

Necessity for post-processing dynamically downscaled climate projections for impact and adaptation studies

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Abstract This work aims to answer if post-processing climate model outputs will improve the accuracy of climate change impact assessment and adaptation evaluation. To achieve this aim, the daily outputs of CSIRO Conformal Cubic Atmospheric Model for periods 1960–1979, 1980–1999 and 2046–2065, and observed daily climate data (1960–1979, 1980–1999) were used by a stochastic weather generator, the Long Ashton Research Station-Weather Generator to construct long time series of local climate scenarios (CSs). The direct outputs of climate models (DOCM) and CSs were then fed into the Agricultural Production System sIMulator—Wheat model to calculate seasonal climate variables and production components at three locations spanning northern, central and southern wheat production areas in New South Wales (NSW), Australia. This study firstly compared the differences in climate variables and production components derived from DOCM and CSs against those from observed climate for period 1960–1979. The impact difference arising from the use of DOCM and CSs for the future period 2046–2065 was then quantified. Simulation results show that (1) both the median/mean and distribution/variation of climate variables and production components associated with CSs were closer to those derived from observed climate when compared to those from DOCM in most of the cases (median/mean, distribution/variation, climate variables, production components and locations); (2) the difference in the mean and distribution of climate

variables and production components derived from DOCM and observed climate was significant in most of the cases; (3) longer dry spells in both winter and spring were found from CSs across the three locations considered in comparison with those from DOCM; (4) the median growing season (GS) rainfall total, GS average maximum temperature, GS average solar radiation, GS length and final wheat yield were lower from DOCM than those from CSs and vice versa for GS rainfall frequency and GS average minimum temperature in 2055; (5) the mean and distribution of these climate variables and production components arising from the use of DOCM and CSs are significantly different in most of the cases. This implied that using the direct outputs of spatially downscaled general circulation model without implementing post-processing procedures may lead to significant errors in projected climate impact and the identified effort in tackling climate change risk. It is therefore highly recommended that post-processing procedures be used in developing robust CSs for climate change impact assessment and adaptation evaluation.

Keywords Direct outputs of climate model · Climate scenarios · Post-processing techniques · Climate components · Wheat production components

1 Introduction

Even though climate change impact assessment and adaptation evaluation have been studied for over 30 years, confusion still exists between climate projections (CPs) and climate scenarios (CSs). The former refers to the direct outputs of climate models (DOCM) including global and regional climate models (GCMs/RCMs). CSs are based on CPs but with post-processing procedures implemented such

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as through the use of stochastic weather generators to link with historical climate characteristics to reduce the bias of GCMs/RCMs. Normally, longer time series (e.g. 100, 300 years etc.) of CSs are constructed based on 20 or 30 years' CPs. The difference between CPs and CSs was first introduced in the Third Assessment Report of the Intergovernmental Panel for Climate Change (IPCC 2001, chap. 3).

Nowadays, spatially and temporally downscaled daily outputs of GCMs are available, which are in line with the temporal resolution of most crop models, but they cannot be directly used by crop models for climate change impact assessment and adaptation evaluation due to climate model biases and poor performance of GCMs at such temporal scale (Carter et al. 1994; Mearns et al. 1990, 1995; Goddard et al. 2001; Luo and Yu 2012; Teutschbein and Seibert 2012). This is especially so for dynamically downscaled outputs of GCMs when compared with statistically downscaled outputs of GCMs. Luo et al. (2013) evaluated the performance of downscaled outputs of GCM against observed climate datasets and found that there were significant differences between modelled and observed climate in some months especially associated with rainfall. Post-processing techniques such as the use of a delta approach, cumulative probability function (CPF) and stochastic weather generators [i.e. Long Ashton Research Station-Weather Generator (LARS-WG), WGEN] were used to circumvent the issues mentioned above. The delta approach is a simple way for correcting climate model biases. Normally, seasonal or monthly mean changes are used to perturb historical climate records to construct local CSs (e.g. Luo and Kathuria 2013; Ouyang et al. 2015 and many others). It should be noted that this method only considered changes in mean climate but not changes in climate variability. Baigorria et al. (2007, 2008) corrected GCM biases associated with hindcast rainfall, temperature and solar radiation based on the CPF approach and quantified the impact of bias correction on maize yield in southeast USA. Specifically, bias correction was applied to a 2-parameter Gamma CPF for rainfall (Ines and Hansen 2006), Beta distribution for solar radiation and Gaussian distribution for temperature. As noted in Ines and Hansen (2006) itself, the bias correction procedures they adopted are unable to recover the observed autocorrelation, and in some instances they can even lead to a deterioration of the statistical properties of the original forecasts (Calanca et al. 2011). Shao and Li (2013) used quantile–quantile transform approach to improve GCM-based rainfall forecasting information in Australia. Wang et al. (2015) examined the spatial and temporal variations of hydro-climatic variables to climate change with climate model biases corrected by using the quantile–quantile transform approach. Mishra et al. (2013) corrected biases in projected rainfall

frequency, intensity and time structure by using both the CPF approach and a stochastic weather generator in the context of crop simulation.

Stochastic weather generators have been widely used for post-processing spatially downscaled outputs of GCMs to be linked with process-oriented crop models for climate change impact and adaptation evaluation worldwide (White et al. 2011). Monthly changes in the mean climate (e.g. mean rainfall) and in climate variability (e.g. average length of dry period) between future and baseline period are derived first (bias correction) and then applied to the weather generator to construct local daily CSs based on historical climate characteristics for a specific location (Semenov 2007; Kim et al. 2007; Wilks 2010, 2012; Ivanov et al. 2007; Luo et al. 2013, 2014, 2015). More details on the LARS-WG can be found in Sect. 2: Materials and methods. The advantage of the weather generator approach over the delta approach is that it has the capacity to consider changes in both the mean climate and in climate variability. Greenhouse induced climatic change not only result in changes in the mean but also in variability. Hence, weather generator is well suited for post-processing GCMs outputs with climate model bias corrected and for producing robust local daily CSs with the problem of poor performance of GCMs/RCMs at daily time scale avoided even though weather generator has its own drawbacks. This study aims to examine the differences in climate variables and crop production components arising from the use of DOCM and CSs. This will justify and promote the use of CSs and therefore reduce uncertainties in climate change impact assessment and adaptation evaluation.

2 Materials and methods

2.1 Study locations

The study focuses on three wheat production areas in New South Wales (NSW), Australia: namely Bingara, Peak Hill and Deniliquin (Fig. 1). The rationale of choosing these three locations is that they are key wheat production areas and span a large geographical region and thus represent different climate patterns. Bingara, located in the northeast of NSW, has a summer-dominant rainfall pattern and a warmer temperature regime while Deniliquin, in the southwest of NSW wheat belt, has a winter-dominant rainfall pattern and a cooler temperature regime. Peak Hill, between these aforementioned two locations, has an intermediate rainfall pattern and temperature regime. These three sites also differ in rainfall amount with Bingara and Peak Hill belonging to medium–high rainfall areas with growing season (GS, May–Oct. inclusive) rainfall of

