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ORIGINAL PAPER

Modelling and evaluating the impacts of climate change on three major crops in south-eastern Australia using regional climate model simulations

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Abstract

The use of regional climate models (RCMs) to localise results from coarse-resolution global climate models has recently attracted more interest in agricultural impact studies. Theoretically, it has advantages over global climate models in terms of realisation of future climate projections. However, there are few studies that have used dynamical downscaling results to assess climate change impacts on Australian cropping systems. In this study, we used post-processing bias-corrected climate data from the NSW/ACT Regional Climate Modelling (NARCliM) project to drive the Agricultural Production Systems SIMulator (APSIM) for modelling and evaluating the response of three major crops (wheat, canola and lupin) to projected climate conditions under various farm management practices in south-eastern Australia. Our results showed that historical crop yields from APSIM simulations forced by RCM output tended to underestimate yields from simulations forced by observations due to large biases in the NARCliM simulations. Therefore, bias correction was used to correct the APSIM outputs before conducting future impact analysis. The bias-corrected results showed that ensemble-mean yields based on 12 RCMs were projected to increase over the study area under the A2 emission scenario. However, the magnitude of yield increase depended on the time periods, crop type and location. Multiple linear regression models showed that the changes of radiation, rainfall and temperature and elevated CO_2 concentration could explain 60–78% of crop yield changes. It is interesting to note that residue incorporation and nitrogen application had a large effect on percentage yield increases for wheat due to future climate change, but had limited effects on the response of lupin and canola yields. Our study suggests that sufficient bias-correction method is needed when using NARCliM outputs in crop models. Although uncertainties (e.g. the choice of emission scenarios and RCMs) still exist in our study, the results are of central importance in the development of high-yield adaptive strategies for local farmers and policy makers in south-eastern Australia.

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1 Introduction

World demand for cereal production in 2050 is predicted to increase by approximately 30% relative to 2007 to meet an increasing global population (Alexandratos and Bruinsma 2012). In order to meet future needs for agricultural products, arable land area across the world may have to increase by about 70 million ha by 2050 (Alexandratos and Bruinsma 2012). However, climate change, which has direct impacts on crop productivity, is accelerating food shortage and presenting huge challenges to governments worldwide (Lychuk et al. 2017; Tai et al. 2014; Wheeler and Von Braun 2013; Ziska et al. 2012). For example, a recent study has reported that climate change would decrease global wheat production by 37 to 52 Mt and 54 to 103 Mt in the 2050s and 2090s, respectively (Balkovič et al. 2014). In this case, local farmers

would face a great challenge to maintain high and stable crop yield. Understanding the impact of climate change on crop yield is an essential step towards the development of appropriate adaptive strategies to deal with climate change.

To study the impact of climate change on crops, process-based simulation models are widely used, which are forced with future climate conditions derived from global climate models (GCMs). However, since GCMs provide only a low-resolution representation of the climate, often on grids with cells hundreds of kilometres across, their outputs must first be downscaled to the finer spatial scales represented by the crop models (e.g. the farm scale). There are numerous studies which have applied a multi-GCM ensemble to agricultural impact studies by using statistical techniques to downscale GCM outputs. For example, Semenov and Shewry (2011) used the Coupled Model Intercomparison Project (CMIP) phase 3 multi-model ensemble of GCMs associated with the weather generator LARS-WG and the Sirius crop model to assess the probability of heat stress in anthesis in serval locations across Europe. These authors highlight the need for new crop cultivars to meet changing climate characterised by more seasonal drought and heat stress in Europe. Wang et al. (2017) used statistically downscaled climate data based on the CMIP5 multi-model ensemble of GCMs to drive the APSIM crop model to estimate the effect of climate change on wheat productivity and water use efficiency in eastern Australia. They reported that elevated CO_2 concentration would make a greater contribution to yield change in drier areas than that in wetter areas. In addition to this, Liu et al. (2017b) used a modelling approach to study the impacts of various residue management practices on crop yields using current climate data and statistically downscaled climate data from 28 GCM simulations under RCP4.5 and RCP8.5. They concluded that residue incorporation was an effective approach to mitigate the negative effects of climate change and led to yield increases ~7 to 16% for canola and wheat, respectively.

The use of regional climate models (RCMs) to localise results from low-resolution GCMs has recently attracted more interest in agricultural studies (Ruiz-Ramos et al. 2016). Dynamical downscaling uses RCMs to obtain high-resolution (approximately 10–50 km) climate information from relatively coarse-resolution GCMs by considering finer scale topography and coastal boundaries (Ramarohetra et al. 2015). In contrast to statistical downscaling techniques, it is able to provide spatially complete, internally consistent datasets containing numerous different climate variables. These datasets can be used as inputs to the biophysical models that are often employed to assess climate change effects (e.g. crop growth model). For example, Cammarano et al. (2017) used the HadRM3 RCM data in combination with three crop models to evaluate the effects of future climate change on crop phenology and yield in the UK. Lychuk et al. (2017) evaluated the climate change impacts and efficacy of adaptation measures on crop yield in the south-eastern US using EPIC model driven by climate data produced by four RCMs nested within GCMs.

The New South Wales (NSW)/Australian Capital Territory (ACT) Regional Climate Modelling project (NARCliM) is a joint initiative between the University of New South Wales and the NSW Government to produce high-resolution (10 km) regional climate projections for south-eastern Australia. NARCliM chose different boundary and initial conditions from four GCMs to drive three RCMs, producing a 12-member climate model ensemble (Evans et al. 2014). The NARCliM regional projections have been used and evaluated in a variety of studies (Di Luca et al. 2017; Fita et al. 2017; Ji et al. 2016). For example, Evans et al. (2017) used the NARCliM ensemble to present future changes in extreme precipitation in south-eastern Australia, and reported that the period of the maximum dry spell was predicted to increase in the future. Di Luca et al. (2017) evaluated the ability of an ensemble of NARCliM simulations to represent snow cover characteristics over the Australian Alps and also assessed future projections of snowpack characteristics. They found that there are large uncertainties in future projections of the snowpack for the study area and the choice of the lateral boundary conditions primarily dominates the uncertainty. In relation to crop modelling, NARCliM outputs have been used with the Agricultural Production Systems SIMulator (APSIM). Macadam et al. (2016) assessed the suitability of the 12 NARCliM simulations for driving APSIM in eastern Australia. All 12 simulations resulted in a realistic spatial pattern of wheat yields across the region but some produced biases in yields, defined relative to yields simulated by APSIM simulations forced with climate observations. As with other regional climate simulations, the NARCliM simulations are subject to bias resulting from deficiencies in both the global forcing fields (Cammarano et al. 2017; Murphy et al. 2004) and the regional climate model itself (Pascal et al. 2011; Ramarohetra et al. 2015), which can affect downstream impact modelling results. Therefore, to obtain more accurate crop simulations, these biases must be reduced or removed (Liu et al. 2018).

In this study, we extend the work of Macadam et al. (2016) to assess climate change impacts on agricultural cropping systems using APSIM forced by NARCliM simulations for the Murray-Riverina region of NSW in south-eastern Australia. Three important field crops namely wheat (*Triticum aestivum* L.), canola (*Brassica napus* L.) and lupins (*Lupinus angustifolius*) were included in the current study to explore the relationship between the changing climate and simulated crop yield. Various farm management practices were also explored by implementing different crop residue and fertiliser application in the APSIM simulations. A bias-correction method was employed to correct the bias in simulated APSIM output. The objectives of this study are (1) to evaluate

climate variables derived from NARCliM simulations across the study area, (2) to investigate the impacts of future climate change on the yield of three major crops in APSIM using post-processing bias-correction method under different management options and (3) uncover relationships between climate change and crop yield in south-eastern Australia.

2 Materials and methods

2.1 The study area and historical climate data

The area of this study is the Murray-Riverina region, which is located in central southern NSW and borders the ACT in the east and Victoria in the south (Fig. 1). The region covers an area of approximately 115,096 km^2 with 14.6% of NSW land mass (Scally et al. 2016). The region provides a large amount of agricultural resources. However, due to its winter-dominated rainfall pattern and high risk of seasonal drought, this region faces substantial risk from climate change. Areas used for cropping occupies approximately 27% of the Murray-Riverina region. Of the 31,000 km^2 of cropland in 2011, wheat was the main crop grown, accounting for approximately 45% of the cropped area. Canola represented approximately 8% of the cropped area. Further detailed information on agricultural land use in the Murray-Riverina region can be found in Riverina Murray agricultural industries final report (Scally et al. 2016) (http://www.planning.nsw.gov.au/Plans-for-Your-Area/Regional-Plans/Riverina-Murray/~/media/E170FEF15B7E41E6821C995058C4EE57.ashx). As our study only focused on crops, we extracted the cropping region from the original Murray-Riverina zone as it also contains some rangeland grazing and production forestry. The annual rainfall in the Murray-Riverina cropping region (MRC) ranges from approximately 600 mm in the east to 300 mm in the west (Liu et al. 2014a). Most of the rainfall in the MRC occurs between the months of June and August. November to February is relatively dry while June to August is relatively wet.

Three hundred seventy sites in the MRC were included in this study (Fig. 1). The daily maximum and minimum temperatures, solar radiation and rainfall at the 370 sites during the period of 1990–2009 were obtained from the SILO (Scientific Information for Land Owners) patched point observational dataset (PPD, http://www.longpaddock.qld.gov.au/silo/ppd/index.php) (Jeffrey et al. 2001).

