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The value of adapting to climate change in Australian wheat farm systems: farm to cross-regional scale

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ABSTRACT

Wheat is one of the main grains produced across the globe and wheat yields are sensitive to changes in climate. Australia is a major exporter of wheat, and variations in its national production influence trade supplies and global markets. We evaluated the effect of climate change in 2030 compared to a baseline period (1980–1999) by upscaling from farm to the national level. Wheat yields and gross margins under current and projected climates were assessed using current technology and management practices and then compared with 'best adapted' yield achieved by adjustments to planting date, nitrogen fertilizer, and available cultivars for each region. For the baseline climate (1980–1999), there was a potential yield gap modelled as optimized adaptation gave potential up scaled yields (tonne/ha) and gross margins (AUD $/ha) of 17% and 33% above the baseline, respectively. In 2030 and at Australian wheatbelt level, climate change impact projected to decline wheat yield by 1%. For 2030, national wheat yields were simulated to decrease yields by 1% when using existing technology and practices but increase them by 18% assuming optimal adaptation. Hence, nationally at 2030 for a fully-adapted wheat system, yield increased by 1% and gross margin by 0.3% compared to the fully adapted current climate baseline. However, there was substantial regional variation with median yields and gross margins decreasing in 55% of sites. Full adaptation of farm systems under current climate is not expected, and so this will remain an on-going challenge. However, by 2030 there will be a greater opportunity to increase the overall water use and nitrogen efficiencies of the Australian wheat belt, mostly resulting from elevated atmospheric CO_2 concentrations.

1. Introduction

Wheat production is known to be sensitive to variations in both temperature and rainfall (Lobell et al., 2011). Changes in climate are expected to have varying impacts in different regions of the globe although negative impacts are expected to be more common than positive ones (Porter et al., 2014). A reduction in Australian wheat production can potentially affect global food security (FAO, 1996) and its global availability (Ingram, 2011), as Australia is the fourth largest wheat exporter in the world (Connor et al., 2011). Its production can affect the global food market, as shown by increased global wheat prices during the drought between 2002 and 2009 (Lobell et al., 2011).

Changes in climate over the past century interact with advances in agricultural technology and farming systems (Lobell et al., 2011). As, greater changes in climate are predicted in the near future compared to the changes of the late 20th century (Parry et al., 2007) continued technology and farming systems adaptations will be needed.

A viable response strategy for regions such as the Australian wheatbelt where climate change is largely anticipated to be negative is via improvement of farm management practices to offset anticipated declines in production and profitability (e.g. Stokes and Howden, 2010). Climate adaptation is the process of adjustment in natural or human systems in response to actual or expected climatic stimuli to moderate harm or exploit opportunities (Parry et al., 2007). In farming, management adaptations vary resource use in accordance with changes in climate and its seasonal variability to gain benefit for example from increased yield (Bassu et al., 2009; Hunt and Kirkegaard, 2012). However,

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there often exists a 'yield gap' between actual farm practices and those which would maximise benefits. This is important when assessing climate change scenarios so as to not conflate closing the existing yield gap with optimised adaptation under climate change (Stokes and Howden, 2010).

Some potential benefits from changes in climate are related to fertilization by elevated atmospheric CO_2, which is an important part of the climate change impact in water-limited environments i.e. the great majority of Australian production (Tubiello et al., 2007). The primary adaptation opportunities arise from managing soil water more efficiently through the growing season (Kirkegaard et al., 2014) by choosing variety, sowing time, sowing density and fertilizer timing and amount. It should be noted that management strategies that are optimized for present-day climate may not necessarily be optimal for future climate. This suggests that it is worthwhile exploring optimal adaptation under projected climate.

Previous evaluations of climate change impacts on Australian wheat production have indicated a substantial decline in production in Western Australia (Ludwig et al., 2009) and a decrease in production in the southern part of the Australian wheatbelt (Ludwig and Asseng, 2006), including cross-regional assessments of impacts and adaptations (Howden, 2002; Howden and Crimp, 2005). However, these analyses of yield and gross margin change have been applied to a limited number of sites and have not included effective methods to scale up the analyses to a national level to provide industry and policy makers with a clearer insight for high level planning.

