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Designing wheat ideotypes to cope with future changing climate in South-Eastern Australia

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ABSTRACT

Global food demand is increasing with the rapid growth of the world's population and improvement in living standards. To meet this demand, crop yields need to increase but climate change presents a potential threat. Genetic and agronomic strategies are helping agriculture adapt to climate change, but introducing new genetic traits into crops is time-consuming and costly. Process-based biophysical modelling is a powerful tool for targeting and accelerating development of new synthetic cultivars, and we have used it to identify the traits of rainfed wheat ideotypes and suitable sowing dates needed to adapt to future climate change in south-eastern Australia. Our simulations involved two Global Climate Models (GCMs) with the driest conditions under a high emission scenario of Representative Concentration Pathway (RCP) 8.5. We compared simulated yields under future climate with those under historical climate with and without changes in cultivar and sowing date. Our results show that wheat yield for the reference cultivar would decrease on average by 23% and 38% in 2061–2100 under RCP8.5 at two contrasting sites (wet and dry, respectively). Ideotypes with an early flowering date, longer grain filling period, larger radiation use efficiency, larger maximum grain size and faster potential grain filling rate, sown on the optimum sowing date proved to be effective at the wet site in reversing these declines, leading to an average yield increase of 20–24% for both GCMs. However, improving cultivars and altering sowing times would have little impact for a drier GCM at the dry site. Although there is some uncertainty in simulations related to the genetic coefficients used in the crop model, climate projections and emission scenarios, we demonstrate that it is possible to enhance wheat production under a future climate if a cultivar with a longer grain filling period and larger yield component parameter was adopted in eastern Australian wheat-growing areas.

1. Introduction

Global food demand continues to increase with the rapid increases in world population and living standards (Watson et al., 2017). To meet this demand, production increases in staple crops such as wheat are required without further expansion of arable land (Balkovič et al., 2014; Cammarano and Tian, 2018; Kastner et al., 2012), but adverse and extreme agro-climatic events (Trnka et al., 2014), pose a huge investment challenge to improving food production sustainably.

Australia contributes 10–15% of the world's annual wheat trade (http://aegic.org.au/australian-grain-production-a-snapshot/), so any variation in Australian wheat production affects global wheat prices. Almost all Australian wheat production is rainfed, so changes in seasonal rainfall patterns and variability, and temperature, contribute directly to fluctuations in crop yields (Feng et al., 2018; Sultan et al., 2014; Wang et al., 2015a). Increased temperatures are expected to accelerate crop development rates and shorten the growing season (Zheng et al., 2012). Altered rainfall patterns affect the amount of water available to plants at different growth stages (Watson et al., 2017), which may result in a mismatch between current agronomic practices and future moisture regimes. Increased frequency of extreme weather events, such as drought (Kirono et al., 2011) and heat stress (Wang

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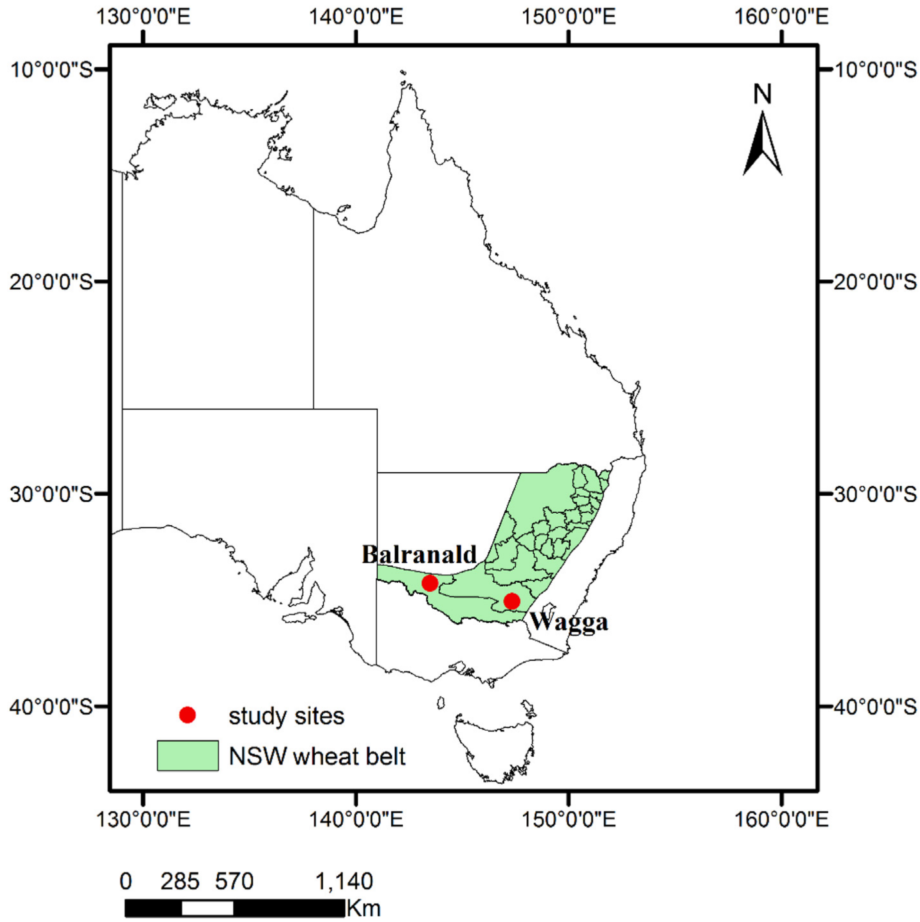

Fig. 1. Location of the two study sites in southern New South Wales (NSW) wheat belt, Australia.

et al., 2016a), is projected to cause further yield losses. In order to maintain and improve wheat yields in Australia, adaptation strategies are needed to match the crop cycle with altered water-temperature environments to minimize or avoid adverse effects of extreme weather events (Shavrukov et al., 2017).