2.2 Regional climate model data

The NARCliM simulations were conducted with the Weather Research and Forecasting (WRF) model version 3.3 (Skamarock et al. 2008). Four GCMs, i.e. MIROC3.2 (MI), ECHAM5 (EC), CCCM3.1 (CC) and CSIRO-Mk3.0 (CS), were used to provide boundary and initial conditions to the WRF simulations (Evans et al. 2014). These were chosen from CMIP3 through a process of first removing unequivocally poor-performing models over Australia, then choosing models that spanned the plausible future change in temperature and precipitation found in the full ensemble, and that had the most independent errors (Evans et al. 2014). Using data

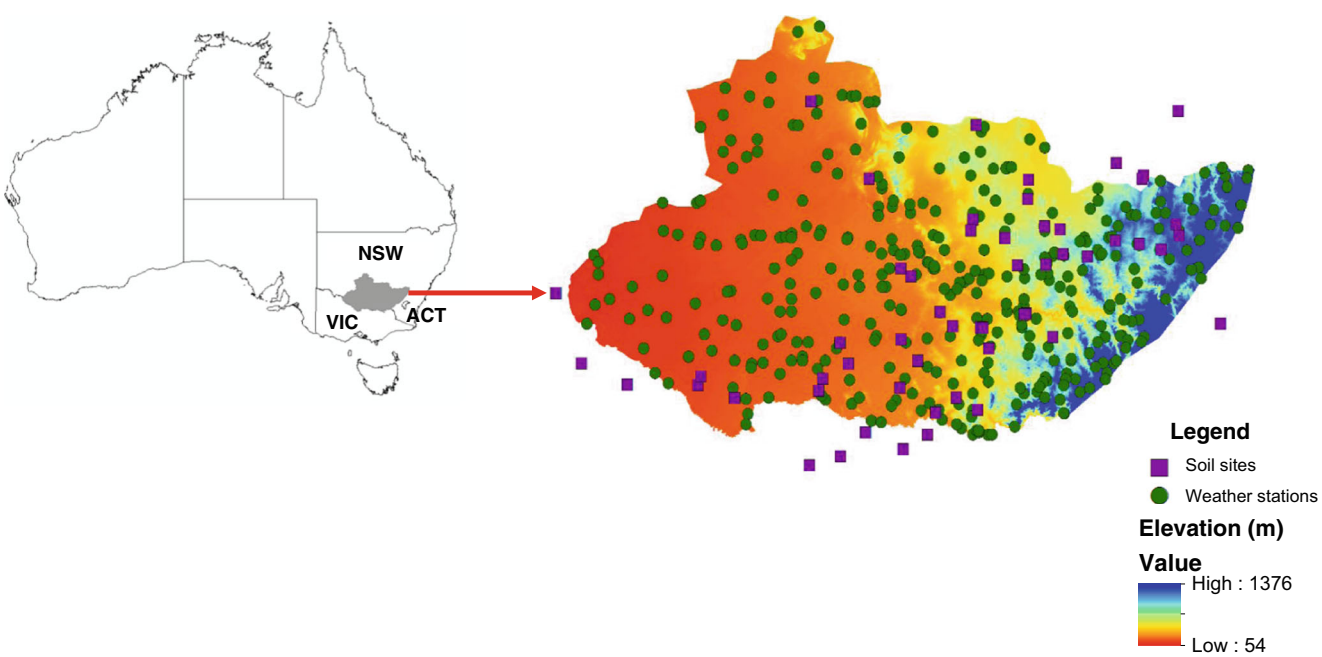


Fig. 1 The study area and distribution of 370 weather stations (green solid circle) used in this study. Purple rectangles denote 57 soil sites used for the simulation, including some soil sites from VIC (Victoria) near the NSW border

from these four GCMs, three different configurations of WRF (R1, R2 and R3) were used to downscale the GCMs to a resolution of 10 km. The WRF configurations included different combinations of parameterisations for the surface layer, planetary boundary layer, cumulus convection, short- and long-wave radiation and cloud microphysics (Evans et al. 2012; Ji et al. 2014). This generated data for 12 RCM-GCM combinations, designated here as CC-R1, CC-R2, CC-R3, CS-R1, CS-R2, CS-R3, EC-R1, EC-R2, EC-R3, MI-R1, MI-R2 and MI-R3. Three time periods were simulated in NARCliM: the baseline (1990–2009), near-future (2020–2039; referred to as 2030s) and far-future periods (2060–2079; referred to as 2070s). For the historical period, the simulations were forced by observed atmospheric greenhouse gas concentrations, aerosols and solar forcing. For the future periods, forcings from the Special Report on Emission Scenarios (SRES) A2 scenario were applied. Under the A2 emission scenario, the projected atmospheric CO_2 concentrations are expected to reach 575 ppm by 2050s and 870 ppm by the end of twenty-first century (Lychuk et al. 2017) and represent the "business-as-usual" case in the SRES family. Additional details about the NARCliM experiment design are available at Evans et al. (2014). Previous assessment of NARCliM simulations indicates that RCMs have strong skills in projecting the rainfall and surface temperature for Southeast Australia, though there is a small cold bias with overestimation of rainfall along the Great Dividing Range (Ji et al. 2015; Olson et al. 2016). The dataset was released in 2014 and has been widely used in impact assessments (http://climatechange.environment.nsw.gov.au/Impacts-of-climate-change). Data from a subsequent generation of GCMs, the CMIP5 GCMs, has since become available, but the NARCliM projections remain the most detailed comprehensive climate projections for NSW.

Daily climate variables including solar radiation, rainfall, minimum and maximum temperatures for the baseline, 2030s and 2070s used in this study were extracted from the nearest gridded data of the 10-km NARCliM simulations. The biases in daily temperature and rainfall have been corrected by a quantile matching technique as described in Piani et al. (2010) which allowed correction of the full distribution of daily precipitation, and maximum and minimum temperatures in NARCliM.

2.3 Crop simulation model

The APSIM version 7.7 is a field-scale multi-year, multi-crop model which is developed as an analytical tool to assess the impact of climate change, soil parameters and farming management on cropping system production (Holzworth et al. 2014). Management practices represented include sowing date, variety selection, irrigation water management, fertilisation application, crop residue management and conservation tillage. APSIM has been calibrated and widely used for studies on climate change impact across Australia and around the world (Anwar et al. 2015; Asseng et al. 2013; Chen et al. 2010; Liu et al. 2017b; Wang et al. 2017).

APSIM allows users to set up management options such as sowing date, cultivar genetic coefficients (e.g. photoperiod, vernalisation and thermal time), fertiliser and irrigation management, soil parameters (e.g. soil organic matter and pH), crop rotation and atmospheric CO_2 concentration. The model has a daily time step. The modelling of crop phenology is primarily based on the thermal time required to each specific stage of crop growing. Thermal time is determined by accumulating growth degree-day (GDD, degree C day^{-1}) during the full crop-growing season (from sowing to maturing). Particularly, for winter crops, the exposure to low, non-freezing temperatures (vernalisation) is required to complete development stage. Crop biomass is accumulated every day during the growing season based on the availability of either water, nutrients or energy, whichever is more limiting. The conversion of water or energy to biomass is governed by the water use efficiency (WUE) and radiation use efficiency (RUE) parameters respectively. The model simulates the function of increasing atmospheric CO_2 concentration on crop physiology by modifying the WUE and RUE. The rate of RUE used in APSIM is 1.24 g MJ^{-1} PAR (photosynthetically active radiation) for wheat, 1.35 g MJ^{-1} PAR for canola and 0.69 g MJ^{-1} PAR for lupin. The harvest index and actual total biomass accumulated at physiological maturity are used to determine crop yield.

2.4 APSIM simulations

The sowing date of the crop was set automatically using "sowing rules" designed to represent common farm management practices. To set a sowing rule suitable at all soils and locations that accounted for the sufficiency of soil moisture, we used the conditions given in the equation proposed in Liu et al. (2018) to determine a sowing decision within a given sowing window. The sowing rules were set as a function of soil water content (SW), the plant available water capacity and day of year. The length of sowing window varied from 71 days (21 Apr–30 June) for wheat, 52 days (1 Apr–22 May) for canola to 38 days (15 May–21 June) for lupin.

Crop residue incorporation is an effective approach to cope with the negative effects of climate change. We simulated two levels of crop residue incorporation (0, 100%; RI0 and RI100, respectively) in our study. The procedures for executing crop RI were similar to those of Liu et al. (2014a) and Liu et al. (2017b). Under the APSIM management module, we derived a new variable to record the amount of crop residue at harvest and calculated the amount of crop residue incorporated into the top 100 mm of soil for each treatment. The actual amount of crop residue incorporated by a single tillage depended on

the amount of crop residue at harvest in the previous year. In this study, we implemented two tillages for RI100 for achieving better stubble incorporation.

Another management option explored in the simulations was nitrogen (N) application. There were 12 levels of N applications, denoted as *N1*, *N2*, …, *N12*. The baseline N-application levels for wheat, canola and lupin are 55, 80 and 50 kg ha^{-1}, respectively, which is denoted as N_{bs}. The amount of N applied for each treatment is calculated as

$$N_i = N_{bs} \times [1 + (i–3) \times 0.4] \qquad i = 1, 2, \ldots, 12 \tag{1}$$

An annual CO_2 concentration is required as an input in APSIM to simulate crop growth correctly in responding to elevated CO_2 concentration levels. We used an empirical equation to determine the relationship between CO_2 concentration and calendar year. For IPCC A2 emission scenario that is used in this study, we calculated CO_2 concentration (Liu et al. 2014a; Yang et al. 2014) according to

$$[CO_2]_{\text{year}} = 2641 + \frac{0.098139 \times \text{year} – 211.71}{3.5566 \times \text{year}^{-0.37996} – 0.19123} \tag{2}$$

There are 57 soil points from the APSoil database available over the MRC region (Dalgliesh et al. 2006) (see Fig. 1). We selected the closest soil type for each of 370 climate stations to simulate yields for the three crops in order to reduce the bias in spatial analysis because of using an unrepresentative soil for a geographic location. Initial water and nitrogen were reset at the 1st of February each year so the accumulative effects of soil water and nitrogen can be minimised. Initial soil water was reset to 10% of plant available water capacity. Soil profile mineral N was reset to 25 kg ha^{-1} nitrate-N and 10 kg ha^{-1} ammonium-N for all soils and crops. The distribution of the amount of N in each soil layer was based on observed N distribution pattern (Probert et al. 1998), with N content rapidly declining with depth.

For each of the 370 sites, historical climate data for the period of 1990–2009 and 12 RCMs projected climate for the periods 2030s and 2070s were used to simulate the 12 nitrogen rates and two levels of stubble incorporation on three crops. A total number of 346,320 simulations were generated.