In this paper we evaluate the impact of climate change and the effectiveness of adaptations for projected climate scenarios in 2030 relative to a historical baseline of 1980–1999 (with current management), in order to estimate the value of adaptation in terms of production and financial returns. We use a bottom-up methodology that optimally exploits local knowledge and data (van Ittersum et al., 2013) and requires extensive biophysical system modelling. We predict wheat production/gross margin in 2030 through the biophysical modelling of unit scale results and use farm survey data and a survey estimation method to upscale results to a cross-regional/ national level.

2. Methods

The impacts of climate change and adaptations were evaluated in terms of the resulting yield (per ha) and gross margin (per ha), which is the difference between estimated income and the fixed and variable costs of production, excluding capital costs. The adapted yield (AY) and adapted gross margin (AG) are upper limits for fully enhanced systems with all adaptation strategies (in this study, all currently-existing technologies) at the efficiency frontier (EF). For historical climate, lower limits are the historical yield (HY) and historical gross margin (HG) under current practice. For future climate we defined lower limits as current practice yield (CPY) and current practice gross margin (CPG). AY and AG are reported in comparison with those of HY and HG for the historical baseline and CPY and CPG for the future. It should be note that AY and AG are fully adapted (enhanced) systems on the EF. These modeled values may not be achievable due to biophysical, management, social, or economic constraints. Here, all projections in 2030 have been associated with the effect of elevated atmospheric CO_2 unless otherwise indicated. Concepts, abbreviations, impact, and adaptation framework are presented in Fig. 1.

2.1. Study area and sites

The study area is the Australian wheatbelt (Fig. 2). Averaged over 1980–1999, about 10.2 million ha of this area has been planted to wheat (ABARES, 2003). Across this region the climate and soil

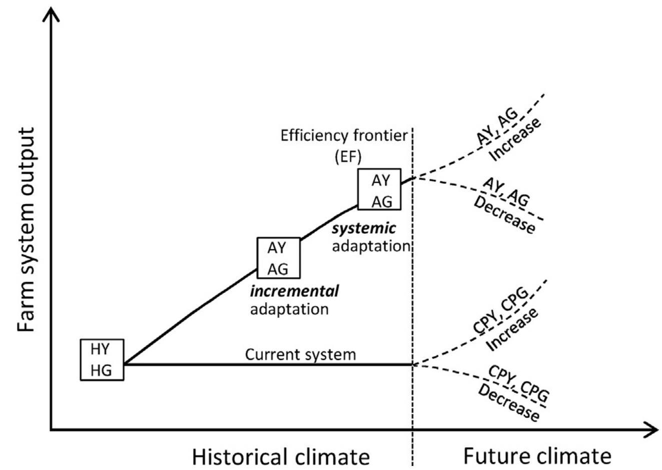

Fig. 1. Concepts and frame work for climate change impact and adaptation analysis. HY: historical yield, HG: historical gross margin, AY: adapted yield, AG: adapted gross margin, CPY: current practice yield, CPG: current practice gross margin. AY and AG are on the efficiency frontier when implementing systemic combination of incremental adaptation options from current technologies.

types (Table 1) and cultivars (Table 2) vary widely. A set of representative wheat farming sites was therefore selected by aggregating statistical areas level 2 within the wheatbelt (SA2s, Australian Bureau of Statistics, 2011) into a set of 30 regions (Fig. 2) so that each region had approximately equal gross value of average agricultural production (GVAP). SA2s were grouped according to their average annual rainfall and land use (i.e. the proportions of GVAP attributable to cropping). A single location (Fig. 1) was then selected from each of the 30 regions to ensure a good spread of sites across the wheat belt (as in Moore and Ghahramani, 2013). The baseline climate was 1980–2010 at each location as recorded by the Bureau of Meteorology.