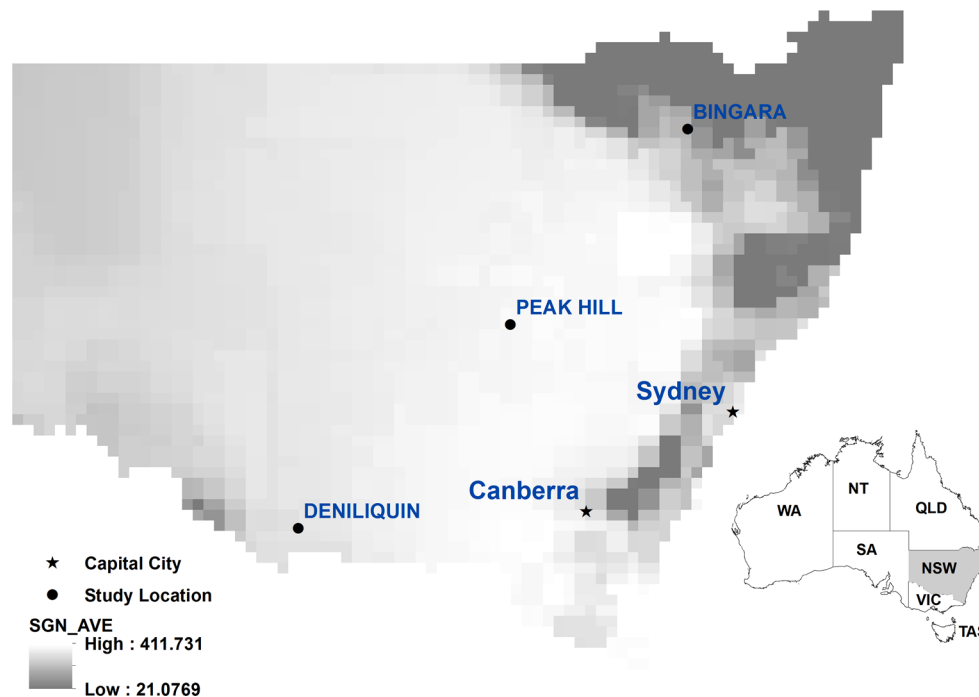


Fig. 1 Study locations and the gridcell of the CSIRO Conformal Cubic Atmospheric Model

349 mm and 305 mm respectively, while Deniliquin belongs to a low rainfall area with GS rainfall of 258 mm.

2.2 Climate projections

Dynamically downscaled daily outputs of the CSIRO Conformal-Cubic Atmospheric Model (CCAM) for the periods 1960–1979, 1980–1999 and 2046–2065 were used in this study. The first period is for validation purpose. The second and third periods are for constructing future CSs. More information on future CSs is given in Sect. 2.3.2.

The CSIRO CCAM is a stretched-grid or variable-resolution climate model and has a roughly uniform grid over the area of interest (15 km by 15 km), and a coarser-resolution grid over the remainder of the globe. More details about CCAM can be found in McGregor and Dix (2008). CCAM was driven by the CSIRO Mk 3.5 model fields under the A2 emission scenario of the Special Report on Emission Scenarios (IPCC 2000), which is the only emission scenario considered by the CCAM due to the large computing resources needed in comparison with statistical downscaling. A detailed description of the CSIRO Mk 3.5 and its performance can be found in Gordon et al. (2010). The rationale for using dynamically downscaled outputs of GCM is that both temperature and rainfall are available for crop model application, which is not always the case from statistically downscaled outputs of GCMs. The latter are often limited by the availability of both high quality

temperature and rainfall data for implementing statistical downscaling at a specific location especially in Australia.

2.3 Climate scenarios

2.3.1 Baseline climate

A baseline climate corresponding to the period 1960–1979 was constructed by using the LARS-WG based on historical daily climate datasets for this period. Historical climate datasets were obtained from the specialised information for land owners (SILO) patched point dataset (PPD) (<http://www.longpaddock.qld.gov.au/silo>, Jeffrey et al. 2001). LARS-WG is a stochastic weather generator based on series approach (Racsko et al. 1991). It produces synthetic daily time series of maximum/minimum temperature (T_{\max}/T_{\min}), precipitation and solar radiation. It utilises semi-empirical distributions for the lengths of wet and dry day series, daily precipitation and daily solar radiation. Daily T_{\max} , T_{\min} and solar radiation are considered as stochastic processes with daily means and daily standard deviations conditioned on the wet or dry status of the day. The occurrence of precipitation is modelled by alternating wet and dry series approximated by semi-empirical probability distributions (Semenov and Brooks 1999). On a wet day the amount of precipitation is modelled using semi-empirical distributions for each month. A detailed description of the LARS-WG is given in Semenov (2007) and Luo et al. (2003). The performance of the LARS-WG

in diverse climates (USA, Europe, Asia and Australia) was evaluated by Semenov et al. (1998), Semenov (2008) and Luo et al. (2014). It was found that the LARS-WG performed reasonably well against observed climate datasets. The LARS-WG is the most widely used weather generator in this research area (White et al. 2011).

2.3.2 Future climate scenario

The construction of future CSs was based on both CPs and historical climate characteristics with the aid of post-processing techniques. These procedures involve three steps. Firstly, observed daily climate data for the period 1960–1979 (independent of the validation period) were used to calibrate the stochastic weather generator, LARS-WG. This produced information on historical climate characteristics. Historical climate datasets for this period were also obtained from the above mentioned SILO PPD datasets. Secondly, the daily outputs of the CCAM for periods 2046–2065 and 1980–1999 were used by the LARS-WG to derive monthly changes in the mean climate (i.e. rainfall) and in variability (i.e. average length of wet/dry spells) between the two periods. The rationale of using monthly climate change to perturb historical climate through the use of the LARS-WG rather than the direct use of the daily outputs of CCAM is that monthly climate change information performs better than that of daily scale. Finally, the monthly climate changes were applied to the LARS-WG to produce 100-year local future CSs based on local historical climate characteristics as obtained from step 1.

2.4 The APSIM-Wheat

DOCM and CSs for the periods 1960–1979 and 2046–2065 derived earlier were coupled with the Agricultural Production System sIMulator (APSIM)-Wheat model (version 7.4) to quantify GS climate and its impact on production components. Figure 2 is the schematic overview of the methodologies adopted in this study. The climate variables quantified included GS rainfall total and GS rainfall frequency (calculated as the number of rainy days within GS), GS average T_{\max} , GS average T_{\min} and GS average solar radiation. A rainy day was defined as a day on which rainfall is greater than 0.2 mm (<http://www.bom.gov.au/climate/cdo/about/definitionsrain.shtml>). These climate variables are major driving forces of crop production. The production components analysed included GS length and wheat grain yield. The rationale of using the APSIM as a quantification tool for deriving GS climate is that the climate information quantified is directly related to a specific crop cultivar (rather than a hypothetical one) and to the actual GS length for that cultivar. The APSIM is a farming systems modelling framework. It contains interconnected models to simulate

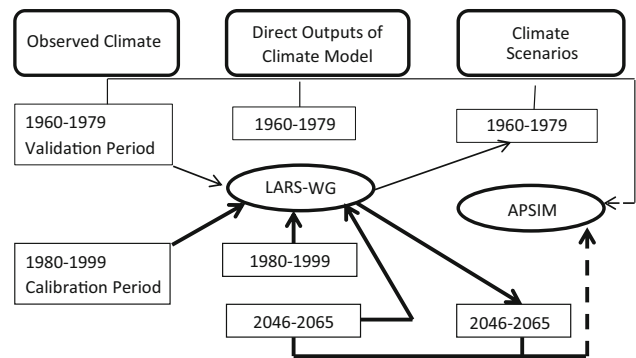


Fig. 2 A schematic overview of research methodologies. *Thin arrows* show the procedures for generating baseline climate scenarios for the validation period 1960–1979. *Thick arrows* show the procedures for producing future climate scenarios. For the latter, outputs of CCAM for the periods 1980–1999 and 2046–2065 were fed into the LARS-WG to derive climate anomalies. Along with historical climate data for the period 1980–1999, these anomalies were then used to construct future climate scenarios

systems comprising soil, crop, tree, pasture and livestock biophysical processes (Holzworth et al. 2014). Validation of this model can be found in Probert et al. (1998). This crop model package has been widely applied to climate change/variability impact studies (White et al. 2011) and in farming system studies in Australia, Europe and China. Two cultivars (Sunvale and Janz) were considered in this study. Sunvale is a mid-late maturity cultivar with vernalisation and photoperiod coefficients of 2.8 and 3.0 respectively. Janz is an early maturing cultivar with vernalisation and photoperiod coefficients of 1.5 and 3.5 respectively. Sunvale is sown when cumulative rainfall in three consecutive days is ≥ 20 mm and ≥ 15 mm for medium and low rainfall areas respectively during the period of 15 Apr–15 June. Janz is sown for the period of 16 June–15 Aug with the same sowing criteria as Sunvale. If these conditions cannot be met, the wheat crop is forced to sow on the last day (15th Aug) of the sowing window. Table 1 shows crop management information across study sites and atmospheric CO_2 concentrations set in the wheat model. A red-brown earth soil was assumed. Soil water, soil nitrogen and residue were reset to their initial conditions on the 1st of March each year. The purpose of this resetting was to exclude the interaction between climate change and soil conditions so that clear messages of climate change impacts on wheat production can be obtained.