2.5 Bias calculations and bias correction of APSIM outputs

Climate models cannot reproduce the statistics of most climate variables precisely and bias-correction methods cannot remove all relevant biases. The NARCliM-simulated data used in this study, even the bias-corrected temperature and precipitation data, contains some biases (Evans et al. 2017). These have the potential to contribute to biases in the outputs of APSIM simulations forced with the NARCliM data. For example, Macadam et al. (2016) noted that the NARCliM bias-correction technique does not eliminate biases in total growing season precipitation in the NSW wheat belt. We therefore analysed biases in both the climate data and APSIM-simulated crop yields. We calculated the mean bias error (MBE) of climate variables relative to observed climate variables and MBE in yields from RCM-driven APSIM simulations relative to APSIM simulations driven by the SILO climate observations.

$$\text{MBE}(\%) = \frac{\overline{P} – \overline{O}}{\overline{O}} \times 100 \tag{3}$$

$$\text{MBE(absolute)} = \overline{P} – \overline{O} \tag{4}$$

where $\overline{P}$ is the average of all predictions including climate variables and APSIM-simulated crop yield over 1990–2009 time period and $\overline{O}$ is the average of all observation in the baseline period.

In this study, we used simulated crop yields driven by SILO observations (Obs-APSIM) to correct the simulated crop yields forced with NARCliM data (RCM-APSIM). Bias correction derived from 1990 to 2009 was applied to the two future periods (2020–2039 and 2060–2079). Consistent with bias-correction schemes for climate model data, we assume that the relationship between RCM-APSIM and Obs-APSIM would be the same for these future periods as for 1990–2009. The bias-correction method corrects both the mean and standard deviation of the RCM-APSIM yield to match the Obs-APSIM yield over the historical period (Hawkins et al. 2013). The corrections are made using Eq. 5.

$$X = \overline{X_{O,bl}} + \frac{S_{O,bl}\left(X_R – \overline{X_{R,bl}}\right)}{S_{R,bl}} \tag{5}$$

where X is the RCM-APSIM yield after correcting the mean and variability, $\overline{X_{O,bl}}$ is the corresponding time-mean Obs-APSIM yield for 1990–2009, $\overline{X_{R,bl}}$ is the RCM-APSIM mean yield for 1990–2009, and X_R is the RCM-APSIM yield for future time periods. $S_{O,\ bl}$ and $S_{R,\ bl}$ represent the standard deviation of RCM-APSIM output and Obs-APSIM output for the 1990–2009 baseline period. The simplified steps in the process of crop yield simulations under future climate change are shown in Fig. 2.

3 Results

3.1 Bias in climate variables during 1990–2009

In this section, we evaluate NARCliM simulations against SILO observation for the 370 study sites. Crop-growing season (April–November) bias in radiation, maximum temperature (Tmax), minimum temperature (Tmin) and rainfall for

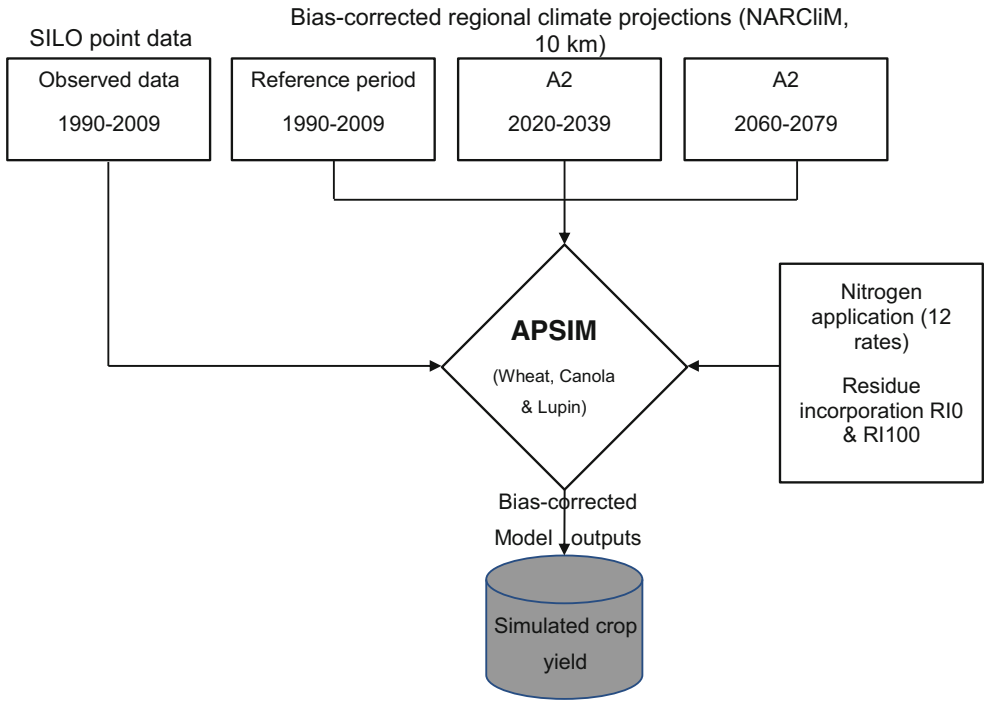


Fig. 2 The flowchart of crop yield simulation under regional climate projection and different agricultural management practices

370 sites are shown as boxplots in Fig. 3. The bias of climate variables in non-growing season (December–March) was included to compare the bias between different seasons. We also included the bias in intra-seasonal standard deviation (SD) to identify the difference in intra-seasonal variations for four climate variables.

It is clear that all RCMs overestimate the mean radiation and intra-seasonal radiation across the study region (Fig. 3a and e). The intra-seasonal SD of radiation (Fig. 3e) tended to have a greater overestimate in the pre-growing season than the growing season for almost all RCMs except EC-R1. Generally, the bias for seasonal maximum temperature and minimum temperature showed similar patterns (Fig. 3b and c). With respect to RCMs, the CS-R2 model had the greatest bias with an overestimation of + 0.8 °C and + 0.6 °C averaged across the 370 sites for non-growing season Tmax and Tmin, respectively. Three models, CS-R1, CS-R2 and CS-R3, underestimated growing season Tmax by − 0.2 to − 0.3 °C while they overestimated non-growing season Tmax by + 0.4 to + 0.8 °C (Fig. 3b). However, the median values of the bias in Tmax for other RCMs were small. Comparable results were found for Tmin (Fig. 3c). It is worth noting that all RCM projections had larger variation for both growing season Tmax and Tmin compared to observed values (Fig. 3f and g). In contrast, the variance of seasonal temperature in December–March was underestimated by the RCMs.

For seasonal rainfall, 9 RCMs (not CC-R1, CC-R2 and CC-R3) overestimated non-growing season rainfall by + 20 to + 50% but underestimated growing season rainfall by − 10 to − 20% (Fig. 3d). Similar results can be found for intra-seasonal variation. That is, CC-R1, CC-R2 and CC-R3 had less variation both in growing and in non-growing season compared to observed values (Fig. 3h). Based on these results, it is difficult to depict which model is the most accurate regional climate simulation. In reality, no one RCM performed well for the four crucial climate variables which determine crop yield. For example, the RCM model that predicts the best growing season maximum temperature (MI-R1) was also the one which projects the worst for seasonal rainfall.

3.2 Projected climate change

Future changes in 2030s and 2070s relative to the baseline period (1990–2009) mean radiation, Tmax, Tmin and rainfall for the growing and non-growing seasons are summarised in Fig. 4. We also included changes in intra-seasonal variance of four climate variables. It is apparent that changes in seasonal radiation were very small for each RCM relative to the baseline period (Fig. 4a). For example, averaged across all 12 RCMs, the ensemble-mean values for projected change in growing season radiation were only − 0.13% for 2030s and − 0.22% for 2070s. Similarly, non-growing season radiation showed a small decrease by − 0.53% in 2030s and − 0.51% in 2070s (Fig. 4a). However, for the two future time periods, a strong warming across the study region for all RCMs was observed (Fig. 4b–c). In particular, growing season Tmax was predicted to increase by + 0.6 °C and + 1.9 °C across all 12 RCMs over all 370 sites in 2030s and 2070s, respectively, with non-growing season Tmax increase by + 0.8 °C for 2030s and + 2.3 °C for 2070s (Fig. 4b). Similar warm trends