2.2. Climate change scenarios

Research has demonstrated that global carbon dioxide (CO_2) emissions, atmospheric CO_2 concentrations, sea-level rise and global temperatures are already tracking along the upper bounds of the previously-projected range (Peters et al., 2012). We therefore used two high-emissions CMIP3 (Meehl et al., 2007) scenarios (A1FI and A2) with high and medium sensitivity that allowed us to sample across the more likely range of possible future climates in the focus year of 2030 using six global climate models (GCM): ECHAM 5 (Roeckner et al., 2003), GFDL 2.1 (Delworth et al., 2006), HADCM3 (Pope et al., 2000), HADGEM1 (Johns et al., 2006), MIROC-H (Burgess et al., 2012), MRI-GCM 232 (Yukimoto et al., 2001). These GCMs were selected based on performance and ranking by 11 criteria (Crimp et al., 2010) of which the most important were (i) demerit points based on criteria for rainfall, temperature and mean sea level pressure (Suppiah et al., 2007), (ii) *M*-statistics representing goodness of fit at simulating rainfall, temperature and mean sea level pressure (Watterson, 2008) and (iii) predictive skill for daily rainfall over Australia (Perkins et al., 2007). At the time of analysis Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) projections were not yet available.

Projections from each GCM were statistically downscaled using the quantile matching (QM) method (Kokic et al., 2013; Burgess et al., 2012) to produce daily weather data sequences for each of the 30 locations. The QM algorithm works by modifying historical weather sequences (in this case for 1980–2010), and therefore preserves spatial correlations in climate; for example a drought at one location is likely to coincide with a drought at nearby locations. This is essential when attempting to scale up effects across the

