APSIM simulated crop yields exhibited a skewed distribution towards low yield, largely due to negative yield biases. Simple secondary bias correction (SBC) was able to produce yield distributions largely consistent with those forced by observed climate data. Impacts of climate change on crop yields were assessed for wheat, barley, canola and lupin and the SBC of crop yields were considered. The ensemble mean yield for the four crops across the MRC region corresponding to the A2 emissions scenario was projected to increase by +2–9% and +8–20% for the 2020 to 2039 and 2060 to 2079 periods respectively, compared to the 1990 to 2009 baseline period. A larger increase in the far future was a result of the higher CO_2 concentration compensating for negative effects. Positive effects on crops at the elevated CO_2 concentrations can be further increased under farm management options, particularly for cereal crops. For example, the rate of yield increased with increased N-application and residue incorporation, which benefited from the interaction between elevated CO_2 and crop higher N level, and from increased soil porosity and reduced soil water evaporation. Therefore, these farm management options can be used as effective adaptation options for cropping systems under future climate conditions.

The study implied that the current bias correction of NARCliM climate data did not result in adequate climate projections that can be used directly for assessment of climate change impacts on agriculture. This could be improved through refinement of the correction method to take into account different biases in different seasons of the year.

6. References

Balkovič J, van der Velde M, Skalsky R, Xiong W, Folberth C, Khabarov N, Smirnov A, Mueller ND, et al. 2014, Global wheat production potentials and management flexibility under the representative concentration pathways, *Global and Planetary Change*, vol.122, pp.107–121.

Dietzel R, Liebman M, Ewing R, Helmers M, Horton R, Jarchow M and Archontoulis S 2015, How efficiently do corn-and soybean-based cropping systems use water? A systems modeling analysis, *Global change biology*, vol.22, no.2, pp.666–681.

Evans JP, Ekstrom M and Ji F 2012, Evaluating the performance of a WRF physics ensemble over South-East Australia, *Climate Dynamics*, vol.39, no.6, pp.1241–1258.

Evans JP, Ji F, Abramowitz G, Ekstrom M 2013a, Optimally choosing small ensemble members to produce robust climate simulations, *Environmental Research Letters*, vol.8.

Evans JP, Fita L, Argüeso D and Liu Y 2013b, Initial NARCliM evaluation, in Piantadosi J, Anderssen RS and Boland J (eds), *MODSIM2013, 20th International Congress on Modelling and Simulation*, Modelling and Simulation Society of Australia and New Zealand, December 2013, pp.2765–2771.

Evans J, Ji F, Lee C, Smith P, Argüeso D and Fita L 2014, Design of a regional climate modelling projection ensemble experiment–NARCliM, *Geoscientific Model Development,* vol.7, pp.621–629.

Evans JP, Argueso D, Olson R and Di Luca A 2017, Bias-corrected regional climate projections of extreme rainfall in south-east Australia, *Theoretical and Applied Climatology*, vol.130, nos3–4, pp.1085–1098.

Fita L, Evans JP, Argüeso D, King AD and Liu Y 2016, Evaluation of the regional climate response to large-scale modes in the historical NARCliM simulations, *Climate Dynamics*, pp.1–15, doi: 10.1007/s00382-016-3484-x.

Haerter J, Hagemann S, Moseley C and Piani C 2011, Climate model bias correction and the role of timescales, *Hydrology and Earth System Sciences*, vol.15, no.3, pp.1065–1079.

Holzworth DP, Huth NI, Devoil PG, Zurcher EJ, Herrmann NI, Mclean G, Chenu K, Van Oosterom EJ, Snow V, Murphy C, Moore AD, Brown H, Whish JPM, Verrall S, Fainges J, Bell LW, Peake AS, Poulton PL, Hochman Z, Thorburn PJ et al. 2014, APSIM – Evolution towards a new generation of agricultural systems simulation, *Environmental Modelling and Software*, vol.62(C), pp.327–350.

Huth NI, Banabas M, Nelson PN and Webb M 2014, Development of an oil palm cropping systems model: Lessons learned and future directions, *Environmental Modelling and Software*, vol.62, pp.411–419.

IPCC 2000, *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, published for the Intergovernmental Panel on Climate Change by Cambridge University Press, Cambridge, UK.

Ji F, Ekstrom M, Evans JP and Teng J 2014, Evaluating rainfall patterns using physics scheme ensembles from a regional atmospheric model, *Theoretical and Applied Climatology*, vol.115, pp.297–304.

Ji F, Evans JP, Teng J, Scorgie Y, Argüeso D and Di Luca A 2016, Evaluation of long-term precipitation and temperature WRF simulations for southeast Australia, *Climate Research*, vol.67, pp.99–115.

Keating BA et al. 2003, An overview of APSIM, a model designed for farming systems simulation, *European Journal of Agronomy*, vol.18, no.3, pp.267–288.