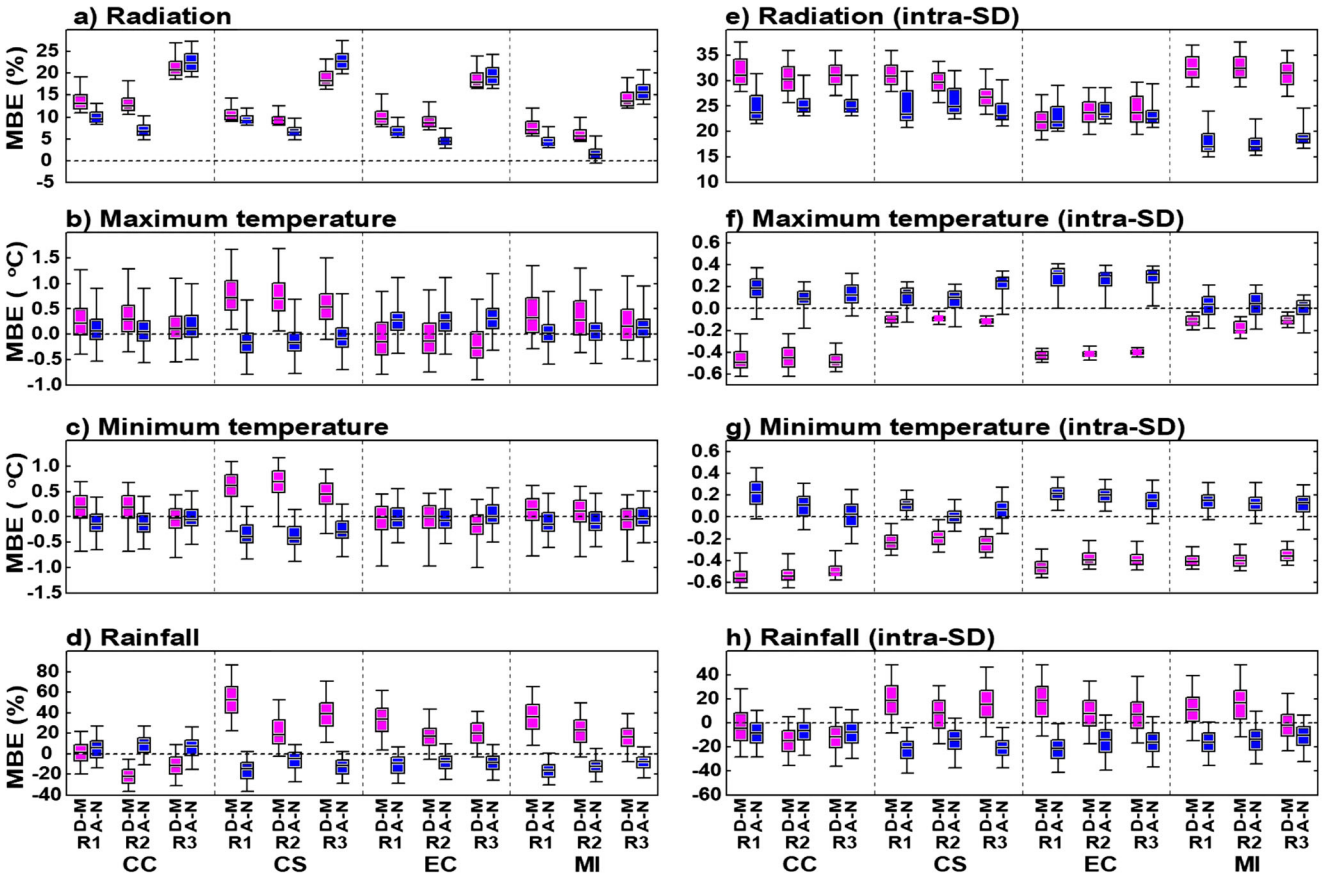


Fig. 3 Present-day (1990–2009) MBE for growing season (April–November, A-N, blue) and non-growing season (December–March, D-M, pink) radiation, maximum temperature, minimum temperature and rainfall for four GCMs (CC, CS, EC and MI) with three different configurations of R1, R2 and R3. The biases of intra-seasonal variation (standard deviation, SD) for these four variables were also included. Boxplot shows the distribution of biases based on 370 sites across the Murray-Riverina cropping region. Box boundaries indicate the 25th and 75th percentiles across 370 sites, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and within each box indicate the multi-site median values

could be found in Tmin with a greater increase in December–March (Fig. 4c).

Large growing season rainfall decreases across the region were observed for half of the 12 RCMs (e.g. CS-R1, CS-R2, CS-R3, EC-R1, EC-R2 and EC-R3) for 2070s, with more moderate decreases for 2030s (Fig. 4d). The other RCMs show increases in growing season rainfall across most of the region for 2070s and mixed small increases and decreases for 2030s. On average across all RCMs, growing seasonal rainfall was projected to decrease by −3.8% and −2.4% for 2030s and 2070s, respectively. It may be worthwhile to mention that increased rainfall occurred in non-growing season across most of the region in 11 RCMs for 2070s and 6 RCMs for 2030s (+5.8% for 2030s and +13% for 2070s).

The variance of future growing season radiation did not appear to change relative to baseline (Fig. 4e); however, the change of the variance of non-growing seasonal radiation varied greatly among RCMs in two future time periods. Almost all RCMs projected increased intra-seasonal variances in temperature (Fig. 4f and g). In contrast, there were large differences in the change of intra-seasonal rainfall variability for RCMs and different parts of the region (Fig. 4h).

3.3 Bias in simulated crop yield during 1990–2009

Figure 5 compares RCM-APSIM-simulated crop yields and Obs-APSIM-simulated yields for the two contrasting crop residue incorporation options (RI0 and RI100) and 12 nitrogen applications. A large bias was observed when using regional climate models (e.g. CS-R1, CS-R2, CS-R3, EC-R1, EC-R2, EC-R3, MI-R1, MI-R2 and MI-R3) to drive the crop model compared to using observed climate data. It is interesting to note that most of RCMs underestimated crop yields across different treatments. However, the magnitude of MBE was dependent on crop type, residue incorporation, nitrogen rates and RCM models. For the three crops, the largest MBE occurred in wheat, followed by canola and lupin.

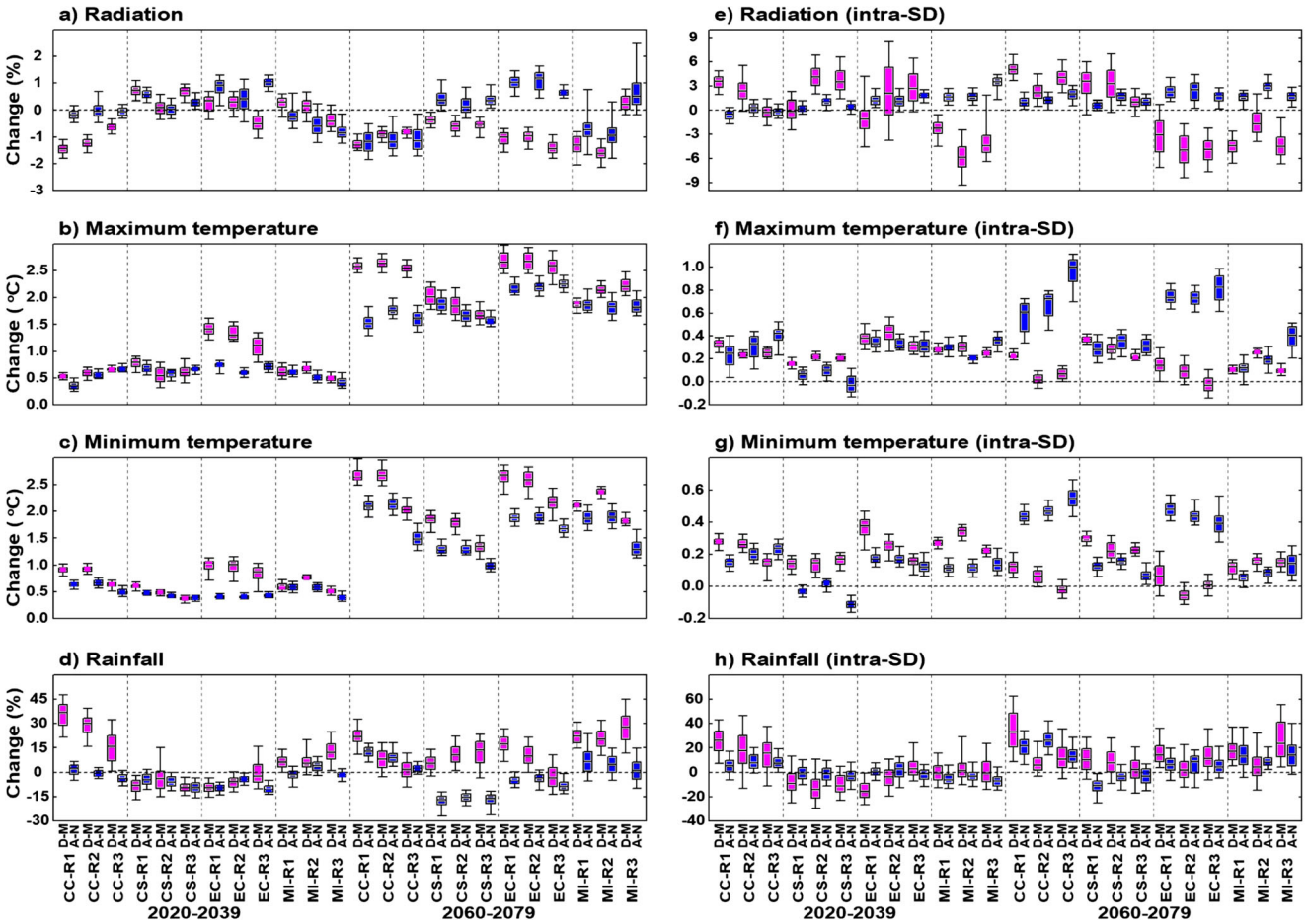


Fig. 4 Projected changes in growing season (April–November, A-N, blue) and non-growing season (December–March, D-M, pink) mean radiation, maximum temperature, minimum temperature and rainfall for four GCMs (CC, CS, EC and MI) with three different configurations of R1, R2 and R3. The changes of intra-seasonal variation (standard deviation, SD) for these four variables were also included. Boxplots show the distribution of changes in 20-year mean values and SD in 2020–2039 (2030s) and 2060–2079 (2070s) relative to 1990–2009 for each of the 12 RCMs. Box boundaries indicate the 25th and 75th percentiles; the black line within the box marks the median; whiskers below and above the box indicate the 10th and 90th percentiles

Overall, N application increased the yield MBE, likely due to less water use and consequently less N obtained by wheat and canola. It is worth noting that nitrogen application had no significant effects on MBE for lupin perhaps due to its nitrogen fixation. Furthermore, crop residue incorporation had a small contribution to the bias between RCM-driven and observation-driven yields for all three crops, though residue incorporation may improve soil conservation and moisture retention. Comparable results could be found in MBE of inter-annual variation of yields for three crops for each RCM under different agronomic practices during 1990–2009 (Fig. 6).

We used a simple post-processing method to correct bias in the RCM-driven crop yields (Eq. 5). The results with bias correction were evaluated over the present climate 1990–2009. The resulting distributions of rain-fed crop yield for all sites and years in 1990–2009 are shown in Fig. 7. For most cases, using non-bias-corrected input produced a yield distribution more skewed towards low yields than the distribution for Obs-APSIM simulations. For example, for wheat, the occurrence of yields lower than approximately 2200 kg ha^{-1} was greater for the RCM-APSIM simulations than for the Obs-APSIM simulation but the occurrence of yields more than 3000 kg ha^{-1} was lower (Fig. 7a). Similar distributions were found in canola and lupin except four GCMs for the R3 RCM for canola (Fig. 7c and e). Although the distributions are still not identical, applying our simple bias correction resulted in yield distribution largely consistent with those generated by historical observations (Fig. 7b, d and f).

3.4 Projected crop yield change

Future changes in the bias-corrected yields were assessed for each of the different combinations of residue incorporation and nitrogen application for each of the 2030s and 2070s.