Agronomic adaptations such as breeding high-yield cultivars and adjusting sowing date have been suggested as climate change adaptation strategies (Ding et al., 2016a; Donatelli et al., 2015; Loison et al., 2017; Mushtaq et al., 2017; Qin et al., 2018). These studies have shown that the use of optimum cultivars is one of the most promising adaptation options to address climate change impacts (Loison et al., 2017; Ramirez-Villegas et al., 2015; Rötter et al., 2015; Tao et al., 2017). An optimum cultivar is usually referred to as the breeding of a crop ideotype that has specific plant properties (e.g. high photosynthetic efficiency, shortened or prolonged growing period, drought-tolerance) to perform optimally under adverse environmental conditions (Martre et al., 2015; Rötter et al., 2015). Loison et al. (2017) reported that a cotton ideotype with a higher photosynthetic rate, earlier flowering date, and longer reproductive duration could potentially produce higher yields under future climate compared to existing cultivars. Similar wheat cultivar features were proposed for the European environment (Semenov et al., 2014). Zheng et al. (2012) reported that a wheat cultivar with a long growing season would be better adapted to changing climate in Australia. In parallel, adjusting sowing date is regarded as the most convenient and effective adaptive farm management strategy in cropping systems (Ding et al., 2016a; Donatelli et al., 2015; Wang et al., 2018). An appropriate sowing date is capable of significantly boosting grain yield compared to other measures (McLeod et al., 1992) because the optimal sowing date for a crop can lead to a suitable pre-anthesis period that allows biomass accumulation and suitable windows of flowering and grain-filling which avoid frost, heat, and terminal drought (Bell et al., 2014). Appropriate sowing dates for particular agricultural environments have been widely discussed among researchers. Bassu et al. (2009) found that in a Mediterranean environment sowing wheat right before the rainfall season starts can minimize the adverse effect of climate change due to the absence of waterlogging. Weiss et al. (2003) also demonstrated that changing sowing date can enhance wheat growth performance and subsequent grain yields in Nebraska (United States). In South Australia, sowing two weeks earlier if soil water is available has been shown to be an effective adaptation strategy for climate change (Luo et al., 2009). Given that both cultivar features and sowing date affect phenology and yield, combinations of cultivar features and sowing dates should be explored to help wheat crops cope with climate change. However, to our knowledge, few studies have explored wheat ideotype and sowing dates under future climate scenarios in Australia.

Both cultivar features and sowing date can affect the timing and occurrence of plant phenological stages, so breeding new cultivars and adjusting sowing dates to best match plant growth requirements and the local environment can be a valuable adaptation strategy. Field-based experiments may be helpful under certain conditions, but are of limited value when considering the wide range of cultivar features, farming management practices, and climate projections and interactions (Senthilkumar et al., 2015). Process-based crop models which simulate the complex interactions between environment, management, and genotype offer an alternative evaluation tool. Cultivars and management practices provide a defined set of parameters that can be modified to explore alternative cultivar selection and farming practices under different environments. In recent years, many researchers have used crop models to design ideotypes (Ding et al., 2016b; Mushtaq et al., 2017; Tao et al., 2017) and adjust sowing date (Kirkegaard et al., 2016; Srivastava et al., 2018) to cope with climate change.

In this study, we used a well-developed crop model, the Agricultural Production Systems Simulator (APSIM), to evaluate the effects of sowing date and cultivar selection on wheat yields under future climate conditions at two contrasting sites representing extreme ranges (wet and dry). Two global climate models (GCMs) were selected, which project "more adverse" future climates under a higher emission scenario (worst case scenario). This study explored the optimum interactions of genotype (genetic coefficients) and agronomic management (sowing date adjustment) to cope with future adverse weather conditions in the south-eastern Australian wheat belt.

2. Materials and methods

2.1. Study sites

Two study sites with contrasting climate, Wagga (35.16°S, 147.46°E, 212 m asl) and Balranald (34.64°S, 143.56°E, 61 m asl) were chosen to represent wheat-growing areas in New South Wales (NSW), south-eastern Australia. The geographical location of the study area and two study sites are shown in Fig. 1. Both sites share a hot summer and cool/cold winter environment, but differ in annual rainfall. Wagga is a wetter site with an average long-term (1961–2000) annual rainfall ~570 mm, while Balranald is drier with about half the long-term annual rainfall of Wagga (~294 mm) over the same period. Temperatures during the wheat growing season are similar at both sites, ranging from 8.7 to 16.3 °C at Wagga and 8.8 to 16.1 °C at Balranald. The wheat growing season rainfall ranges from 227 mm to 447 mm for Balranald and Wagga, respectively. Wheat in the NSW wheat belt is generally sown between April and June and harvested during September and November.

2.2. Climate data

The observed daily climate data for solar radiation, rainfall, maximum and minimum temperature for the period 1961–2000 at the two sites were downloaded from SILO (Scientific Information for Land Owners) operated by Queensland Government's Open Data program (https://legacy.longpaddock.qld.gov.au/silo/) (Jeffrey et al., 2001).

For future climate scenarios, the period 2061–2100 was studied and compared with the historical period 1961–2000. We focused on a high emission scenario of the Representative Concentration Pathway (RCP) experiments RCP8.5, which represents a future of no climate policy featured by the radiative forcing of 8.5 W m^{-2} by 2100. The equivalent atmospheric CO_2 concentration will rise to 936 ppm by 2100 under this scenario (Van Vuuren et al., 2011). Monthly climate data from 28 GCMs included in the Coupled Model Intercomparison Project Phase 5 (CMIP5, http://cmip-pcmdi.llnl.gov/cmip5/index.html) (Table 1) were firstly downscaled to daily temperature, rainfall and radiation at the two selected sites, following a statistical downscaling method developed by NSW Department of Primary Industries Wagga Wagga Agricultural Institute (Liu and Zuo, 2012). This method uses monthly gridded GCM temperature, rainfall and radiation data and parameters derived from climate observations and GCM projections to produce realistic time series of daily temperature, rainfall and solar radiation to drive crop models. It is different to other statistical downscaling methods that require numerous climatic predictors to establish the relationship between the predictand and predictors based on daily and/or monthly scales. The method has been extensively employed in climate change studies (Li et al., 2017; Liu et al., 2017a; Wang et al., 2016b; Wang et al., 2018). Further details of the downscaling approach can be found in Liu and Zuo (2012).

The daily temperature and rainfall data downscaled from 28 GCMs was then used to calculate changes in the wheat-growing season rainfall and temperature at the two contrasting study sites, by comparing the period of 2061–2100 with 1961–2000. Fig. 2 shows the changes in rainfall and temperature projected by 28 GCMs. All GCMs predicted that the growing season temperature would increase by the end of twenty-first century with an average warming of 3.4 to 3.8 °C. Multi-

Table 1
List of 28 GCMs evaluated in this study. The CSIRO-Mk3.6.0 (CSI) and GFDL-ESM2M (GF4) were selected as extreme dry projections under future climate change.