Liu DL, Anwar MR, O'Leary G and Conyers MK 2014, Managing wheat stubble as an effective approach to sequester soil carbon in a semi-arid environment: Spatial modelling, *Geoderma*, vol.214–215, pp.50–61.

Liu DL, O'Leary GJ, Ma Y, Cowie A, Li FY, McCaskill M, Conyers M, Dalal R, Robertson F and Dougherty W 2016, Modelling soil organic carbon 2: Changes under a range of cropping and grazing farming systems in eastern Australia, *Geoderma*, vol.265, pp.164–175.

Liu DL, Zeleke KT, Wang B, Macadam I, Scott F and Martin RJ 2017, Crop residue incorporation can mitigate negative climate change impacts on crop yield and improve water use efficiency in a semiarid environment, *European Journal of Agronomy*, vol.85, pp.51–68.

Liu DL, Wang B, Evans J, Ji F, Waters C, Macadam I, Yang X and Beyer K 2019, Propagation of climate model biases to biophysical modelling can complicate assessments of climate change impact in agricultural systems, *International Journal of Climatology*, vol.39, pp.424–444, https://doi.org/10.1002/joc.5820.

Lychuk TE, Hill RL, Izaurralde RC, Momen B and Thomson AM 2017, Evaluation of climate change impacts and effectiveness of adaptation options on crop yield in the Southeastern United States, *Field Crops Research*, vol.214(Supplement C), pp.228–238.

Macadam I, Pitman AJ, Whetton PH, Liu DL and Evans JP 2014, The use of uncorrected regional climate model output to force impact models: a case study for wheat simulations, *Climate Research*, vol.61, no.3, pp.215–229.

Macadam I, Argüeso D, Evans JP, Liu DL and Pitman AJ 2016, The effect of bias correction and climate model resolution on wheat simulations forced with a regional climate model ensemble, *International Journal of Climatology*, vol.36, no.14, pp.4577–4591.

OEH 2013, *Scientific Rigour Position Statement*, NSW Office of Environment and Heritage, www.environment.nsw.gov.au/-/media/OEH/Corporate-Site/Documents/Research/Our-science-and-research/oeh-scientific-rigour-position-statement-2013.pdf.

O'Leary GJ, Liu DL, Ma Y, Li FY, McCaskill M, Conyers M, Dalal R, Reeves S, Page K, Dang YP and Robertson F 2016, Modelling soil organic carbon 1: Performance of APSIM crop and pasture modules against long-term experimental data, *Geoderma*, vol.264(Part A), pp.227–237.

Piani C, Haerter J and Coppola E 2010, Statistical bias correction for daily precipitation in regional climate models over Europe, *Theoretical and Applied Climatology*, vol.99, nos1–2, pp.187–192.

Probert M, Dimes J, Keating B, Dalal R and Strong W 1998, APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems, *Agricultural systems*, vol.56, no.1, pp.1–28.

Skamarock WC, Klemp JB, Dudhia J, Gill DO, Barker DM, Duda MG, Huang XY, Wang W and Powers JG 2008, *A description of the advanced research WRF Version 3,* NCAR Technical Note, National Center for Atmospheric Research, Boulder Colorado, USA.

Tai AP, Martin MV and Heald CL 2014, Threat to future global food security from climate change and ozone air pollution, *Nature Climate Change*, vol.4, no.9, pp.817–821.

Turpin JE, Robertson M, Haire C, Bellotti W, Moore A and Rose I 2003, Simulating fababean development, growth, and yield in Australia, *Crop and Pasture Science,* vol.54, no.1, pp.39–52.

Wang B, Evans J, Ji F, Waters C, Macadam I, Feng P and Beyer K 2019, Modelling and evaluating the impacts of climate change on three major crops in south-eastern Australia using regional climate model simulations, *Theoretical and Applied Climatology*, vol. 136, nos1–2, pp. 509–526, 10.1007/s00704-019-02843-7.

Wheeler T and Von Braun J 2013, Climate change impacts on global food security, *Science*, vol.341(6145), pp.508–513.

Yang Y, Liu DL, Anwar MR, Zuo H and Yang Y 2014, Impact of future climate change on wheat production in relation to plant-available water capacity in a semiarid environment, *Theoretical and Applied Climatology*, vol.115, nos3–4, pp.391–410.

Yang Y, Liu DL, Anwar MR, O'Leary G, Macadam I and Yang Y 2016, Water use efficiency and crop water balance of rainfed wheat in a semi-arid environment: sensitivity of future changes to projected climate changes and soil type, *Theoretical and Applied Climatology*, vol.123, pp.565–579.

Ziska LH, Bunce JA, Shimono H, Gealy DR, Baker JT, Newton PCD, Reynolds MP, Jagadish KSV, Zhu C, Howden M and Wilson LT 2012, Food security and climate change: on the potential to adapt global crop production by active selection to rising atmospheric carbon dioxide, *Proceedings of the Royal Society of London Proceedings B*, 279(1745), pp.4097–4105.