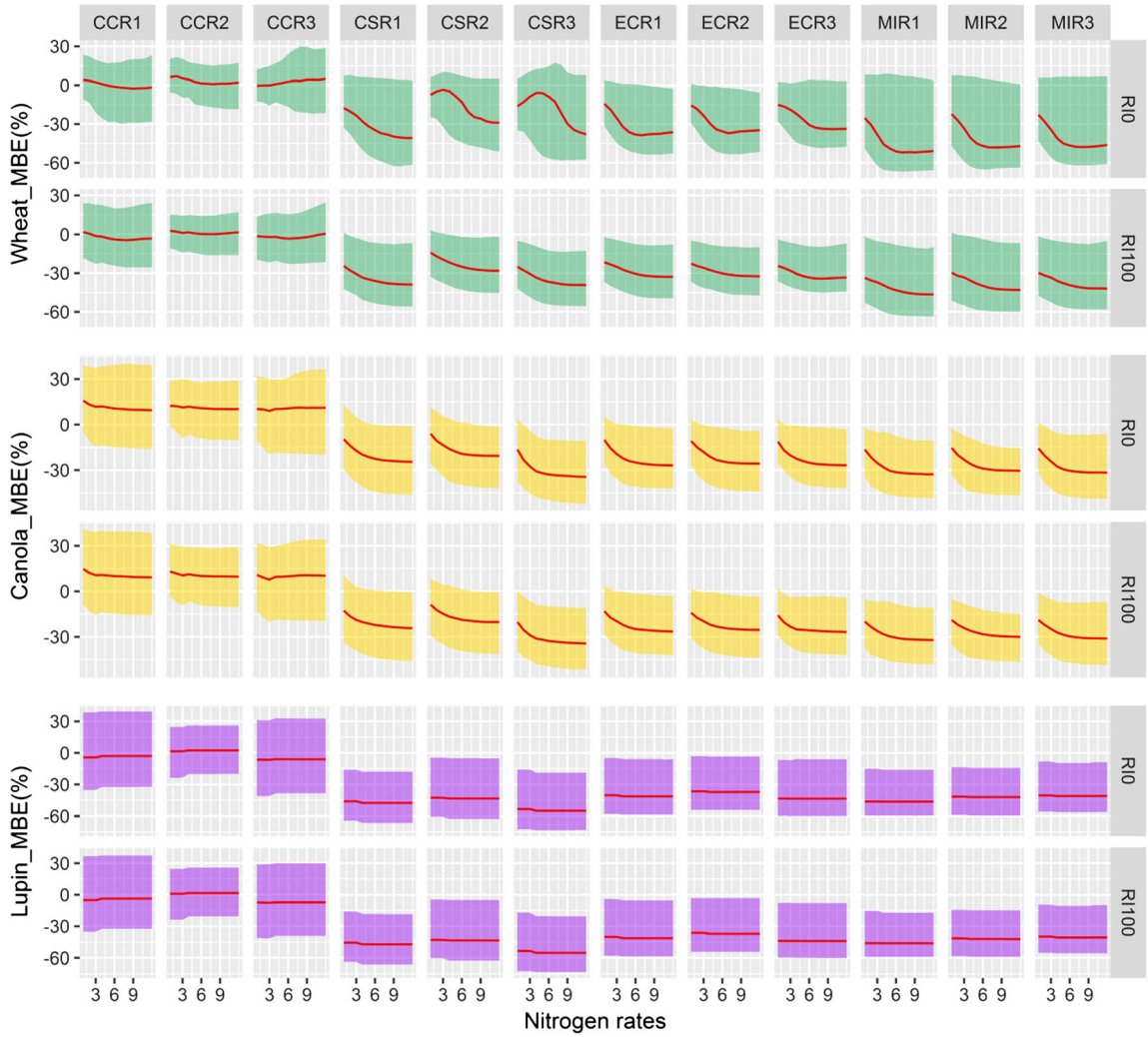


Fig. 5 The 10 (below red line), 50 (red line) and 90 percentiles (above red line) of mean bias error (MBE, %) of mean crop yields (wheat, canola and lupin) during 1990–2009 simulated by the APSIM driven by 12 RCMs of NARCliM projections and observed climate data based on 370 sites across MRC region associated with two residue incorporation rates (RI0, 0%, and RI100, 100%) and 12 N-application rates

Changes in crop yields were presented as the baseline mean (1990–2009) subtracted from the future mean 2030s and 2070s. Figures 8, 9 and 10 show the NARCliM ensemble-mean yield changes for three crops at RI0 and RI100 and different N applications over the MRC region. Only four N applications (N1, N3, N6 and N9) are presented for the sake of simplicity. The simulated change in future crop yields varied across the MRC study region. Overall, under the A2 emission scenario, the ensemble-mean yield for the three crops across the region was predicted to increase for both future time periods in comparison with the baseline period (Figs. 8, 9 and 10). The magnitude of increase in ensemble-mean crop yields was larger in the far future due to the higher CO_2 concentration offsetting any negative impacts.

For wheat, spatial maps of simulated ensemble-mean yield based on 12 RCMs showed a more pronounced increase in 2070s occurred in the western area of MRC than those in the eastern area (Fig. 8). When residue was completely removed in the model and nitrogen application was at N1 treatment, wheat ensemble-mean yield was projected to increase by + 2.6% and + 10.5% in response to climate change by the 2030s and 2070s, respectively (Fig. 8a and b). Such increase is likely to be caused by the combined impacts of varied growing season rainfall, increased temperature and elevated CO_2 concentrations. However, the percentage change in yield increased with the increased rate of nitrogen application in most cases, especially when 100% residue incorporation was included (Fig. 8). This is likely due to crop residue incorporation increasing soil porosity and reducing water evaporation. The largest percentage increase of + 24.9% for wheat yield was found in 2070s with high amount of N and 100% RI (Fig. 8p).

For canola, different treatments had little effect on the response of yield to climate change, though the simulated ensemble-mean yield increased more in the far future 2070s (Fig. 9). Specifically, N application and RI had limited contribution to yield increase in each time period. For example,