Model ID	Name of GCM	Abbreviation of GCM	Institute ID	Country
01	BCC-CSM1.1	BC1	BCC	China
02	BCC-CSM1.1(m)	BC2	BCC	China
03	BNU-ESM	BNU	GCESS	China
04	CanESM2	CaE	CCCMA	Canada
05	CCSM4	CCS	NCAR	USA
06	CESM1(BGC)	CE1	NSF-DOE-NCAR	USA
07	CMCC-CM	CM2	INGV CMCC	Italy
08	CMCC-CMS	CM3	INGV CMCC	Italy
09	CSIRO-Mk3.6.0	CSI	CSIRO-QCCCE	Australia
10	EC-EARTH	ECE	EC-EARTH	Europe
11	FIO-ESM	FIO	FIO	China
12	GISS-E2-H-CC	GE2	NASA GISS	USA
13	GISS-E2-R	GE3	NASA GISS	USA
14	GFDL-CM3	GF2	NOAA GFDL	USA
15	GFDL-ESM2G	GF3	NOAA GFDL	USA
16	GFDL-ESM2M	GF4	NOAA GFDL	USA
17	HadGEM2-AO	Ha5	NIMR/KMA	Korea
18	INM-CM4	INC	INM	Russia
19	IPSL-CM5A-MR	IP2	IPSL	France
20	IPSL-CM5B-LR	IP3	IPSL	France
21	MIROC5	MI2	MIROC	Japan
22	MIROC-ESM	MI3	MIROC	Japan
23	MIROC-ESM-CHEM	MI4	MIROC	Japan
24	MPI-ESM-LR	MP1	MPI-M	Germany
25	MPI-ESM-MR	MP2	MPI-M	Germany
26	MRI-CGCM3	MR3	MRI	Japan
27	NorESM1-M	NE1	NCC	Norway
28	NorESM1-ME	NE2	NCC	Norway

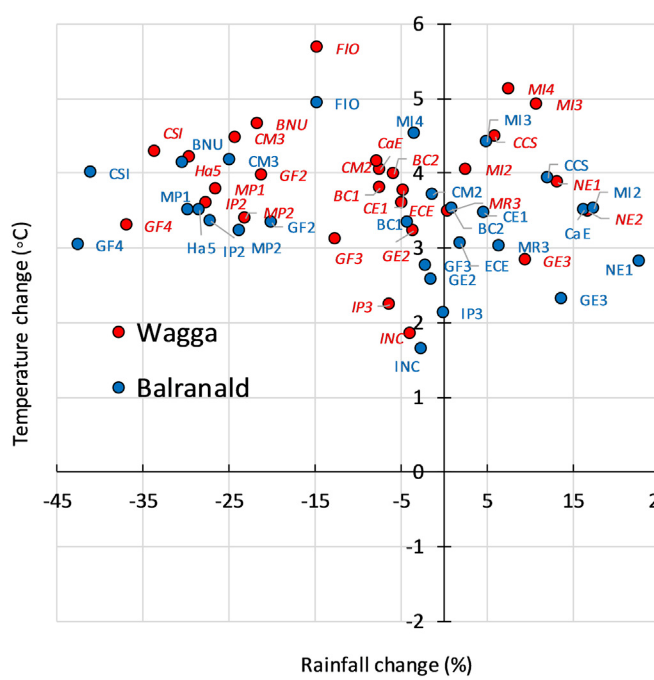

Fig. 2. The relationship between projected changes in temperature and rainfall for 28 GCMs under RCP8.5 in 2061–2100 compared to 1961–2000 at two study sites. The abbreviation of GCM can be found in Table 1.

Table 2
The definition and range of seven cultivar parameters used in the simulations with the APSIM model. The 4^7 = 16,384 virtual cultivars were generated by all possible combinations of different steps selected between minimum and maximum value of each parameter.

Cultivar parameters	Definition	Unit	Minimum value	Maximum value	Step
tt_end_of_juvenile (X1)	Thermal time from sowing to end of juvenile	°C·day	300	600	100
tt_floral_initiation (X2)	Thermal time from floral initiation to flowering	°C·day	455	755	100
tt_start_grain_fill (X3)	Thermal time from start grain filling to maturity	°C·day	445	745	100
Grains_per_gram_stem (X4)	Kernel number per stem weight at the beginning of grain filling	g	10	55	15
Potential_grain_filling_rate (X5)	Potential daily grain filling rate	$g{\cdot}grain^{-1}{\cdot}day^{-1}$	0.001	0.004	0.001
Max_grain_size (X6)	Maximum grain size	g	0.021	0.081	0.02
RUE (X7)	Radiation use efficiency	$g{\cdot}MJ^{-1}$	1.04	1.64	0.2

GCMs ensemble mean predicted growing-season rainfall would decrease by 9% at Wagga and 6% at Balranald. Compared with other GCMs, CSIRO-Mk3–6-0 (CSI) (Jeffrey et al., 2013) and GFDL-ESM2M (GF4) (Dunne et al., 2013) predicted a greater amount of rainfall decrease at the two study sites (Fig. 2). Therefore these two dry GCMs were used in the following analyses to represent the most unfavourable conditions under climate change.

2.3. Crop simulation model

The Agricultural Production Systems Simulator (APSIM) is a flexible framework that simulates crop growth and development in response to management practices and/or environmental change (Holzworth et al., 2014). It is able to mimic variation in crop development due to climate, soil water, soil carbon, nitrogen and phosphorus dynamics and their interactions within different cropping management systems. APSIM is an effective tool for studying the potential effects of future climate change on crop yields (Anwar et al., 2015; Liu et al., 2017b). It has been used to assess alternative management options including cultivar selection, sowing date, irrigation and soil type against trial data across various environments and applied in more than 110 countries worldwide (http://www.apsim.info/apsim/Publish/apsim/cowpea/docs/cowpea_science.htm). We used APSIM model version 7.7 to simulate the responses of wheat yields to cultivar change, sowing time and climate change. The modules used include wheat, soil water, soil nitrogen, surface residue and fertilizer. More details of the model can be found at http://www.apsim.info/Wiki/Module-Documentation.ashx.

APSIM mimics crop growth development on a daily time-step (Keating et al., 2003), forced with daily minimum and maximum temperatures, rainfall and solar radiation. The model is able to simulate both spring and winter varieties, the former of which was the focus of this study (see cultivar description below). In the model, wheat phenological development is described in terms of thermal time accumulation using 11 crop stages and 10 phases (time between stages) (https://www.apsim.info/Documentation/Model,CropandSoil/Crop-ModuleDocumentation/Wheat.aspx). The duration of each stage is determined by the accumulation of thermal time which is calculated as the sum of the average daily temperature above a base temperature required. The daily thermal time values are likely to be further influenced by photoperiod, vernalization and other environmental factors such as drought and heat stress. Potential daily biomass production is calculated using radiation use efficiency (RUE). Under non-limiting conditions, the model simulates biomass growth rate through multiplying RUE by light interception. However, an interpolation function is used in the model to simulate how RUE would be influenced by the major constraining factors in the wheat growing season such as water or nitrogen deficit and heat or frost stress. The rate at which biomass can be allocated to different parts of the crop depends on the phenological phase. Grain yield is determined by grain numbers and average kernel weight at maturity. Crop growth and yield are also affected by carbon dioxide (CO_2) through radiation use efficiency, transpiration efficiency and leaf nitrogen concentrations.