2.5 Statistical analyses and tests

For validation period 1960–1979, climate variables and production components derived from CSs and DOCM were compared with those derived from observed climate datasets. Details of climate variables analysed on a seasonal scale were given in Sect. 2.4. In addition to seasonal scale,

Table 1 Management information and CO₂ concentrations as set in the APSIM-Wheat model

Study sites	Planting		Starting N (kg/ha)	Initial residue (kg/ha)	[CO ₂] (ppm) under A2	
	Density (plants/m ²)	Depth (mm)			Baseline	2055
Deniliquin	100	30	137	1000	384	559
Bingara & Peak Hill	150	30	187	2000		

climate variables including their mean and variability (standard deviation: SD) and extreme climate events were also analysed on a monthly basis. Extreme climate events comprised frost frequency (defined as the number of days with daily T_{\min} less than or equal to 2.2 °C in September) and the frequency of heat stress (defined as the number of days with daily T_{\max} greater than or equal to 30 °C in October). The reason for choosing these types of extreme climate events and the timeframes is that frost risk in September and heat stress risk in October have significant economic implication for the wheat industry. Seasonal variables were statistically tested by using the Wilcoxon rank-sum test and Kolmogorov–Smirnov (KS) test. The former compares the mean value while the latter compares the distribution of two datasets in question. The mean value and distribution are the most important statistical parameters in describing a dataset. Hence they were selected and statistically tested in this study to see how close the comparing datasets are.

For future period 2046–2065, climate variables and crop production components derived from CSs and DOCM were compared against each other and statistically tested by using the same tests as for the validation period. Exploratory data analyses were conducted first to determine which Two-Sample Tests to use in the significant test analyses. Wheat yields for the period 2046–2065 from both CSs and DOCM at Bingara were analysed. It was found that wheat yield from DOCM would not be normally distributed (data not shown). This justified the use of the Wilcoxon test rather than t test in testing the difference in the mean of climate variables and crop production components derived from DOCM and CSs.

3 Results

3.1 Comparison of climate variables and production components derived from DOCM and CSs against those from observed climate for the period 1960–1979

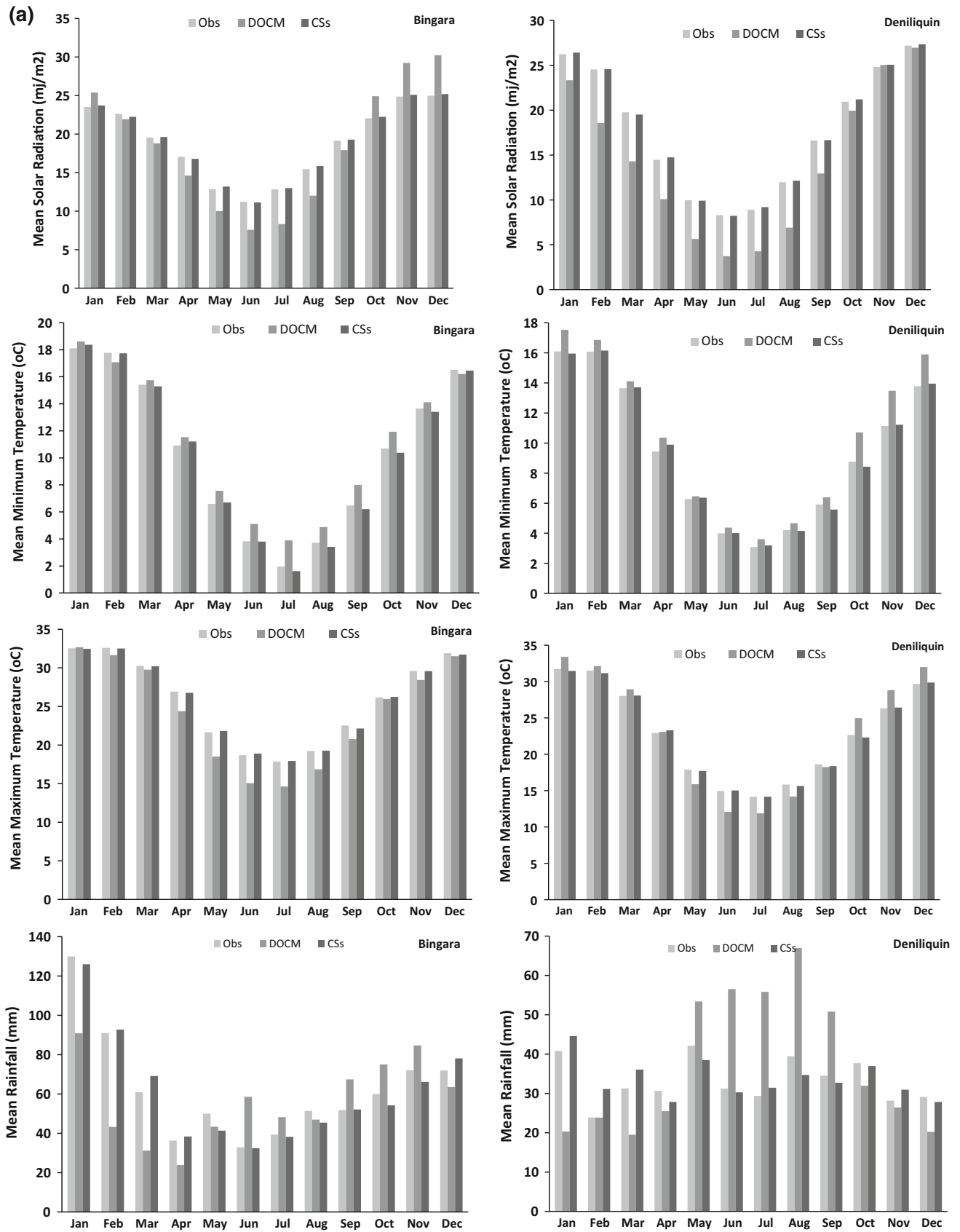
3.1.1 Monthly climate variables

Figure 3a shows the mean value of the five climate variables (solar radiation, T_{\max} , T_{\min} , rainfall and rainfall frequency) derived from DOCM, CSs and observed climate at

Bingara and Deniliquin. DOCM led to a bias range of –6.0 to 5.2 mj/m^2 while CSs led to a bias range of –0.4 to 0.4 mj/m^2 in estimating the mean of solar radiation across the two locations. DOCM led to a bias range of –3.6 to 2.5 °C while CSs led to a bias range of –0.4 to 0.2 °C in estimating the mean of T_{\max} . The bias in estimating the mean of T_{\min} ranged from –0.7 to 2.3 °C associated with DOCM and from –0.3 to 0.5 °C associated with CSs. The bias in estimating mean rainfall ranged from –47.7 to 27.5 mm in relation to the use of DOCM and from –8.6 to 8.2 mm in relation to the use of CSs across the two locations. For the mean frequency of rainfall, DOCM resulted in a bias range of –1 to 6 days while CSs resulted in a bias range of –4 to 1 day across the two locations. It was found that mean climate variables derived from CSs were much closer to those derived from observed climate when compared with those from DOCM across variables and months.