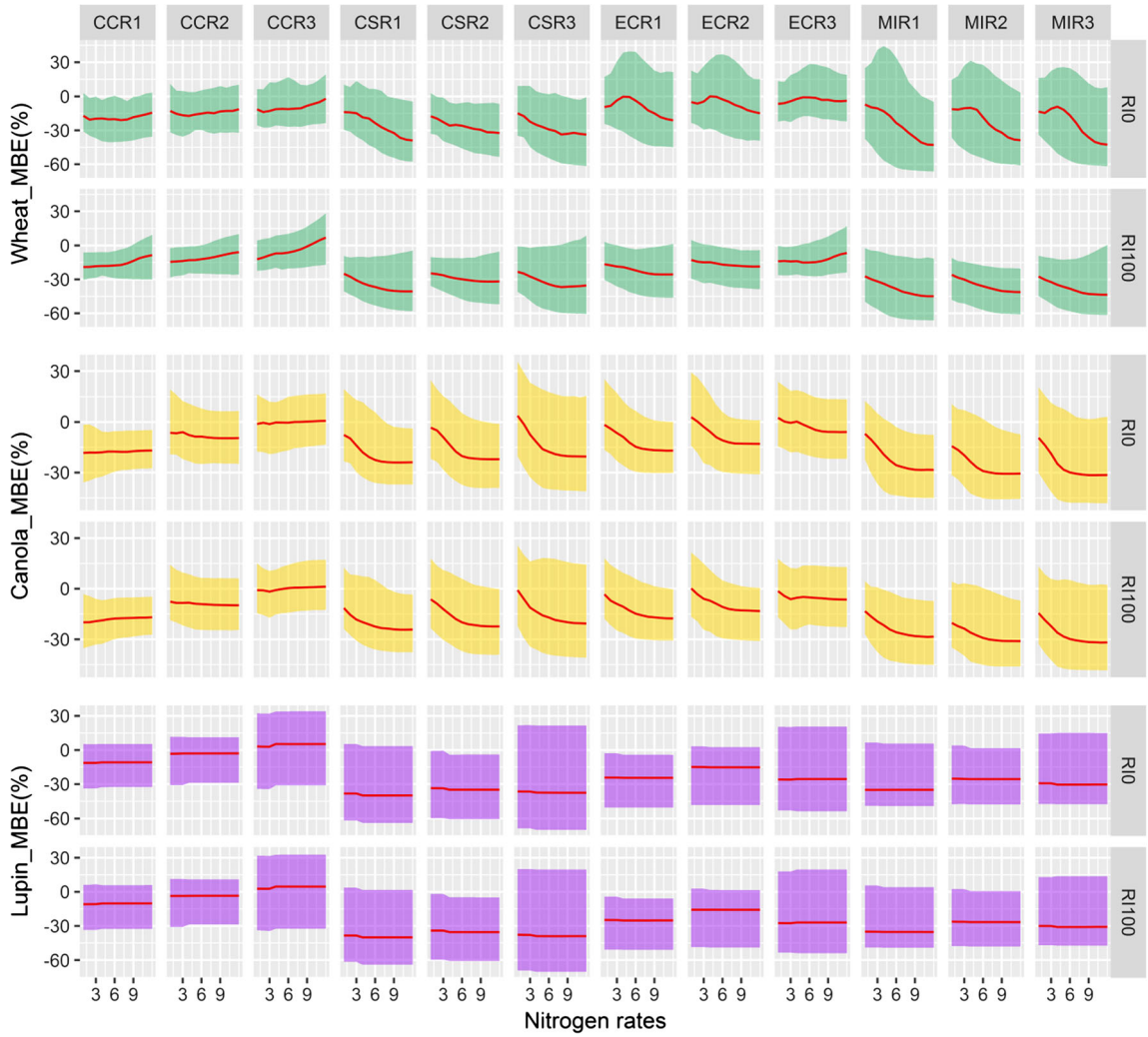


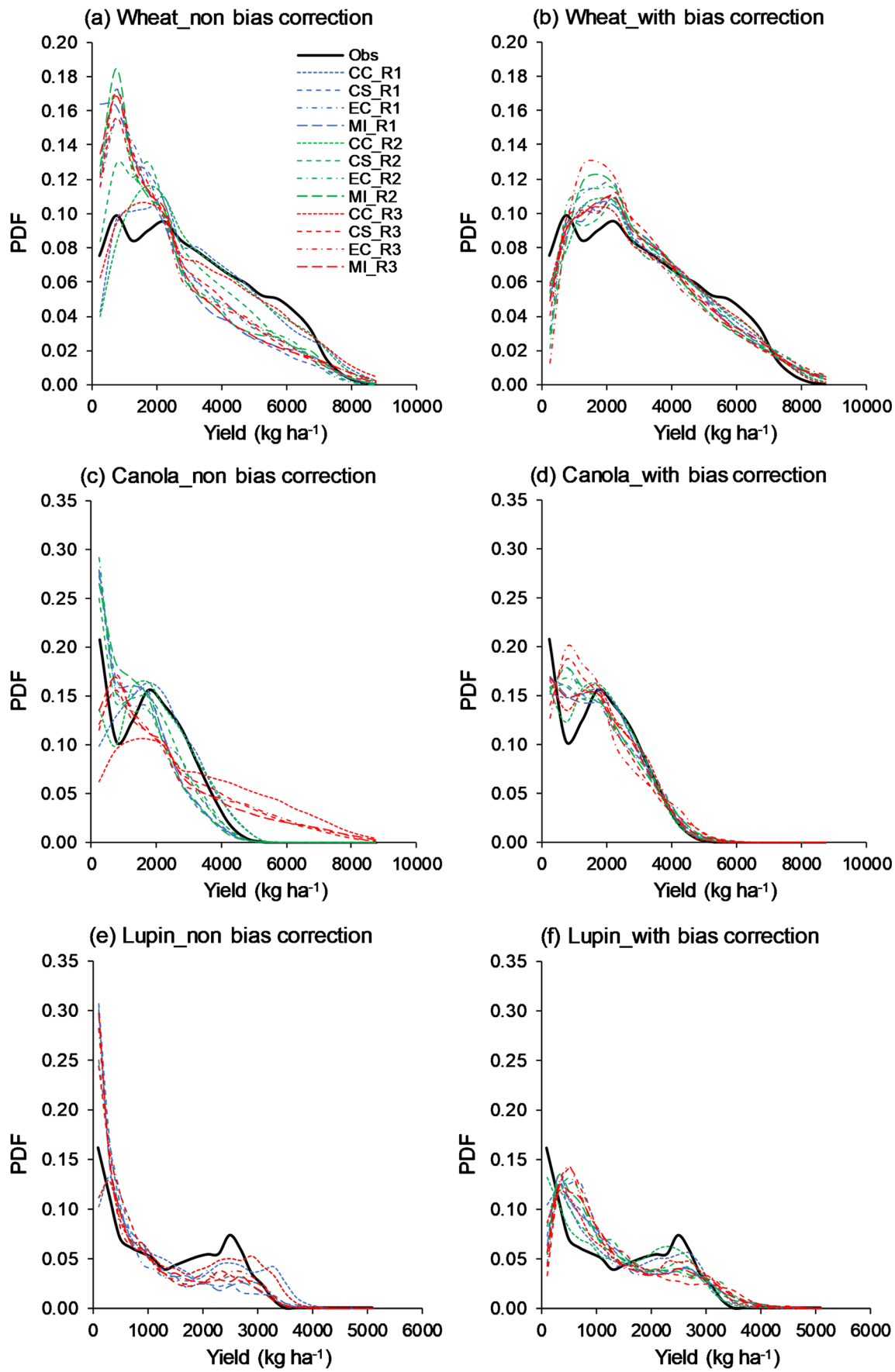
Fig. 6 The 10 (below red line), 50 (red line) and 90 percentiles (above red line) of mean bias error (MBE, %) of crop (wheat canola and lupin) yields inter-annual variation (standard deviation, SD) during 1990–2009 simulated by the APSIM driven by 12 RCMs of NARCliM projections and observed climate data based on 370 sites across MRC region associated with two residue incorporation rates (RI0, 0%, and RI100, 100%) and 12 N-application rates

canola yield only increased from + 34.7 to + 39.4% in response to climate change by the 2070s when N was increased from 16 kg ha^{-1} (N1) to 272 kg ha^{-1} (N9) at 100% RI (Fig. 9d and p). For lupin, it was unsurprising that yield had a small response to nitrogen increase, as this crop can fix N, although averaged ensemble-mean yield was expected to increase by + 5.0% in the 2030s to + 29.5% in the 2070s across the MRC region with little response to residue incorporation (Fig. 10).

3.5 The relationship between climate change and crop yield

We included the changes in 20-year means of climate variables and elevated CO_2 concentrations in a multiple linear regression model to identify the contribution of these variables to crop yield change as shown in Ruan et al. (2018) and Anwar et al. (2015). Based on this regression analysis, the relative contribution of each climate variable to yield change is able to be uncovered. For all three crops, the change in yield was significantly positively correlated with future rainfall change and the magnitude of impact increased gradually from wheat, canola and lupin (Table 1). For example, there was a significant ($p < 0.01$) + 0.86% grain yield change for wheat for one percentage change in rainfall in comparison with significant ($p < 0.01$) + 1.06% and 1.30% grain yield change for canola and lupin, respectively. It was evident that the change in yield for the three crops was

Fig. 7 Probability distribution (PDF) of 1990–2009 APSIM-simulated yields driven by historical observed climate data (black solid line) and 12 RCMs climate data with non-bias-corrected values and bias-corrected values by mean and variation correction method. Bias-correcting yield largely eliminated the distributional discrepancies against the yield driven by observed climate


(a) Wheat_non bias correction
(b) Wheat_with bias correction
(c) Canola_non bias correction
(d) Canola_with bias correction
(e) Lupin_non bias correction
(f) Lupin_with bias correction
Obs
CC_R1
CS_R1
EC_R1
MI_R1
CC_R2
CS_R2
EC_R2
MI_R2
CC_R3
CS_R3
EC_R3
MI_R3
PDF
Yield (kg ha-1)

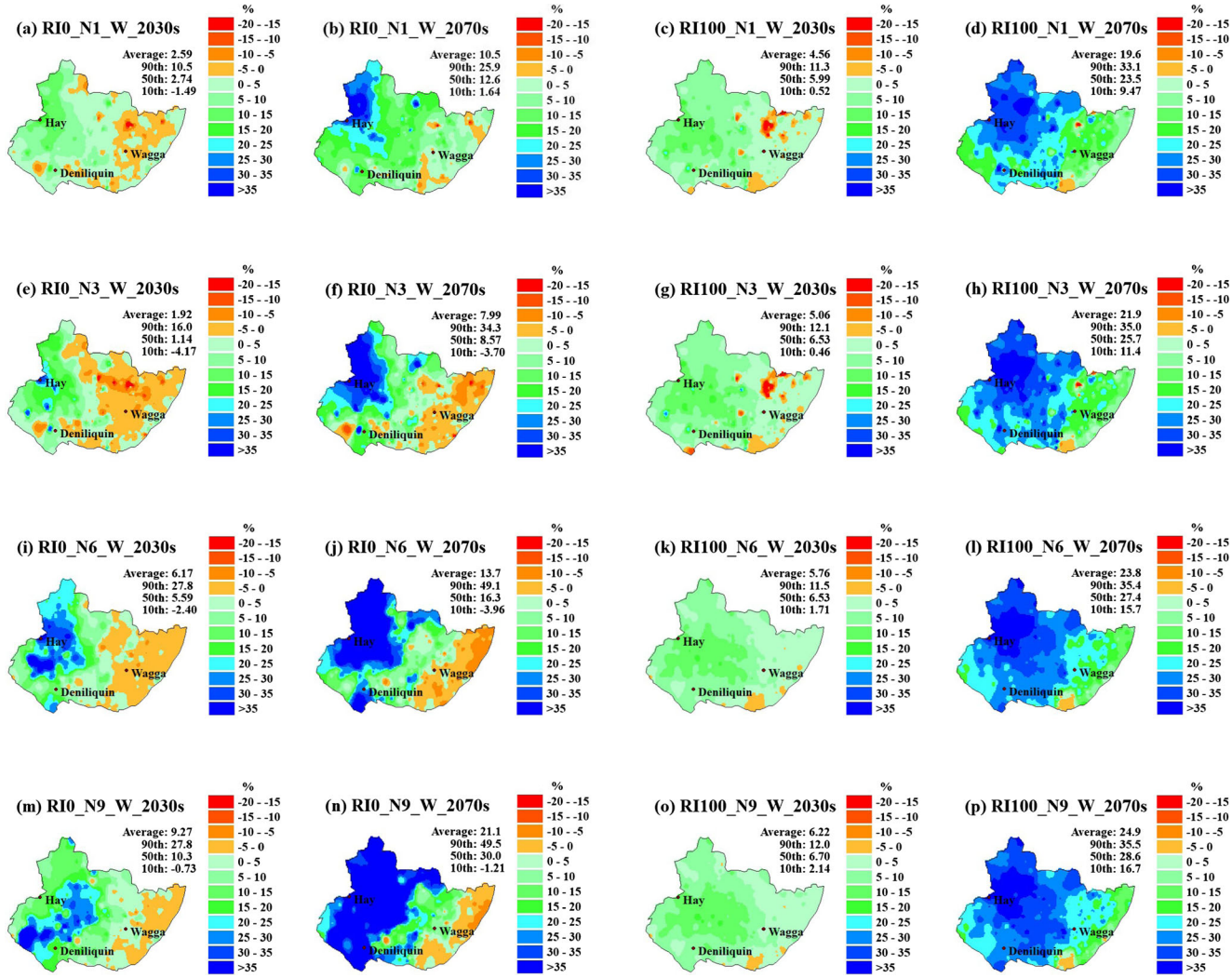


Fig. 8 Projected changes in ensemble-mean wheat (W) yield based on 12 RCMs at two contrast residue incorporation (RI0, 0%; RI100, 100%) and four N-application (N1, N3, N6 and N9) in 2030s and 2070s compared to 1990–2009 over the MRC region

negatively correlated to the change in future growing season radiation, but the magnitude of these effects depended on crop types. The negative correlation between the yield and radiation is due to a positive correlation between yield and rainfall and a negative correlation between solar radiation and rainfall as shown in Wang et al. (2015). In addition, growing season Tmax and Tmin had a combined negative effect on wheat and lupin yield, but a small effect was found in canola. It is unsurprising that crop yields benefited significantly from CO_2 fertilisation, because APSIM mimics the effects of CO_2 fertilisation through an increase in transpiration efficiency.