2.4. Cultivar parameters and model setting

The crop cultivar parameters in APSIM describe how particular genotypes are able to respond to environmental factors. In order to generate virtual cultivars (VCs) with different characteristics, a spring wheat cultivar (*Yitpi*) requiring less vernalization was used as a reference cultivar and the values of genetic parameters for VCs were created by modifying the parameters of *Yitpi*. There are two reasons why we selected *Yitpi* as a reference cultivar. One is that it has been widely sown in south-eastern Australia (Matthews et al., 2018). The other reason is that the removal of vernalization required for winter crops has proved to be a promising strategy that may cope with future warmer conditions (Ruiz-Ramos et al., 2018; Tao et al., 2017; Wang et al., 2015b). Based on the study of Zhao et al. (2014), seven genetic coefficients were selected to explore cultivar adaptive traits under future climate change. Detailed definitions of these coefficients can be found in Table 2. Three of them (tt_end_of_juvenile, tt_floral_initiation and tt_start_grain_fill) affect wheat phenology, and four (RUE, potential_grain_filling_rate, grains_per_gram_stem and max_grain_size) determine wheat yield formation. Four parameter values were assigned to each trait (Table 2). Changing these parameters altered wheat growth and development characteristics. In total, 4^7 = 16,384 possible combinations of parameter values were simulated. Ideotypes that performed better than reference cultivar *Yitpi* were considered cultivars that might be better adapted to future climate.

Optimal sowing date was also explored to match the life cycle of developed cultivars to future climate and to avoid drought and heat stress. Wheat in south-eastern Australia is usually sown from 1 April to 31 July when cumulative rainfall in ten consecutive days exceeds 25 mm (Wang et al., 2017). In a warmer future climate, early sowing may benefit wheat growth, so we conducted simulation analyses for 20 sowing dates at 5-day intervals across a sowing window from 15 March to 18 June. To avoid the failure of seed germination due to water stress, 15 mm water was irrigated on sowing date. At each site, a typical soil was used for the simulations, i.e. Red Sodosol (No550-YP) for Wagga and Loam (No616-YP) for Balranald, which are geographically closest to the two contrasting sites. The parameters of soil characteristics required by APSIM were extracted from the Australian Soil Resource Information Systems (http://www.asris.csiro.au/mapping/hyperdocs/APSRU/). Wheat was sown at 30 mm depth with a density of 120 plants m^{-2}. For all simulations, the initial soil water was reset on 1 January each year at 20% of maximum available water relative to lower limit of the soil (Dreccer et al., 2018). Simulations were performed by applying 60 kg ha^{-1} nitrogen at the two study sites following current best management practice. For the RCP8.5 scenario, elevated CO_2 concentrations during 2061–2100 was fitted with calendar years according to Liu et al. (2017b).

$$[CO_2]_{year} = 1034.3 + \frac{267.78 - 1.6188 * y}{4.0143 + \frac{53.342}{y^{5.2822}}} + 21.746 * \left(\frac{y - 2010}{100}\right)^3 + 100.65 * \left(\frac{y - 1911}{100}\right)^3$$

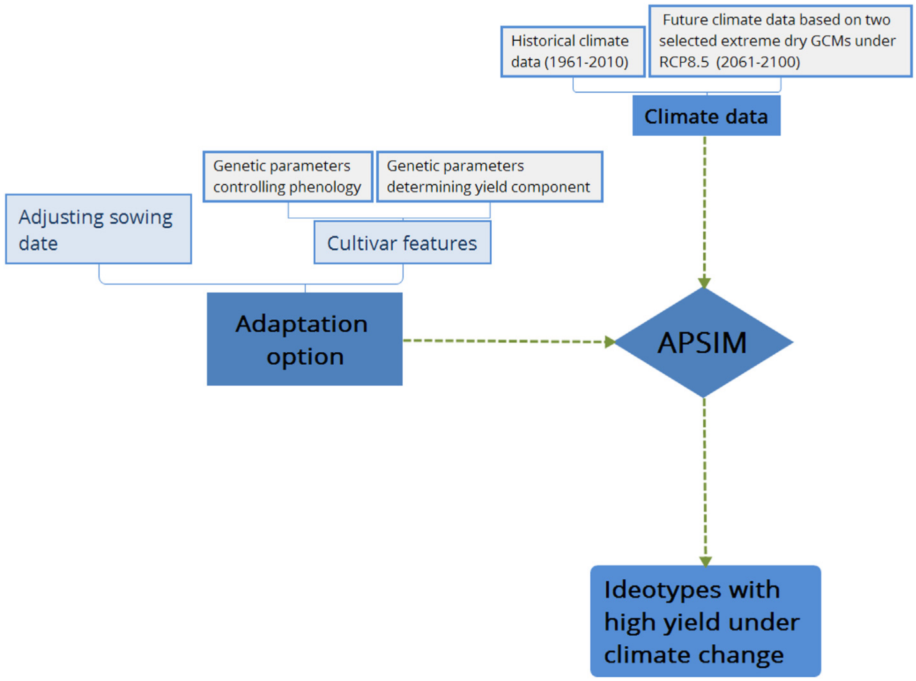

Fig. 3. The flowchart of designing wheat ideotypes with adjusting sowing date under adverse climate conditions.

In total, 1, 310,720 (4^7 virtual cultivars * 20 sowing dates * 2 sites * 2 GCMs) simulations were run and evaluated using customized codes in the R software (R-Core-Team, 2016) with different packages based on multiple high-performance workstation computers. The overall framework, shown in Fig. 3, illustrates the procedure used in this study to explore the wheat yield response to various cultivars and sowing date adjustment under the most adverse climate conditions.

In order to test how different combinations of cultivar parameters and sowing dates would respond to climate change, we considered two sets of cultivar parameters related to wheat phenology (***Phe***) and yield formation (***Yil***). Therefore, there were three adaptation options: (1) adjusting cultivar thermal time requirements and changing sowing date (***SW*** + ***Phe***) (2) changing cultivar parameters for yield formation and changing sowing date (***SW*** + ***Yil***) (3) changing all cultivar parameters and sowing time (***SW*** + ***Phe*** + ***Yil***).

3. Results and discussion

3.1. Simulated yield response to climate change under different adaptation options

Fig. 4 shows highest wheat yields under optimal combinations of ***Phe*** or/and ***Yil*** on 20 sowing dates for each site and each GCM under RCP8.5 in 2061–2100. As a benchmark we used yields of reference cultivar *Yitpi,* an early-mid maturing cultivar, sown on 19 May under baseline climate conditions (Matthews et al., 2018). Our simulated average yields for *Yitpi* during 1961–2000 were approximately 3297 kg ha^{-1} and 1375 kg ha^{-1} for Wagga and Balranald respectively, comparable to historical yields reported by Fitzsimmons (2001) and Potgieter et al. (2002). At the two sites, early sowing of all virtual cultivars enhanced crop yield under both baseline and future climate scenarios (Fig. 4). The optimum sowing date for all sets of cultivar parameters (***Phe*** or/and ***Yil***) was three to four weeks earlier than the reference sowing date (19 May) at Wagga (Fig. 4a and b) and Balranald (Fig. 4c and d). Farmers in south-eastern Australia have already advanced sowing times to ensure that booting and flowering occur before the onset of heat and drought (Ghahramani et al., 2015). Earlier sowing of cold-sensitive winter crops may have become possible because warmer winter and spring reduce the risk of frost damage (Zheng et al., 2012).