Figure 3b shows the SD of the five climate variables derived from DOCM, CSs and observed climate at Bingara and Deniliquin. DOCM led to a bias range of –2.1 to 0 mj/m^2 while CSs led to a bias range of –0.8 to 0.1 mj/m^2 in estimating the SD of solar radiation across the two locations. DOCM led to a bias range of –0.6 to 1.0 °C while CSs led to a bias range of –0.8 to –0.1 °C in estimating the SD of T_{\max} . The bias in estimating the SD of T_{\min} ranged from –0.7 to 1.1 °C associated with DOCM and from –0.7 to –0.3 °C associated with CSs. The bias in estimating the SD of rainfall ranged from –8.9 to 2.0 mm in relation to DOCM and from –0.4 to 1.1 mm in relation to CSs. As to the SD of rainfall frequency, DOCM led to a bias range of –3 to 3 days while CSs led to a bias range of –2 to 0 days across the two locations. It was found that the SD of solar radiation, rainfall and rainfall frequency for both locations and the SD of T_{\min} at Deniliquin derived from CSs were much closer to those of observed than those of DOCM in most/all of the months while the SD of T_{\max} at both locations and T_{\min} at Bingara derived from DOCM were closer to those of observed when compared with those derived from CSs in most of the months.

For extreme climate events, the median frost frequency in September (Fig. 4a) and the median frequency of heat stress in October (Fig. 4b) from CSs were much closer to those from observed climate in comparison with those from DOCM at all three locations except frost frequency at Peak Hill.



◀ **Fig. 3** Comparison of the effects of climate scenarios (CSs) and the direct outputs of climate model (DOCM) on monthly climate variables against those from observed climate for the period 1960–1979 across locations: **a** monthly mean, **b** monthly variability (*SD* standard deviation)

3.1.2 Seasonal variables

The modelled medians and distributions of GS rainfall derived from CSs were closer to those derived from observed climate when compared with those derived from DOCM, which overestimated median GS rainfall across locations (Fig. 5a). However, the differences in the means and distributions from both CSs and DOCM were not significant against those from observed climate except those from DOCM and observed climate at Deniliquin (Table 2). The medians and distributions of GS rainfall frequency derived from CSs were closer to those from observed at Bingara and Peak Hill while they were closer to observed arising from the use of DOCM at Deniliquin (Fig. 5b). In contrast to GS rainfall, the means and distributions of GS rainfall frequency derived from both CSs and DOCM were significantly different from those derived from observed climate except those from DOCM and observed climate at Deniliquin (Table 2).

The median GS T_{\max} based on CSs was closer to that obtained from observed climate at Bingara and Peak Hill, while it was slightly closer to the observed when derived from DOCM at Deniliquin (Fig. 5c). The differences in the mean of T_{\max} were significant derived from DOCM and observed at Bingara, and from CSs and observed at Deniliquin (Table 2). The distributions of GS T_{\max} based on DOCM were closer to those of observed at Peak Hill and Deniliquin (Fig. 5c). The differences in the distributions of GS T_{\max} were significant derived from CSs and observed climate for the three locations considered and also from DOCM and observed climate at Bingara (Table 2). Similar to median GS rainfall, median GS T_{\min} from CSs matched those from observed climate better than those from DOCM across locations. The differences in the means of GS T_{\min} between DOCM and observed were significant at Bingara and Deniliquin (Table 2). The distribution of GS T_{\min} from CSs was closer to that of observed except the case at Peak Hill (Fig. 5d). The differences in the distributions of GS T_{\min} from DOCM and observed were significant at Bingara and Deniliquin, and from CSs and observed at Peak Hill (Table 2). Once again, the medians and distributions of GS solar radiation from CSs were closer to those of observed than those from DOCM across locations (Fig. 5e). The differences in both the means and distributions of GS solar

radiation were significant from DOCM and observed, and insignificant from CSs and observed (Table 2).

The medians and distributions of GS length from CSs were closer to that of observed at Peak Hill than those from DOCM while they were different from observed values at the other two locations from both CSs and DOCM (Fig. 5f). However, the differences in the means and distributions of GS length from both CSs and DOCM were insignificant against those from observed climate (Table 2). The medians and distributions of wheat grain yields from CSs were closer to those of observed across locations (Fig. 5g). There were significant differences in the means and distributions of wheat grain yield from DOCM and observed climate at Peak Hill and Deniliquin (Table 2).

3.2 Comparison of climate variables and production components from CSs and DOCM for the period 2046–2065

The differences in the distributions of winter and spring dry spells existed arising from the use of DOCM and CSs for the period centred on 2055 (Fig. 6). Longer dry spells in both winter and spring seasons were projected from CSs than those from DOCM at all three locations.

Figure 7 shows the medians and distributions of GS climate variables and production components derived from DOCM and CSs for the period centred on 2055 across the three locations. Significant test results of climate variables and production components from DOCM and CSs are given in Table 3. Median GS rainfall from DOCM would be lower than that from CSs at Bingara and Peak Hill but slightly higher at Deniliquin (Fig. 7a). Statistical tests of significance showed that there would be significant differences (at 95 % confidence level) in both the means and distributions of GS rainfall at Bingara but not at the other two locations (Table 3). The median frequency of GS rainfall from DOCM would be much higher than that from CSs across the three locations considered (Fig. 7b). Differences in the means and distributions of GS rainfall frequency from DOCM and CSs would be significant at 99.99 % confidence level (Table 3). Like the pattern of median GS rainfall, median GS T_{\max} from DOCM would be lower than that from CSs at Bingara and Peak Hill and very close to each other at Deniliquin (Fig. 7c). Significant differences (at 99 % confidence level) would be found in the means and distributions of GS T_{\max} across locations except for the mean of GS T_{\max} at Deniliquin (Table 3). The median GS T_{\min} from DOCM would be slightly lower than that from CSs at Bingara, but much higher than that from CSs at Peak Hill and Deniliquin (Fig. 7d). The means