4 Discussion

4.1 Biases from RCM models

In this study, we assessed the suitability of the NARCliM data for driving a crop model in part of eastern Australia. Although very limited climate impact studies on crop productivity analyse the error produced by different downscaling methods in Australia (Liu et al. 2017a), we found that NARCliM data is likely to introduce a large dispersion on simulated crop yields. This is consistent with the findings of Macadam et al. (2016) which showed the biases in simulated yields for different high-resolution products of NARCliM. The dispersion arising from crop model simulations was mainly due to the bias in climate variables, especially in rainfall events. For example, Liu et al. (2018) found that the MBE of NARCliM rainfall was generally positive for rainfall probability and negative for intensity, which subsequently resulted in APSIM simulating negative biases for runoff and deep drainage and positive bias in soil evaporation. Bias in soil water balance and water availability inevitably resulted in less plant transpiration and less N uptake, which ultimately leads to large negative biases in crop yields. Nevertheless, this bias in climate variables is largely inherited from the GCMs because the NARCliM simulations driven by the same GCM had similar biases for relevant

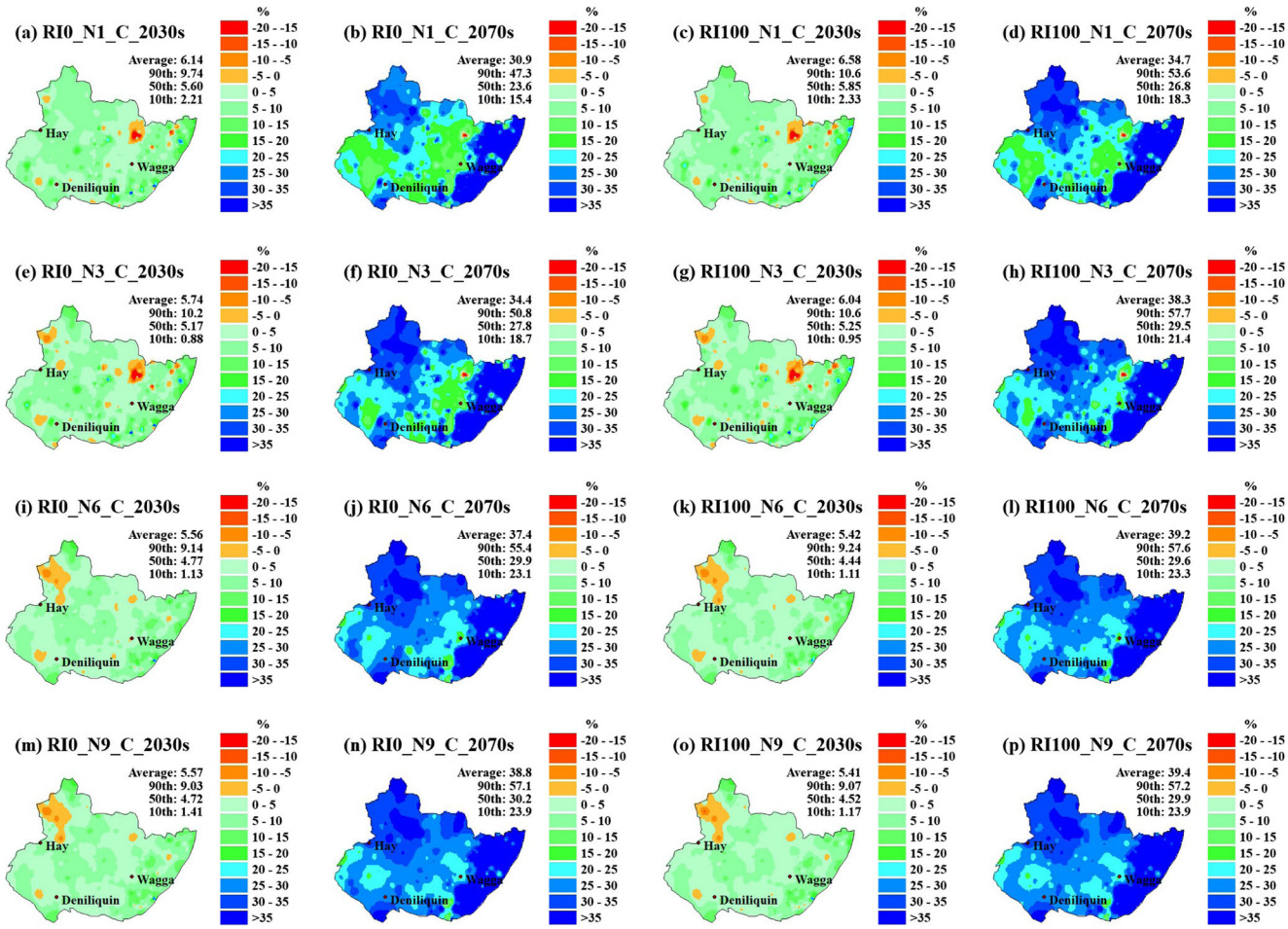


Fig. 9 Projected changes in ensemble-mean canola (C) yield based on 12 RCMs at two contrast residue incorporation (RI0, 0%; RI100, 100%) and four N-application (N1, N3, N6 and N9) in 2030s and 2070s compared to 1990–2009 over the MRC region

aspects of the climate (Macadam et al. 2016). Thus, some studies have suggested that it is possible to bias-correct the GCM or reanalysis forcing data prior to regional climate simulation (Colette et al. 2012; Hwang et al. 2014).

Our results show that there are relevant biases in NARCliM climate data. Although they have used a quantile matching technique to correct the full distribution of daily rainfall, Tmax and Tmin at an annual scale, Liu et al. (2018) found that existing post-bias correction in NARCliM data does not produce adequate climate projections that can be directly used for the assessment of climate change in agricultural studies; thus, post-bias correction of the RCM outputs on a seasonal or monthly basis should be focused to improve the RCM simulations. It is more obvious that there were biases in the radiation data as this is not bias-corrected in NARCliM data. Despite crop growth is mainly water-limited in this dry rain-fed condition, solar radiation is also important for crop biomass and yield formation (Wang et al. 2015; Yu et al. 2014). Since crop simulation models require daily climate data as inputs, the MBE of intra-seasonal SD in radiation and rainfall is likely to intensify simulated yield bias (Cammarano et al. 2013; Liu et al. 2017a). Macadam et al. (2014) concluded that growing season rainfall bias in NARCliM is mainly responsible for yield bias due to the strong relationship between rainfall and yields. Further findings from our study indicate that the magnitude of the MBE depends on the choice of crop, location and agricultural management practices. For example, the yield bias became larger with increasing nitrogen application rates for wheat and canola. Therefore, due to the aggravated bias in N application, special attention should be drawn when using regional climate modelling data for historical yield analysis and future climate change impact assessments with nitrogen-fertiliser management.

Bakker et al. (2014) suggests that the use of RCM output only makes sense after sufficient bias correction because such climate simulations contain large bias as regards the average and variation for most relevant climate variables. These biases are likely to result in some inaccurate effects on crop yield projection (Liu et al. 2018; Macadam et al. 2016), leading to uncertainties in the impacts of climate change. Numerous studies have applied different bias-correction methods to reproduce the mean and

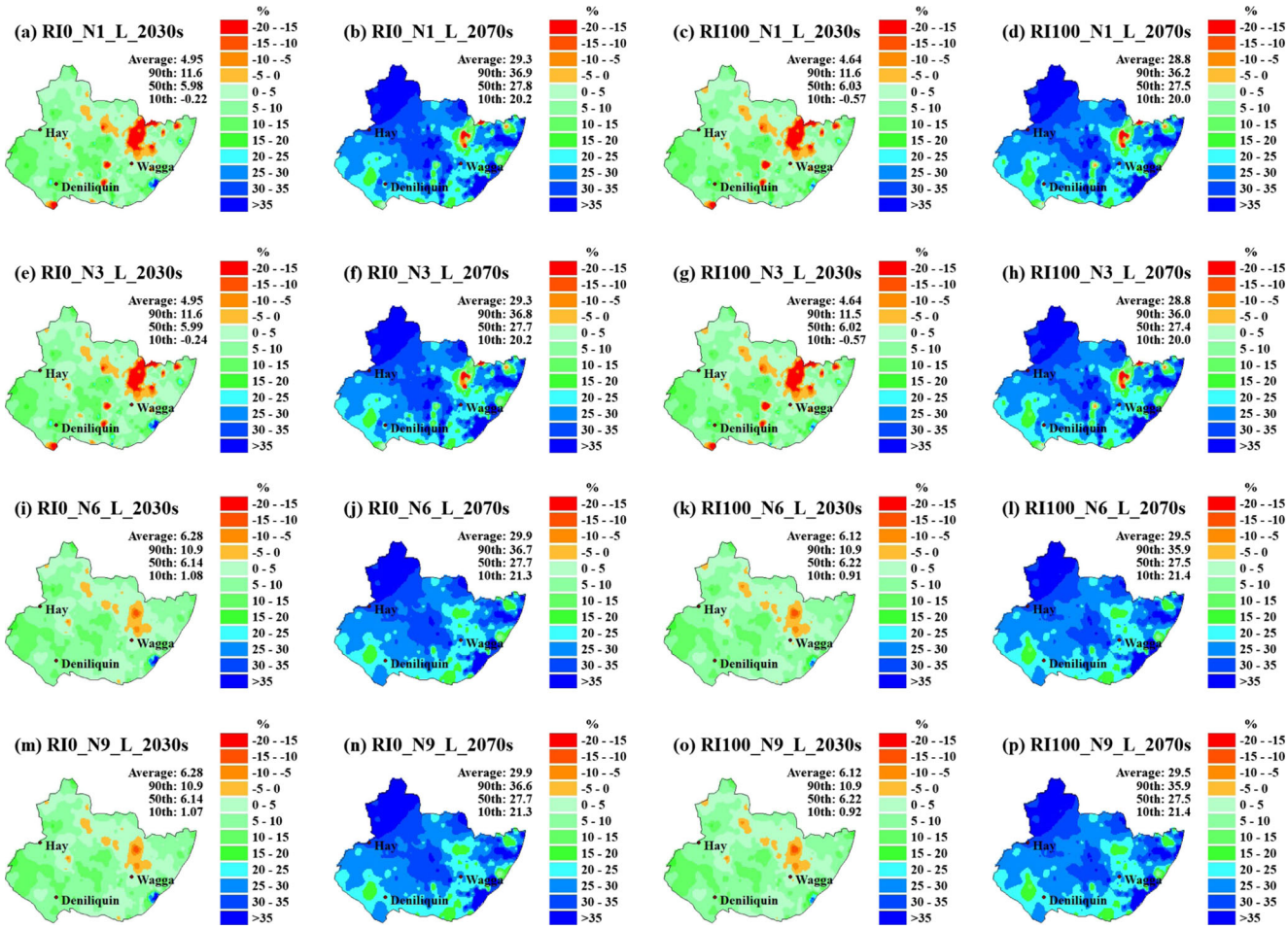


Fig. 10 Projected changes in ensemble-mean lupin (L) yield based on 12 RCMs at two contrast residue incorporation (RI0, 0%; RI100, 100%) and four N-application (N1, N3, N6 and N9) in 2030s and 2070s compared to 1990–2009 over the MRC region