We found that, without adaptation options, simulated yields decreased by 19–27% at Wagga and 31–46% at Balranald under RCP8.5 compared to the reference cultivar (Fig. 5). Under ***SW*** + ***Phe***, yields decreased by 13–16% at Wagga and 9–34% at Balranald. Under ***SW*** + ***Yil***, yields increased by 9–10% at Wagga but only 0.9% at Balranald using the CSI model, and decreased by 27% under the GF4 model. When the idealized types and early sowing (***SW*** + ***Phe*** + ***Yil***) were adopted, simulated yield increased by 20–24% at Wagga compared to baseline. For Balranald, yield increased by 21% in the CSI model but decreased by 13% in the GF4 model.

Our results reveal that adaptation strategies can be effective in reversing adverse climate change effects on wheat yields, as shown by the remarkable yield increase at the wetter site (Wagga). However areas with a projected drop in growing season rainfall may not benefit from these adaptations, as shown by the minimal yield increase for a dry GCM at the dry site (Balranald). Shifts in cultivars and planting dates are not enough to offset the adverse effects of climate change at dry locations. Donatelli et al. (2015) showed that in some parts of Europe which experience drought, developing new cultivars and changing sowing date could not lead to a yield increase. Selecting cultivars with smaller leaves or more efficient water uptake by roots to transpiration, giving them greater tolerance to heat and drought, has been suggested as a priority in dry areas (Mäkinen et al., 2017; Semenov et al., 2014).

3.2. Wheat ideotypes

For each site and each GCM, we selected the VCs with highest wheat yield on the optimum sowing date compared with the current wheat cultivar *Yitpi* (Fig. 6). All VCs were sown on 20 different sowing dates in 2061–2100 to test whether they can outyield cultivar *Yitpi*. Due to increased temperature and reduced rainfall under RCP8.5, most VCs were unable to outyield *Yitpi* at our contrasting study sites. VC896 had the highest 40-year average grain yield under RCP8.5 for both CSI and GF4 at Wagga. VC895 and VC896 were the cultivars with the highest yields for CSI and GF4 at Balranald, respectively. The values for optimum cultivar parameters are shown in Table 3. We also used Classification

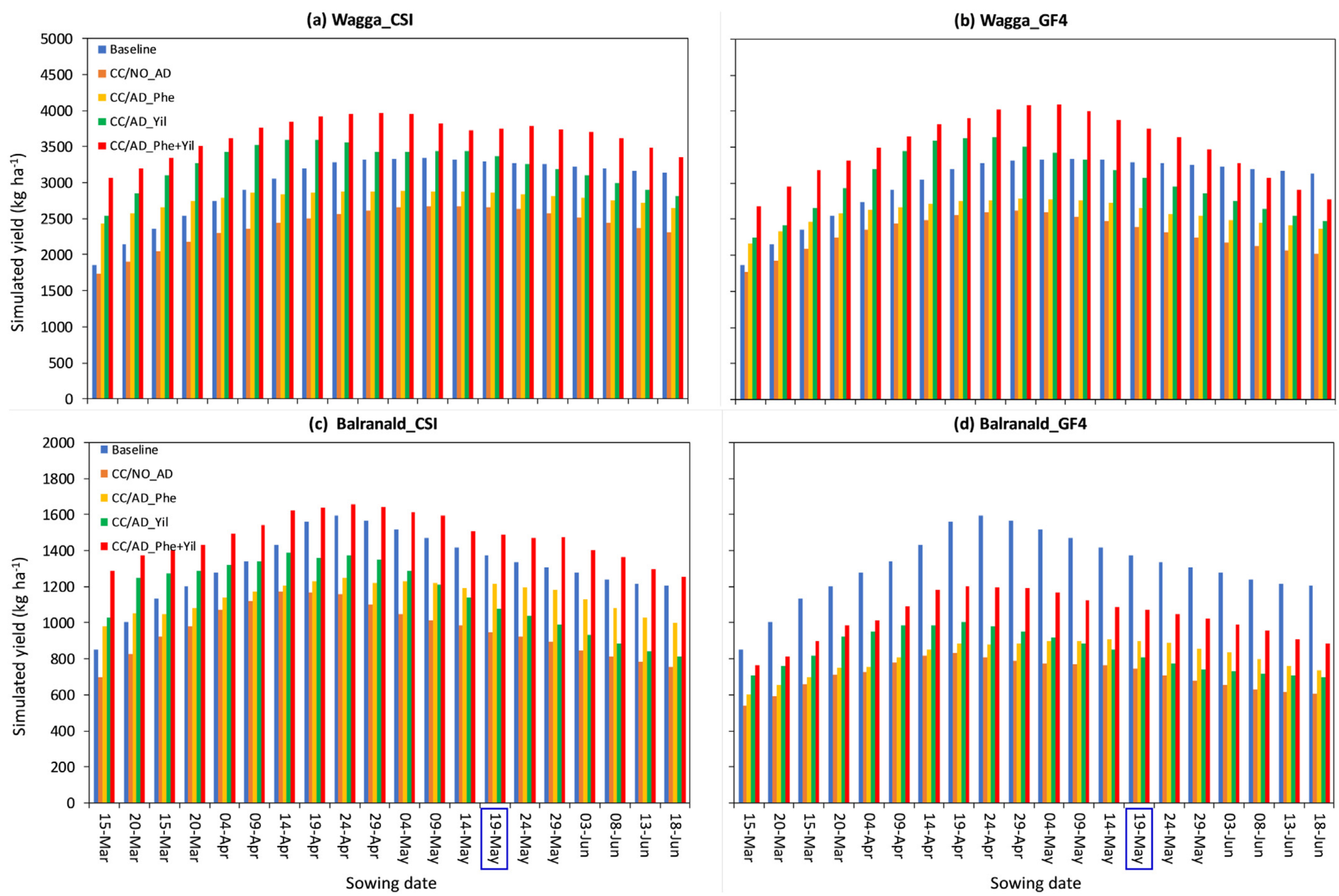

Fig. 4. Simulated wheat yield for reference cultivar *Yitpi* under baseline climate in 1961–2000 and the highest yield achieved under different adaptation options (***CC/NO_AD***: climate change without adaptation option implemented; ***CC/AD_Phe***: climate change with adaptation option of only changing cultivar pheneology parameters; ***CC/AD_Yil***: climate change with adaptation option of only change cultivar parameters determining yield formation; ***CC/AD_ Phe + Yil***: climate change with adaptation option of ideotypes used) under RCP8.5 for two GCMs (CSI and GF4) in 2061–2100 on 20 various sowing dates at Wagga and Balranald. Reference cultivar *Yitpi* sown on 19 May was used as the benchmark.