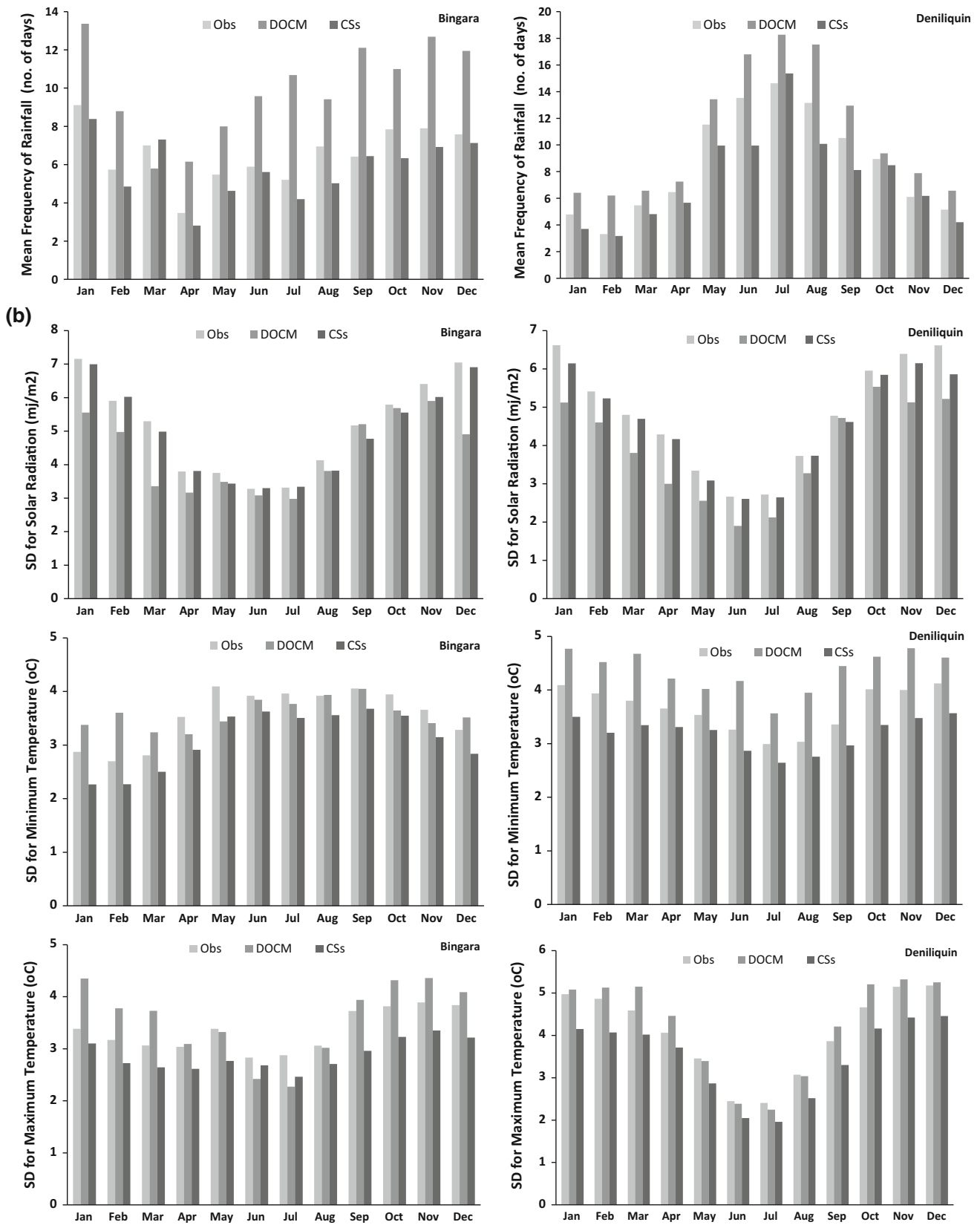


Fig. 3 continued

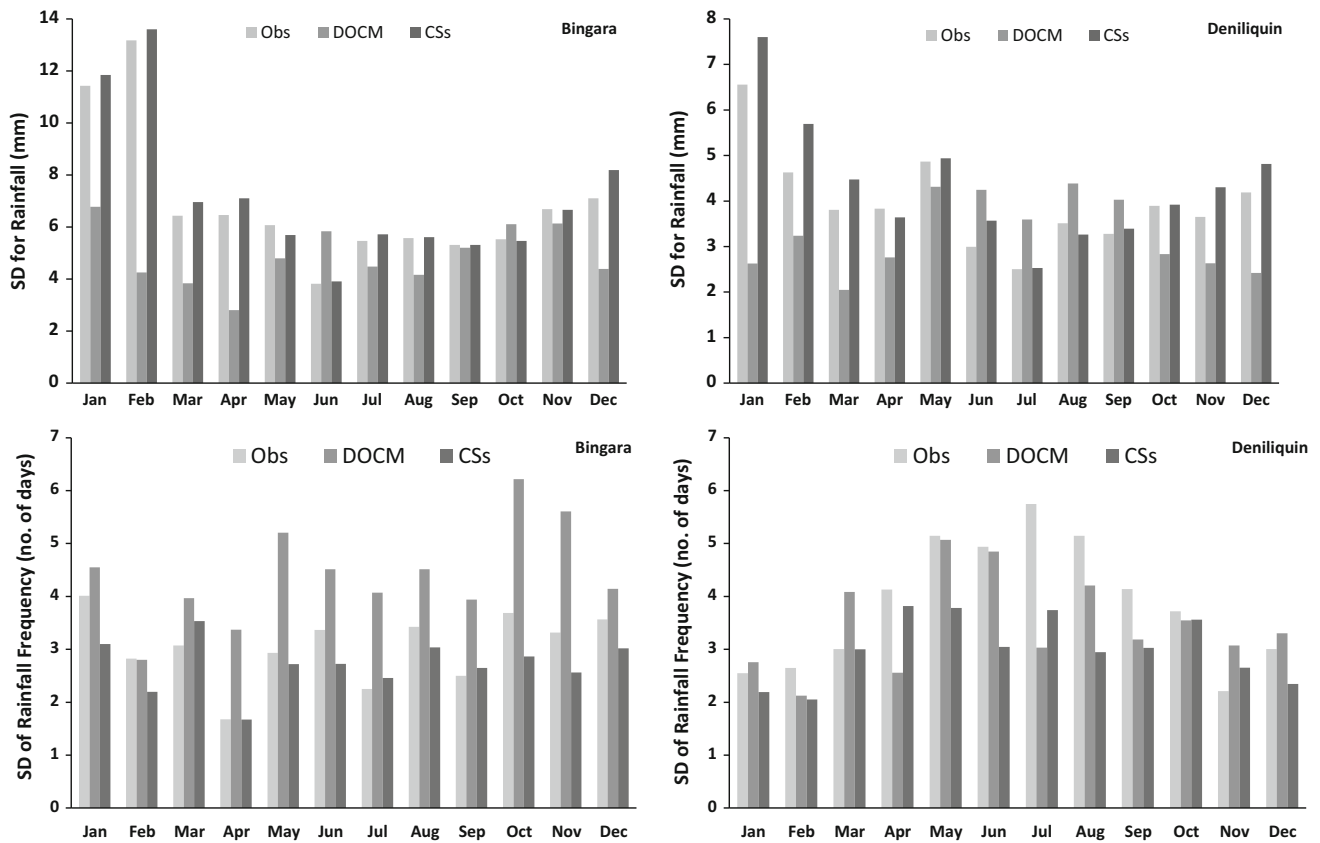


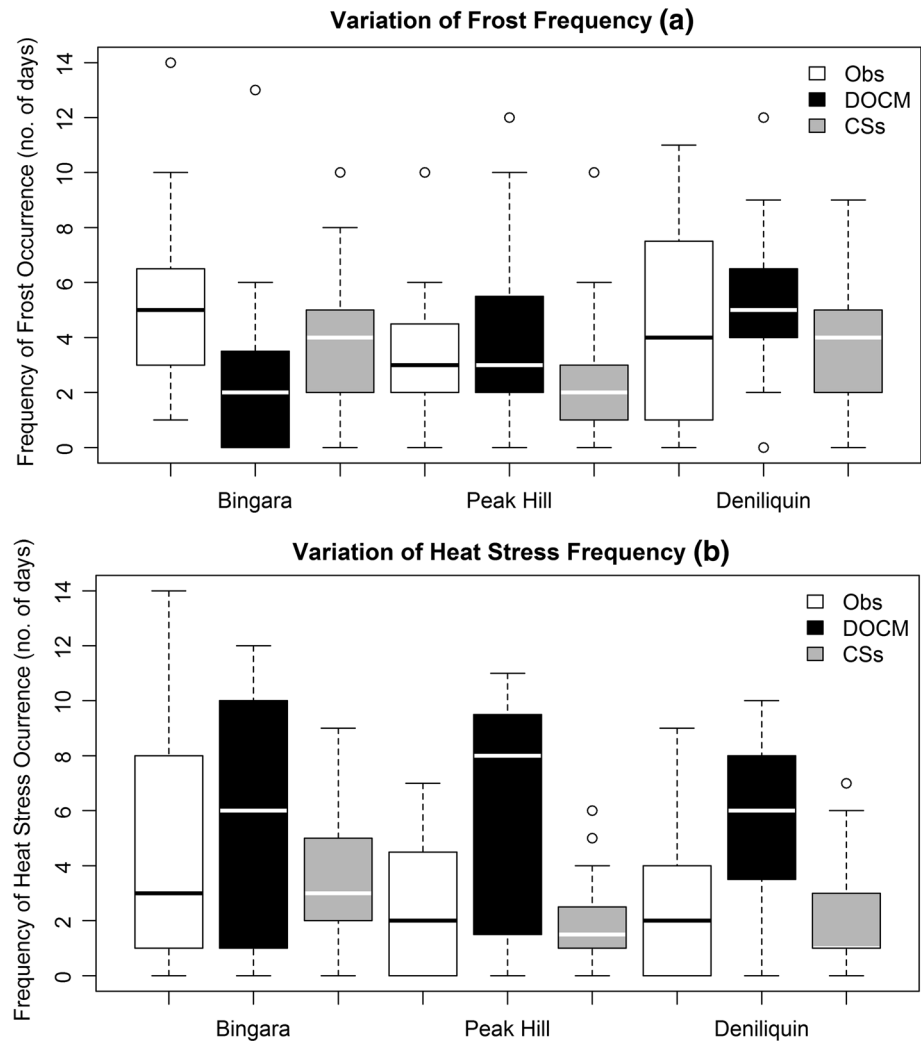
Fig. 3 continued

and distributions of GS T_{min} would be significantly different (at 100 % confidence level) at Peak Hill and Deniliquin but not at Bingara (Table 3). The median GS solar radiation from DOCM would be lower than that from CSs across locations (Fig. 7e). Once again, significant differences (at 99.97 % confidence level) would be found in the means and distributions of GS solar radiation across locations except for the mean at Bingara (Table 3). As with the median GS T_{max} , median GS length would be shorter from DOCM than from CSs (Fig. 7f). The means of GS length from DOCM and CSs would be significantly different (at 95 % confidence level) at Bingara and Deniliquin but not at Peak Hill (Table 3). The distributions of GS length from DOCM and CSs would be significantly different at Peak Hill (at 95 % confidence level) but not at Bingara and Deniliquin. All these differences in climate variables would lead to different wheat yields derived from DOCM and CSs (Fig. 7g). Lower median wheat yields would be projected from DOCM than those from CSs. Significant differences (at 95 % confidence level) would be found in the means and distributions of simulated wheat yields from DOCM and CSs across locations except for the mean wheat yields at Peak Hill (Table 3).

4 Discussion and conclusions

To have confidence in quantified climate change impact and the effectiveness of adaptation options, the first important step is to construct robust local CSs. This study tackled an important issue faced by climate impact community: bias correction of downscaled GCM outputs. This process is essential as it will increase robustness and confidence/credibility of projected local climate change. The climate impact community has long been in a dilemma about whether the spatially downscaled outputs of GCMs can be used directly, or if further post-processing procedures are needed prior to linking with impact models. If GCMs outputs are directly used by impact model, which baseline should be used for comparison, a modelled baseline or historical baseline? If a modelled baseline is to be compared, the impact results may be far from the reality because of climate model system error. If a historical baseline is to be used, climate model bias is embedded (not comparable between future period and historical baseline period). This work set up a framework for constructing more accurate local CSs with climate model biases corrected, changes in climate variability considered, the issue

Fig. 4 Comparison of the effects of climate scenarios (CSs) and the direct outputs of climate model (DOCM) on extreme climate events against those from observed climate for the period 1960–1979 across locations: **a** frequency of frost occurrence in September, **b** frequency of heat stress occurrence in October. The horizontal bar within the box represents the median. The parts above and below the median line within the box are upper and lower quartiles. Whiskers and outliers constitute the data beyond the quartiles