variability of climate features produced by RCM before running a crop model (Bakker et al. 2014; Liu et al. 2014b; Pascal et al. 2011; Ruiz-Ramos et al. 2016). These authors suggest better results are obtained for simulated crop yields compared with uncorrected RCM simulations. However, the quality of adjusted RCM rainfall and temperature strongly relies on the choice of the correction algorithm both for historical and for future climate conditions (Teutschbein and Seibert 2012). In our study, as well as using bias-corrected climate data, we tested a simple bias-correction method which was applied to APSIM-simulated yields driven by climate data from 12 different GCM-RCM combinations. Our present results indicate that post-processing technique to correct the mean and variability of simulated yield seems a promising approach for improving the results, which has been further tested in the study of Liu et al. (2018). It is worth mentioning that at the very least, post-processing method makes baseline yields for different climate model simulations similar, making it more meaningful to couch climate change results in terms of percentage changes in yield. However, some of the bias can be corrected using statistical methods, while some cannot. We also assumed that the bias in the average and variability are constant for the control and future periods (Bakker et al. 2014).

Table 1 The coefficients of the multiple regression analysis of the APSIM-simulated yield change (ΔY, %) as a function of changes in growing season mean radiation (ΔRad, %), mean maximum temperature (ΔTmax, °C), mean minimum temperature (ΔTmin, °C), rainfall (ΔRain, %) and CO_2 concentrations (ΔCO_2, 100 ppm). The model was showed in form of $\Delta Y = a\Delta\text{Rad} + b\Delta\text{Tmax} + c\Delta\text{Tmin} + d\Delta\text{Rain} + e\Delta CO_2$. All regression coefficients were significant ($p < 0.01$)

Crop	a	b	c	d	e	R^2
Wheat	− 1.39	− 10.75	− 2.67	0.86	12.63	0.63
Canola	− 0.27	1.21	− 0.80	1.06	11.49	0.78
Lupin	− 0.28	2.48	− 6.39	1.30	15.75	0.60

4.2 Impact of future climate on crop yields based on RCMs

Some of the results based on climate change impact analyses in the present study are consistent with those reported in recent studies which explored simulated yield changes in eastern

Australia using statistically downscaled climate data. For example, Wang et al. (2017) used statistically downscaled daily climate data based on 13 CMIP5 GCMs to evaluate the effects of future climate change on the NSW crop belt. They found that wheat yield could increase by 0.2–9.0% by 2061–2100 relative to 1961–2000 for the wheat belt. Although RCP4.5-driven simulations presented a little decrease of wheat yield in the south-western parts of the study area, the higher CO_2 concentration in higher emission scenarios could offset any adverse impacts, leading to a yield increase of 12.6% in RCP8.5 in the north-western parts of the wheat belt. Nevertheless, some studies have found negative effects as a result of climate change in similar environmental conditions. Yang et al. (2014) showed that by 2050 wheat yields were likely to be reduced by 2–5% for some sites in eastern Australia. In addition, Anwar et al. (2015) reported that the effects of future climate on crop yields were not consistent among crops and sites over Australia. Of the crops in their study, lupin was vulnerable to the future climate change and its yield declined from 3 to 13%, depending on the location. These previous results based on different studies indicate the underlying uncertainties in climate change impact analyses in the study region. Possible reasons for such results may include the use of relatively short time periods for historical analysis (1990–2009) and the uncertainty inherent in regional climate models used for climate impact simulations.

Due to the positive effects of higher atmospheric CO_2 concentration on plant photosynthesis, increases in productivity for three crops under different management practices were identified for two future time periods across the MRC region. Our results suggested that APSIM model was sensitive to the CO_2 fertilisation effect, notably offsetting the detrimental climate change impacts on crop yields. For example, the yield of wheat, canola and lupin increased by 12.6%, 11.5% and 15.8% $(100\ ppm)^{-1}$ in response to elevated CO_2 concentrations in our multiple linear regression models, respectively. These results are comparable to previous studies in rain-fed conditions (Sultan et al. 2014; Wang et al. 2011, 2017). On the other hand, recent analyses of Free-Air CO_2 Enrichment (FACE) experiments show that observed wheat yield will increase by 26% under unstressed conditions when atmospheric CO_2 concentration is at 550 ppm, above current CO_2 concentration by 185 ppm in Australian dry farmland (Fitzgerald et al. 2016; O'Leary et al. 2015). Verrillo et al. (2017) reported that elevated CO_2 concentrations and interaction with other environmental factors are likely to affect agronomic performance by increasing production but negatively impacting grain quality. The response of crop growing to elevated CO_2 concentration in the APSIM model is based on radiation use efficiency and transpiration efficiency (Reyenga et al. 1999). However, stomatal resistance increases with elevated atmospheric CO_2 concentrations, which in turn increases canopy temperature, resulting in an amplification of leaf senescence and possible shortening in the length of the growing period (Raymundo et al. 2017). This process is not considered in the current crop model. Therefore, a contribution of elevated CO_2 concentration cannot be directly quantified without further examination based on more field experiment data.

Although we report an overall increasing trend of projected yields for three crops in the MRC region, the magnitude of projected change largely depends on crop types and the geographic location. The most pronounced yield increment occurs in canola, followed by lupin and wheat. Spatially, the projected increase for wheat yield in the western MRC is larger than that in the eastern MRC region. Results from our study also show that residue incorporation and N application are management practices that may have a large effect on percentage wheat yield increases due to future climate change. However, these management practices have a small effect on the responses of canola and lupin yield to climate change. This agrees with the finding of Liu et al. (2017b) which demonstrated that the average yield increased from RI0 to RI100 in the future period (2021–2100) was 43% for wheat, 13% for canola and 3% for chickpea. The use of N fertilisation may be a very useful option to mitigate climate change effects, but will also increase farm input costs, therefore potentially increasing risk to enterprise profitability. By contrast, residue incorporation can be an effective adaptation measure for mitigating the impacts of climate change on winter crops by improving water use efficiency (Liu et al. 2017b). Lower fuel and labour costs, as well as improved soil conservation and moisture retention, are the most acceptable reasons for the adoption of conservation agriculture by Australian farmers (Kirkegaard et al. 2014; Liu et al. 2017b).

4.3 Uncertainty

Previous studies have assessed the impact of climate change on agricultural production and food security with and without adaptation options, but results varied largely because of differences in climate projections, crop models, emission scenarios and input data incorporated along the entire modelling chain (Adhikari et al. 2016; Dettori et al. 2017; Katharina et al. 2015; Teixeira et al. 2018; Vanuytrecht et al. 2014; Yang et al. 2017). It is worth noting that pests and diseases related to climate and crop management practices are not simulated by the APSIM model. The susceptibility of extreme weather events, such as heat stress and seasonal drought, are not considered either. Our projected climate change impacts heavily rely on the coupled GCM/RCM outputs in the study area and emission scenarios. Further studies are warranted, as uncertainties associated with crop model and climate scenarios are large (Asseng et al. 2013; Osborne et al. 2013). Using a large number of climate projections, different downscaling approaches, crop models and various bias-correction algorithms is recommended to provide a more reliable yield

simulations under future climate change. This will assist in more fully sampling uncertainty and in developing rigorous adaptation measures to climate change for crop production in south-eastern Australia.

5 Conclusion

This study presents future change in crop yields simulated by APSIM forced with the NARCliM regional climate ensemble across the MRC region in eastern Australia. Although high-resolution NARCliM data were employed to project climate change impact on crop productivity, it was not sufficiently accurate to simulate observed averages and variability of crop-growing season rainfall, temperatures and radiation, and existing bias-corrected datasets did not eliminate this problem. As a result, there were situations where the yield simulated by NARCliM climate data substantially differentiated from that simulated using observed climate data. In addition, yield bias increased with increasing nitrogen application for wheat and canola. We found that the bias correction of crop model outputs appeared to be a reliable and promising approach for the assessment of impact of climate change on crop yield. However, more bias-correction techniques still need to be explored to reduce or remove the bias hidden behind NARCliM climate data.

We projected that future climate change would have positive effects on three crops in the MRC region due to the fertilising effect of elevated CO_2 content and its interaction with climate variables. However, the spatiotemporal change of crop yields is likely to be highly dependent on the climate scenario applied and on the downscaling method and bias-correction technique used. It is interesting to note that residue incorporation and nitrogen application had a large effect on percentage change in wheat yield under future climate change, but had limited effects on the response of lupin and canola yields. Therefore, a wide range of management practices, such as using new cultivars and changing sowing date, need to be further tested to deal with climate change. Based on NARCliM climate data, we believe this study would provide some useful information for local farmers and policy makers with respect to evaluating the impacts of climate change on three major crops in south-eastern Australia. Still, there are plenty of work (e.g. more work on representing the effect of bias-correction method, climate extremes or elevated CO_2 in APSIM) to be done to increase our confidence in accurately projecting future yield change.

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