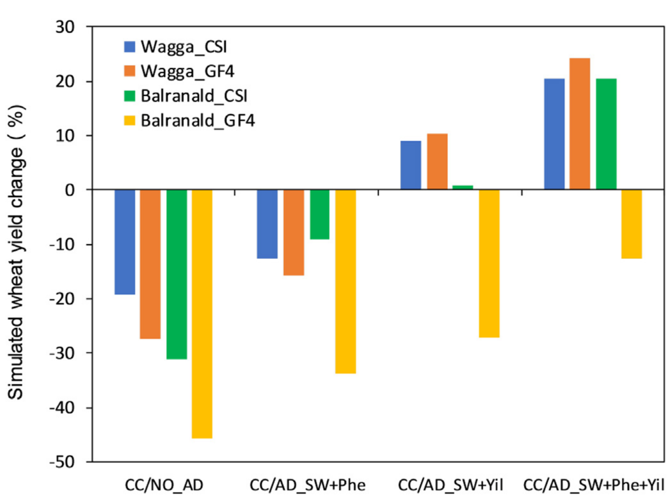

Fig. 5. Simulated yield change for two GCMs (CSI and GF4) at Wagga and Balranald in 2061–2100 under climate change with different adaptation option (***CC/NO_AD***: climate change without adaptation option implemented; ***CC/AD_SW + Phe***: climate change with adaptation option of sowing date adjustment and only changing cultivar pheneology parameters; ***CC/AD_SW + Yil***: climate change with adaptation option of sowing date adjustment and only change cultivar parameters determining yield formation; ***CC/AD_SW + Phe + Yil***: climate change with adaptation option of sowing date adjustment and ideotypes) compared to reference cultivar in 1961–2000.

and Regression Tree (CART) analysis to identify the combinations of seven cultivar parameters that provided a high simulated wheat yield under future climate conditions. Although wheat was sown on 20 different sowing dates, we show only the simulated yield of the 16,384 virtual cultivars sown on the optimal sowing date. Fig. 7 shows that the parameter X4 (Grains_per_gram_stem) was selected in the primary data split for both two GCMs to achieve high yields, followed by X5 (Potential_grain_filling_rate) in Wagga and X1 (tt_end_of_juvenile) in Balranald. Parameters tt_floral_initiation and tt_start_grain_fill were not selected into decision trees to determine yield in Wagga (Fig. 7a & 7b); RUE and tt_start_grain_fill were not used in Balranald (Fig. 7c & 7d). The overall patterns for the major parameters selected by CART were that greater values of the cultivars parameters (e.g. Grains_per_gram_stem, Potential_grain_filling_rate, Max_grain_size) would result in a higher yield.

It is interesting to note that VC896 and VC895 shared common wheat growth characteristics (Table 3). For example, thermal time needed from the start of grain filling to maturity was longer compared to *Yitpi*, because ideotypes were able to achieve higher grain yields with a longer grain filling period. Our wheat ideotypes are consistent with previous studies in similar climatic regions. For example, Tao et al. (2017) and Semenov et al. (2014) found that longer thermal time requirement for the grain filling period would increase crop yields in Europe under climate change characterized by reduced rainfall and increased temperatures. Our results show that both ideotypes had the traits of early flowering. Ludwig and Asseng (2010) demonstrated that earlier flowering cultivars tended to increase wheat yield potential