of poor performance of GCMs/RCMs at a daily time scale addressed, and the modelled baseline and historical baseline integrated/connected through the use of the LARS-WG.

This study found that the monthly means and SDs of climate variables derived from CSs were much closer to those of observed climate for the period 1960–1979 when compared with those from the DOCM in most of the cases (climate variables and months, Fig. 3) except for T_{\max} at Bingara and Deniliquin and T_{\min} at Bingara. Similar finding was found for seasonal climate variables. The medians and distributions of GS climate variables and wheat production components from CSs were closer to those of observed climate when compared with those from the DOCM for the period 1960–1979 except for a few cases associated with both the medians and distributions of GS rainfall frequency and T_{\max} at Deniliquin and the distributions of both T_{\max} and T_{\min} at Peak Hill (Fig. 5; Table 2). This is reasonable as CSs were linked to historical climate. This implied that the use of post-processing

techniques such as the LARS-WG is essential in producing more robust CSs for future climate impact assessment. This is in line with the findings of Teutschbein and Seibert (2012), Ehret et al. (2012) and Halmstad et al. (2013). Luo et al. (2013) also noted the significant difference between observed climate and hindcast information from the CCAM for the same locations as considered in this study.

The larger differences in the monthly variability (SD) of T_{\max} at Bingara and Deniliquin and T_{\min} at Bingara (Fig. 3b) and in the seasonal distributions of T_{\max} and T_{\min} at Peak Hill and T_{\max} at Deniliquin from CSs (Fig. 5c, d) and observed climate may be due to the use of the LARS-WG. One limitation of weather generators is a marked tendency to underestimate the observed inter-annual variance at various temporal scales (Srikanthan and McMahon 2001; Schoof 2008; Wilby et al. 2009; Kim et al. 2012; Wilks 2012). The same is true for the LARS-WG, which does not explicitly model inter-annual variability, underestimating temperature variability and that the LARS-WG tends to underrate extreme values of the statistical

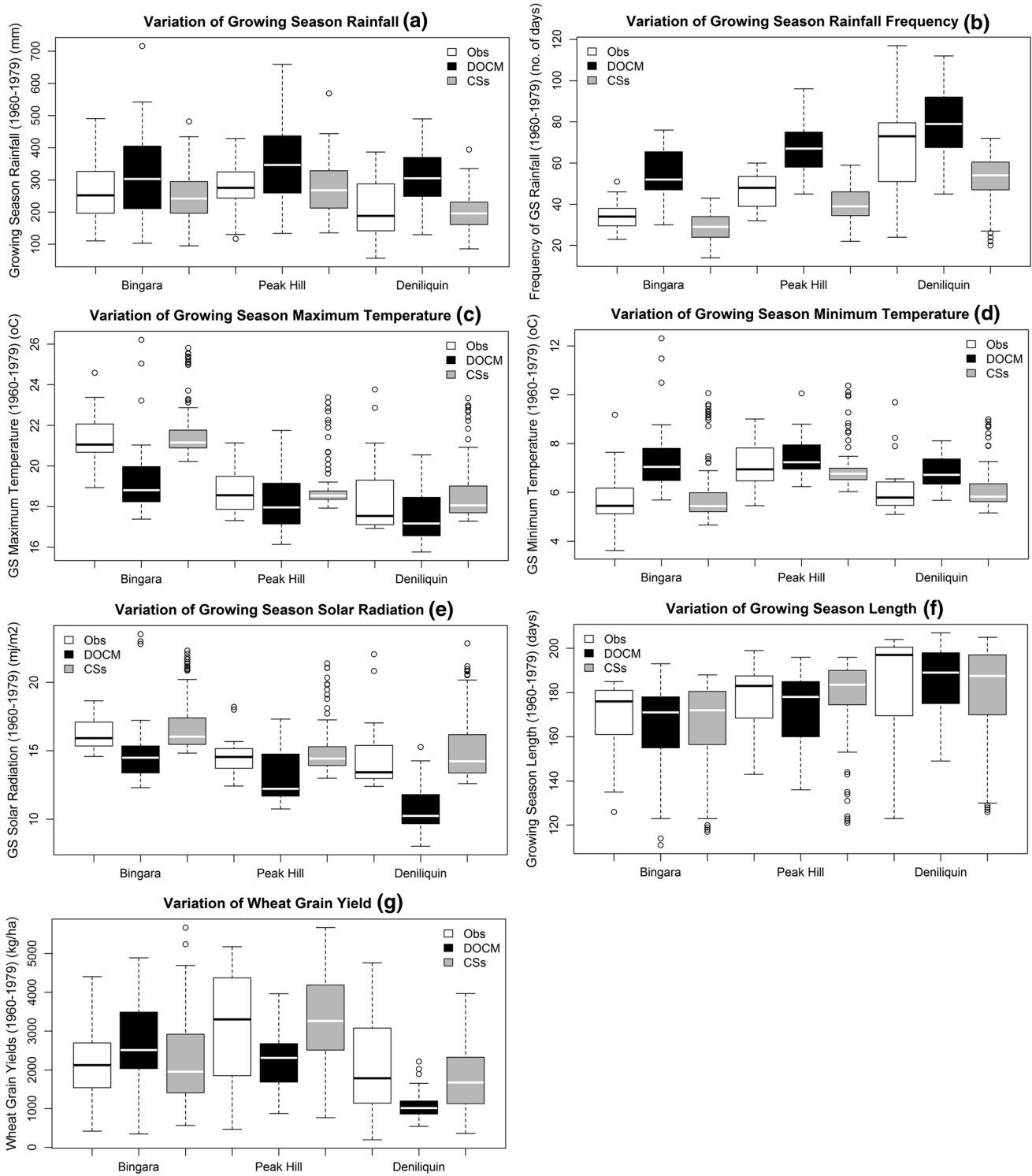


Fig. 5 Comparison of the effects of climate scenarios (CSs) and the direct outputs of climate model (DOCM) on growing season (GS) climate variables and crop production components against observed climate for the period 1960–1979 across locations: **a** GS rainfall total, **b** GS rainfall frequency, **c** GS maximum temperature, **d** GS minimum

temperature, **e** GS solar radiation, **f** GS length, **g** wheat grain yield. The *horizontal bar* within the *box* represents the median. The parts *above* and *below* the *median line* within the *box* are *upper* and *lower* quartiles. Whiskers and outliers constitute the data beyond the quartiles