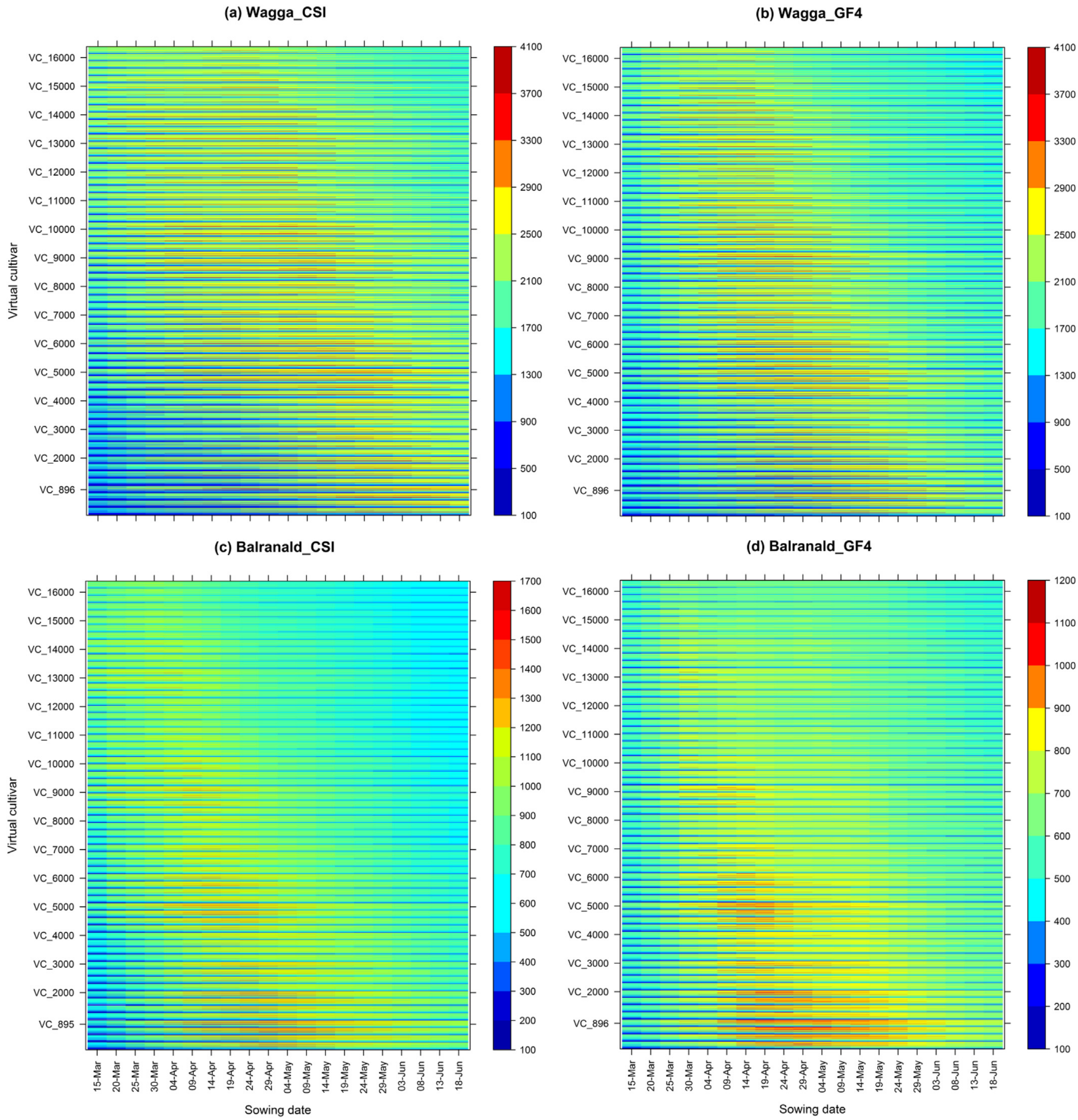

Fig. 6. Simulated average wheat yield on 20 different sowing dates for 16,384 virtual cultivars (VC) at Wagga and Balranald in CSI and GF4 model under RCP8.5 in 2061–2100. VC896 sown on 29 April and VC896 sown on 4 May shows the highest yields at Wagga for CSI and GF4, respectively. VC895 sown on 24 April and VC 896 sown on 19 April have the highest yields at Balranald for CSI and GF4, respectively.

under Australian dry rainfed conditions because the grain filling period occurred in the cooler and wetter part of the season. Early flowering may offer a useful strategy to avoid excessive heat and drought stress in the reproductive stage (Shavrukov et al., 2017).

The two ideotypes have common adaptive characteristics that determine wheat yield potential. The values of all seven parameters increased compared to the reference cultivar, except grains_per_gram_stem. VC896 has a large radiation use efficiency which is likely to increase potential aboveground biomass (Chen et al., 2010). The amount of radiation captured influences the rate of crop growth and photosynthesis (Tao et al., 2017). This is consistent with the results of Qin et al. (2018), who found that projected yield would increase by 4–9% when RUE increased. These latter authors concluded that increasing RUE of the reference cultivar was an effective way to promote wheat biomass production under future climate change. The max_grain_size is also an important parameter determining wheat grain while the potential_grain_filling_rate controls the grain filling rate in the reproductive period. Although grains_per_gram_stem also influences grain numbers in the APSIM wheat module, it is similar to the reference cultivar in our study. This is probably due to an interaction between

Table 3
Optimal genetic parameters with highest yield under RCP8.5 in 2061–2100 at two sites for two GCMs used in this study. The values of genetic parameters for reference cultivar were also included. VC896 is the ideotype for CSI and GF4 at Wagga. VC895 and VC896 are ideotypes at Balranald for CSI and GF4, respectively.

Cultivar parameters	Unit	Reference cultivar (*Yitpi*)	Wagga		Balranald	
			CSI (VC896)	GF4 (VC896)	CSI (VC895)	GF4 (VC896)
tt_end_of_juvenile	°C·day	400	300	300	300	300
tt_floral_initiation	°C·day	555	455	455	455	455
tt_start_grain_fill	°C·day	545	745	745	745	745
RUE	$g{\cdot}MJ^{-1}$	1.24	1.64	1.64	1.44	1.64
Potential_grain_filling_rate	$g{\cdot}grain^{-1}{\cdot}day^{-1}$	0.002	0.004	0.004	0.004	0.004
Grains_per_gram_stem	g	25	25	25	25	25
Max_grain_size	g	0.041	0.081	0.081	0.081	0.081

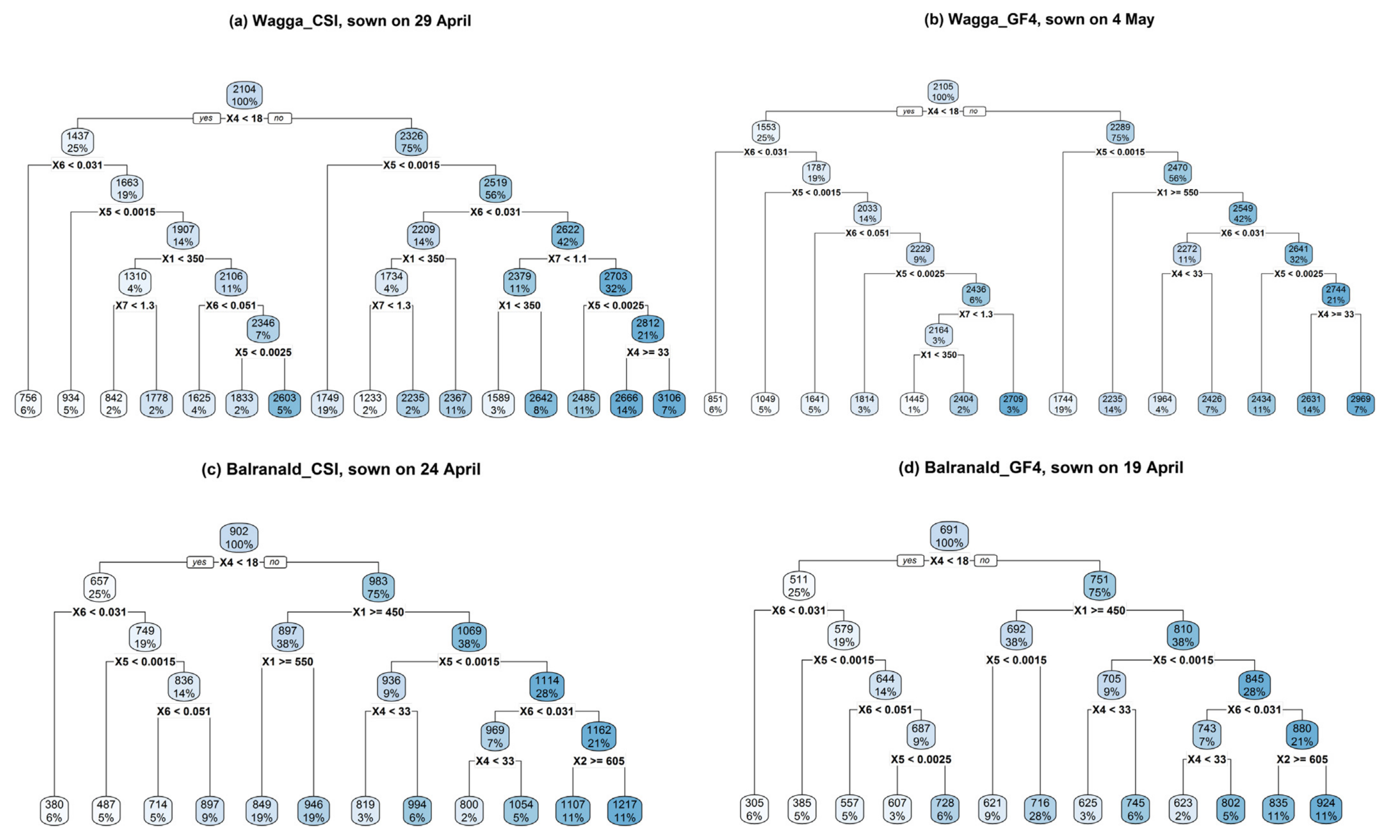

Fig. 7. Classification and regression tree analysis (CART) of simulated yield of wheat sown at the optimal sowing time for two climate models (CSI and GF4) at two sites (Wagga and Balranald). The CART analysis forms a decision tree which classifies the yield from a set of cultivar parameters. X1: tt_end_of_juvenile, X2: tt_floral_initiation, X4: Grains_per_gram_stem, X5: Potential_grain_filling_rate, X6: Max_grain_size, X7: RUE. Detailed description on each parameter could be found in Table 2.