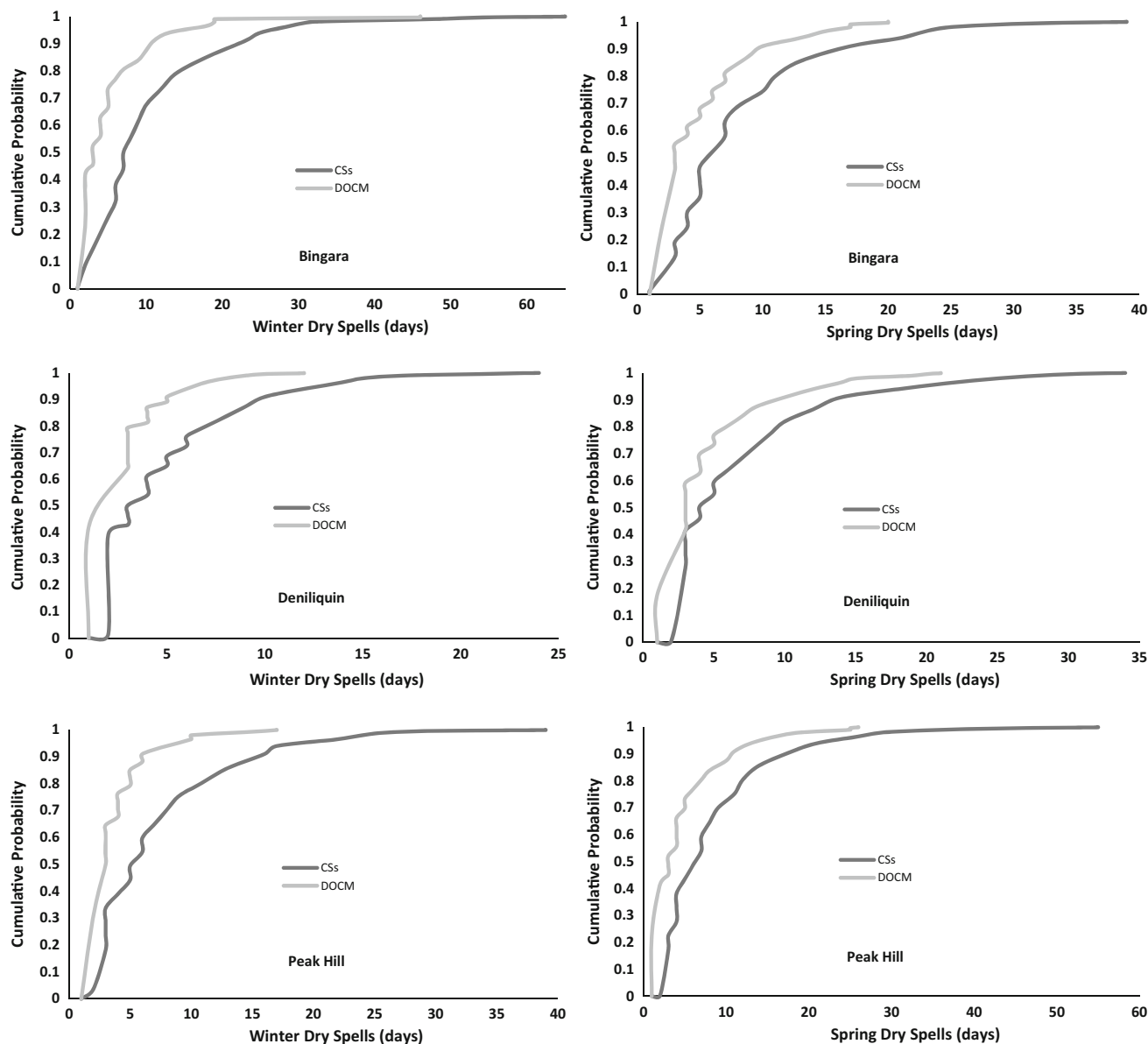


Fig. 6 Cumulative probability of winter and spring dry spells for the period centred on 2055 derived from climate scenarios (CSs) and the direct outputs of climate model (DOCM) across locations

distributions of climate variables (Semenov 2008), which has significant implications for agricultural applications. Hence future CSs produced by using the weather generator approach will have lower inter-annual temperature variability. Attempts have been made to solve the low inter-annual variability issue arising from the use of weather generators (Schoof 2008; Kim et al. 2012).

It was found that there would be significant differences in the means and distributions of GS climate variables and production components arising from the use of DOCM and CSs for the future period (Figs. 6, 7; Table 3). This implied that using the direct outputs of spatially downscaled GCMs without implementing post-processing procedures may

lead to significant errors in projected climate impact and the identified effort in tackling climate change risk. The tendency to project shorter dry spells (Fig. 6), lower median GS rainfall (Fig. 7a) and higher median frequency of GS rainfall (Fig. 7b) resulted from the use of DOCM in comparison with those from CSs reflected the behaviour of GCMs in simulating rainfall occurrence, which tend to simulate more rainfall events (shorter dry spells) but with lower intensity (Carter et al. 1994; Mearns et al. 1990, 1995; Goddard et al. 2001; Charles et al. 2013) in comparison with real situation. The higher rainfall frequency and light rainfall amount from DOCM could not easily meet early sowing criteria as given in the Section:

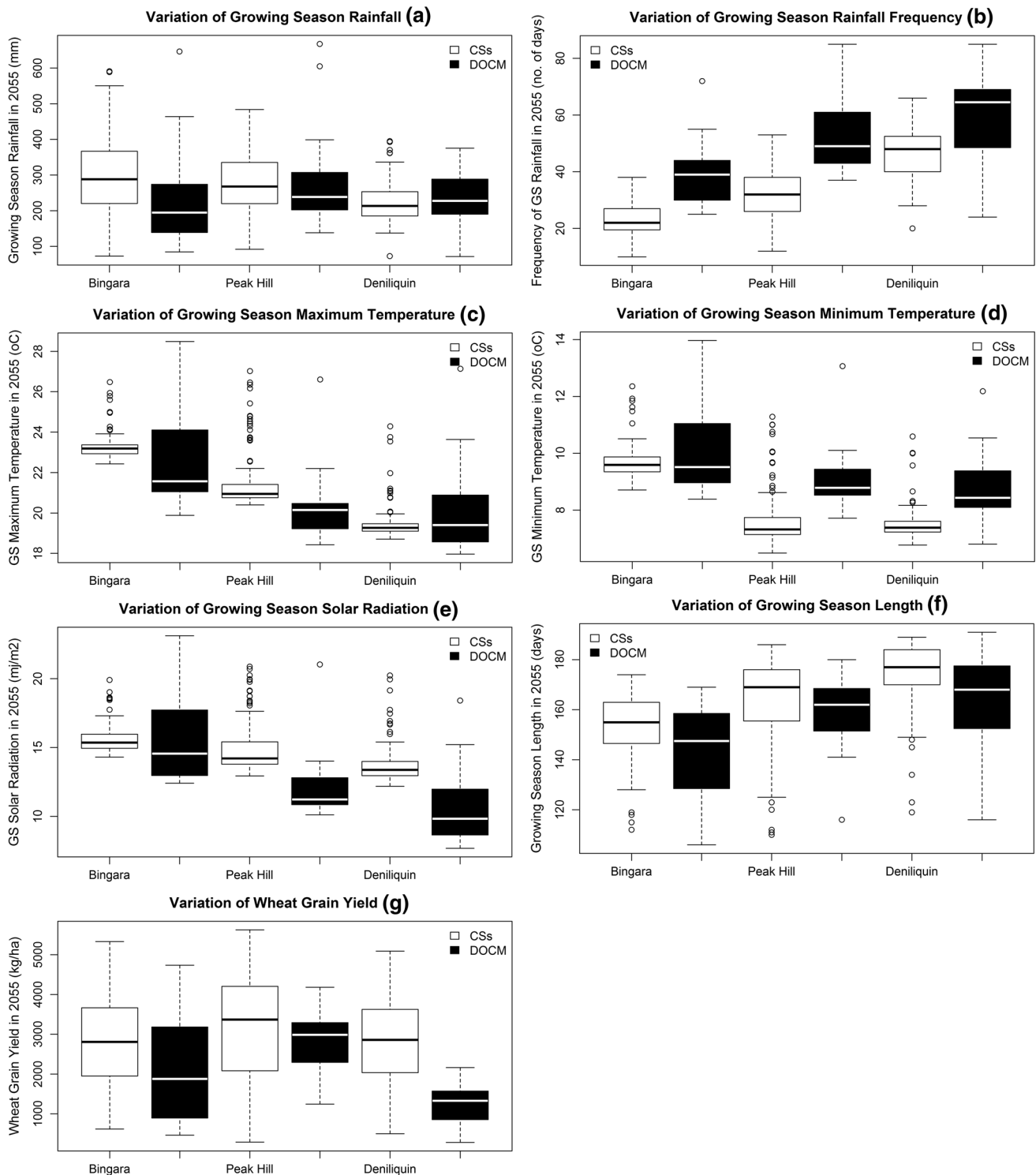


Fig. 7 Variation of growing season (GS) climate variables and production components for the period centred on 2055 derived from climate scenarios (CSs) and the direct outputs of climate model (DOCM) across locations: **a** GS rainfall total, **b** frequency of GS rainfall, **c** GS maximum temperature, **d** GS minimum temperature,

e GS solar radiation, **f** GS length, **g** wheat grain yield. The horizontal bar within the box represents the median. The parts above and below the median line within the box are upper and lower quartiles. Whiskers and outliers constitute the data beyond the quartiles

Table 2 p values of significant tests for seasonal climate variables and production components derived from climate scenarios (CSs) and the direct outputs of climate model (DOCM) for the period 1960–1979

	Bingara		Peak Hill				Deniliquin					
	CSs versus Obs ¹		DOCM versus Obs		CSs versus Obs		DOCM versus Obs		CSs versus Obs		DOCM versus Obs	
	WRS ²	KS ³	WRS	KS	WRS	KS	WRS	KS	WRS	KS	WRS	KS
GSR ⁴	.6014	.9454	.2970	.5379	.6065	.4539	.1157	.1532	.8732	.2371	.0154	.0267
GSR Frequency	.0026	.0290	.0000	.0000	.0073	.0328	.0001	.0002	.002	.0001	.1181	.5379
GS ⁵ T _{max} ⁶	.1784	.0369	.0010	.0002	.4884	.0294	.1912	.1532	.0397	.0052	.0747	.1532
GS T _{min} ⁷	.8419	.5879	.0002	.0007	.3364	.0348	.4181	.5379	.6398	.8059	.0034	.0028
GS Radiation	.3328	.4079	.0082	.0092	.7033	.7255	.0141	.0028	.0903	.0903	.0000	.0000
GS Length	.4635	.4893	.5785	.8081	.5886	.8185	.3809	.8081	.2241	.1669	.4650	.3057
Wheat yield	.9624	.9344	.1157	.3057	.9162	.6231	.0182	.0028	.6398	.4634	.0319	.0267

P values of ≤ 0.05 shown as bold figures are considered as significant

1 observed climate, 2 Wilcoxon rank-sum, 3 Kolmogorov–Smirnov, 4 growing season rainfall, 5 growing season, 6 maximum temperature, 7 minimum temperature

Table 3 p values of significant tests for seasonal climate variables and production components derived from climate scenarios and the direct outputs of the CCAM for the period centred on 2055

	Bingara		Peak Hill		Deniliquin	
	WRS ¹	KS ²	WRS	KS	WRS	KS
GSR ³	.0048	.0166	.3208	.1290	.4140	.6836
GS frequency	.0000	.0000	.0000	.0000	.0001	.0000
GS ⁴ T _{max} ⁵	.0031	.0000	.0000	.0000	.9411	.0097
GS T _{min} ⁶	.7917	.0862	.0000	.0000	.0000	.0000
GS radiation	.0931	.0003	.0000	.0000	.0000	.0000
GS length	.0358	.1290	.0936	.0352	.0167	.0697
Wheat yield	.0240	.0352	.1139	.0127	.0000	.0000

1 Wilcoxon rank-sum, 2 Kolmogorov–Smirnov, 3 growing season rainfall, 4 growing season, 5 maximum temperature, 6 minimum temperature

P values of ≤ 0.05 shown as bold figures are considered as significant

Materials and Method, and would lead to more late sowings with early maturity cultivar (Janz) (i.e. 40 % chances from DOCM and 17 % chances from CSs at Bingara), resulting in lower median GS length compared to that of CSs (Fig. 7f). Lower median GS rainfall and/or shorter median GS length and/or ineffective use of rainfall due to the very light rainfall amount (lost as soil evaporation) are possible causes of lower median wheat yields from DOCM in comparison with those from CSs (Fig. 7g). The shorter dry spells associated with DOCM (Fig. 6) would lead to lower inter-annual variability of wheat yields (Fig. 7g). This finding is in line with the study of Dubrovský et al. (2000).

This study highlighted the importance of post-processing procedures for constructing robust local CSs. Even

though the coupling between spatially downscaled outputs of GCMs with crop models through a stochastic weather generator is not a novel practice in itself (Wilks 1992; Weiss et al. 2003; Luo et al. 2003, 2013, 2014), it is an essential step for accurate impact assessment and adaptation evaluation. This work will increase climate impact community's awareness about the difference between the direct outputs of RCMs and CSs and hence foster the adoption of appropriate post-processing techniques in constructing robust local CSs for impact assessment if the performance of RCMs against observed climate is not ideal. This, in turn, will lead to more accurate impact assessment and avoid under/over or even maladaptation. This post-processing approach used in this study can also be applied to produce more accurate local daily seasonal and intra-seasonal climate forecast information for strategic and tactic decision—making in the agricultural and water industries as intra-seasonal (long-range weather) and seasonal forecast systems move from statistical-based phase systems to GCM-based dynamic forecast systems.

5 Limitations

The bias correction approach adopted in this study has its own limitations and assumptions such as that model biases are invariant (the same) between baseline and future period. However, this assumption has been questioned by Christensen et al. (2008) and Maraun et al. (2010). More sophisticated and flexible bias correction procedures need to be developed in this important research area (Buser et al. 2010). Haerter et al. (2011) used a cascade bias correction method to address the non-stationarity issue of the bias across different time periods. The LARS-WG uses

identical monthly changes for all quantiles of the statistical distribution of the climate elements. While this choice is reasonable in many situations, it is inconsistent with CPs, if this choice also entails a change in the shape of the distribution. Quantile–quantile mapping (Deque 2007; Maruan et al. 2010) and other techniques could be used in this case to provide a more realistic forcing of the LARS-WG.

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