these yield-formation parameters in APSIM. In common with the results of Loison et al. (2017) for cotton in Africa, Tao et al. (2017) for barley in Europe, and Qin et al. (2018) for wheat in Canada, crop ideotypes should have an earlier flowering date and a longer reproductive period with an increase in the radiation use efficiency or maximum photosynthetic rate. Using a process-based crop modelling approach for designing ideotypes consistently shows that increased grain number and grain filling rate contribute genetic crop yield improvements (Loison et al., 2017; Semenov et al., 2014; Tao et al., 2017).

3.3. Uncertainty and limitations of the study

Based on a previous study of Zhao et al. (2014) who conducted a sensitivity analysis of a series of cultivar parameters in APSIM, our study investigated seven cultivar parameters linked mainly to phenology and yield components. APSIM involves numerous parameters that are able to interact with cultivar parameters and environmental variables to influence crop biomass and yield. However, we did not classify more parameters and explore their sensitivity to the future climate. This could result in the uncertainty in proposed ideotypes because of a dependence on genetic coefficients that have been selected. For example, Tao et al. (2017) found that APSIM suggests a smaller photoperiod and vernalization sensitivity for barley ideotypes at a warm site in Spain while a large value of vernalization was required at a cold site in Finland. In contrast, we did not include the effects of photoperiod and vernalization on wheat phenology in APSIM, but used thermal time required at different growth stages. In addition, other management practices such as fertilization rates, crop rotation and stubble management to increase water use efficiency were not considered as part of our study due to the heavy computational load. Similarly, previous studies designing new crop cultivars only considered the combination of different genetic coefficients which did not include the development of agronomic management (Semenov et al., 2014; Tao et al., 2017). More importantly, only adapting ideotypes is unable to fully overcome negative effects of climate change under extreme dry scenarios. It would be useful to incorporate agronomic management and new genotypes into future climate change scenarios to ensure food production and security, given the diversity, complexity and uncertainty of climate projections. We constrained our analysis to concentrate on the biophysical aspects of climate effects without considering the future development of the world economy or yield changes due to improvements in agro-technologies (Deryng et al., 2014). Adaptation measures such as changing fertilizer application rates would require economic analysis (Xing et al., 2017) beyond the scope of the current study.

In addition to uncertainty arising from cultivar parameters used, the large climate variation across the wheat belt of eastern Australia implies that the use of a few sites may not fully reflect the wheat cropping system. Ludwig and Asseng (2010) found that the effects of different plant traits on yield under climate change is also subject to soil type at different locations. For example, yield gains for early vigour traits are likely be higher on a sandy loam than on a heavier clay soil. Among different soil types, crop yield is likely to vary as a consequence of differences in water and nutrients assimilated by different cultivars. As soil moisture and fertility maintain crop growth and development under various adverse conditions, soil types may offer a buffer to reduce the impacts of climate variation, which will influence the results of different combinations of cultivar traits. Therefore, our future work should provide a more detailed and comprehensive regional analysis at a high resolution to gain a richer understanding of the response of optimum cultivar to future climate change in eastern Australia.

The number of climate and crop models also limited the simulations. We used only two extreme GCMs (CSI and GF4) to reduce the computational load but they do not fully capture the range of worst-case scenarios linked to the abiotic stresses (water and heat stress) caused by climate change. In addition, although APSIM has well simulated the effects of climate change on wheat growth and development, and the responses of wheat yield to various agricultural managements, the current model does not sufficiently take into account yield reduction due to diseases, pests, weeds and extreme weather events (e.g. floods, droughts and extreme heat). Moreover, only one crop model was considered in our study, which omits the uncertainty of crop model structure to changing climate (Tao et al., 2018; Zhang et al., 2017). We did not include more crop models due to computational constraints caused by the huge number of combinations of possible genetic parameters and changing sowing dates. Although APSIM has been widely used for climate change assessment studies globally, a single model is likely to be overconfident. Multi-model ensembles are generally considered more reliable than single models due to multi-model ensembles providing information from all participating models. For example, Tao et al. (2017) developed an ensemble approach using eight crop models to design idealized barley varieties to cope with future climate change. They found some contradictions among crop models when generating genetic coefficients to design barley ideotypes. For instance, one of the models suggested a smaller value of parameter LAI_{max}, unlike the other models. This contradiction is likely due to differences in model framework and structure. Tao et al. (2017) proposed a crop model ensemble technique to design more reliable ideotypes for plant breeders based on crop simulation modelling. We acknowledge that the results presented here depend on the scenario and climate model as well as crop model chosen. Our future work will use more comprehensive analyses (e.g. crop model ensemble, and incorporation of more agronomic practices in ideotypes) when exploring optimum adaptations to cope with climate change.

4. Conclusions

This study explored wheat yield changes using different cultivars and sowing dates in the future period of 2061–2100 for the “business-as-usual” scenarios (RCP8.5) compared with the yield simulated from a widely used reference cultivar in the historical period 1961–2000. Our research, presented here for the first time, shows how wheat ideotypes and earlier sowing strategies respond to future climate change in south-eastern Australia. There is a great potential for adapting wheat systems to adverse climate conditions by breeding new cultivars and adopting earlier sowing strategies. Adaptation options used in this study could increase crop yield under future climates and may be particularly beneficial under dry scenarios in higher rainfall (~450 mm wheat growing season rainfall) environments of the south-eastern Australia wheat belt. In drier environments (wheat growing season rainfall less than ~230 mm), simulated future yields could not outyield the reference cultivar due to a large decrease of growing season rainfall. Future research should focus on testing other efficient agronomic practices (e.g. crop rotations and stubble management to increase water use efficiency in different soil types) in dry sites to combat climate change. In addition, a multi-crop-model ensemble approach should be explored to reduce uncertainty caused by using the structure and parameter selection of a single crop model. We also suggest that future breeding technology should focus on developing cultivars with a shorter vegetative phase (earlier flowering) and longer reproductive periods as well as a higher RUE (more biomass potential) with greater dry matter accumulation during the grain filling period. Our results provide insights based on model-aided crop ideotypes to inform plant breeders and agronomists in determining which characteristics are important for crop yields under adverse future climate change conditions.

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