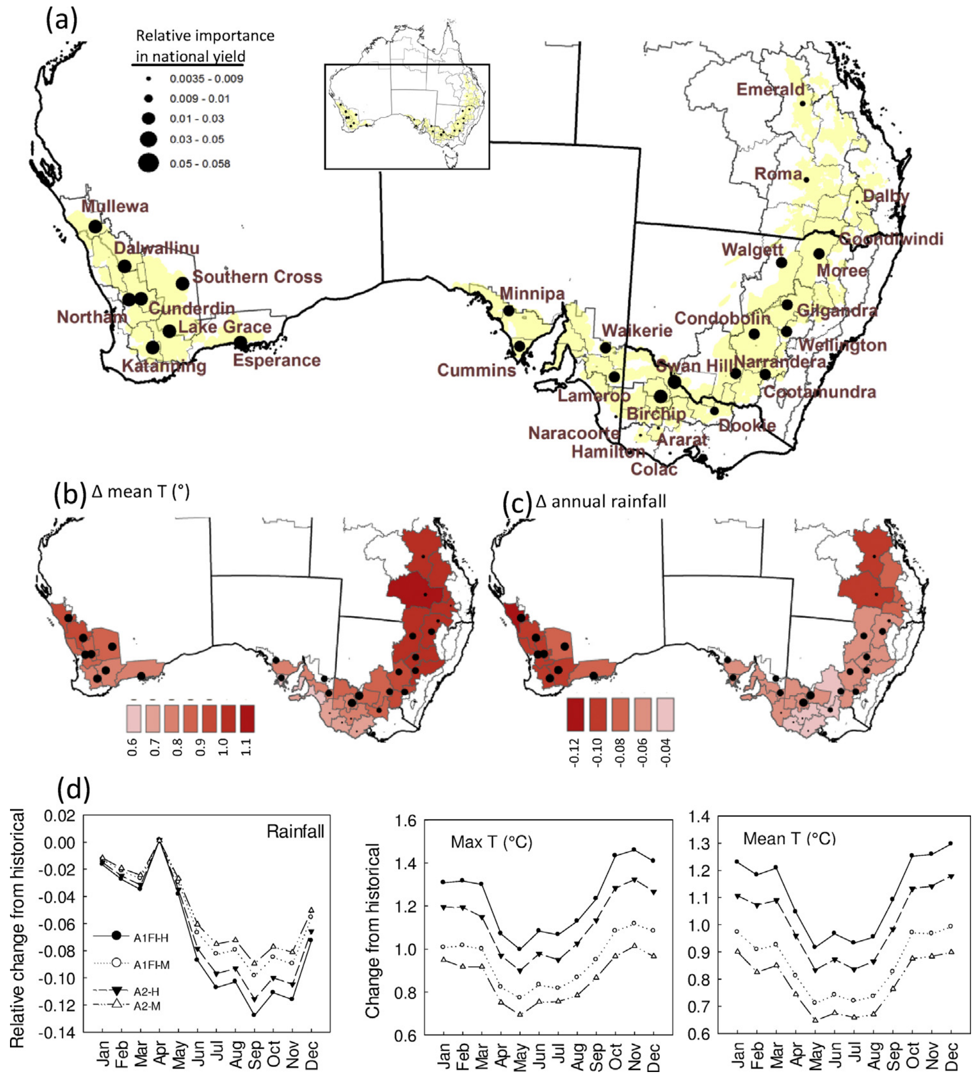

Fig. 2. (a) Simulated sites across the wheatbelt (yellow) and within ABARES farm survey regions with point size represents relative contribution in cross-regional scale production during baseline, (b) change in annual mean temperature in 2030 across all GCMs, sensitivities, and scenarios (see text), (c) relative change in mean annual growing season rainfall in 2030 across all GCMs, sensitivities, and scenarios, (d) relative change in median in 2030 that averaged across sites for rainfall, and changes in maximum temperature (Max *T*), and minimum temperature (Min *T*) from historical period. Legend caption inside Fig denotes to the climate scenarios (A1FI and A2) and examined sensitivity (High and Medium). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

country. Atmospheric CO_2 concentrations of 350 ppm for historical climate and 449 and 444 ppm for 2030 under the A1FI and A2 scenarios were assumed (Houghton et al., 2001).

2.3. Simulation setup and base parameters

APSIM (the Agricultural Production Systems Simulator) version 7.5 was used to simulate biophysical processes. We applied additional functions to account for frost and heat stress further to APSIM's current formulation (Bell et al., 2015; Farre et al., 2010), because the effects of frost and heat are expected to contribute to a direct decline in yield (Porter et al., 2014). The time period 1980–1999 was used as the historical baseline. Soil parameters for all locations except Hamilton (Rennick Peries, Victoria, DPI, personal communication) were selected from the APSoil data base (Dalgliesh et al., 2006).

A set of simulations were performed for parameterization of soil characteristics. Initial soil Nitrogen (N) of each location was estimated from a longer term historical run (1957–2010) under continuous sowing without resetting soil N at the end of each year. A test simulation with extractable soil water (esw) varied between 20% and 100% of soil water holding capacity showed that it took less than 10 years to stabilize yields if esw was not reset each year. Thus, initial years prior to 1980 were removed to equilibrate soil water. Models were setup for continuous sowing (Bryan et al., 2014) while soil nitrogen was reset at the end of each year.

The baseline sowing window and reference wheat cultivar for each location were selected based on local conditions (Chenu et al., 2013; Hunt and Kirkegaard, 2012) and expert opinions (e.g. personal communications with James Hunt of CSIRO and David Bowran of the Department of Agriculture and Food of Western Australia via producer workshops). Sowing was simulated when 3-day total rainfall exceeded 10 mm and plant available soil water (PASW) exceeded a threshold (Chenu et al., 2013). Long term simulation results (1957–2010) indicated that a PASW threshold of 0 mm was appropriate in all locations except those in Queensland and northern New South Wales where 50–150 mm PASW thresholds were required for sowing (Table 2). Water use efficiency parameters (Moore et al., 2011) were modelled for each site and management × climate combinations.

Statistical data collection in Australia is inadequate to allow current practice for N input rates to be identified across our

Table 1
Attributes of modeled wheat production systems. ABM is weather station code. PASW is plant available soil water used in sowing rule.

Location name	Longitude	Latitude	State	Soil description	ABM Id	Annual rainfall (mm)	Annual mean temperature (°C)	PASW threshold for sowing (mm)
Dalwallinu	116.6619	−30.2772	WA	Red sandy loam	008039	378	16.7	0
Mullewa	115.5142	−28.5367	WA	Red sandy earth	008095	347	17.1	0
Esperance	121.8925	−33.8300	WA	Sand over clay	009789	497	15.8	0
Cunderdin	117.2511	−31.6597	WA	Grey deep sandy duplex	010035	374	16.6	0
Northam	116.6703	−31.6408	WA	Grey deep sandy duplex	010111	423	16.5	0
Katanning	117.5553	−33.6886	WA	Sandy duplex	010579	466	15.0	0
Lake Grace	118.4625	−33.1006	WA	Yellow sodsol	010592	353	15.6	0
Southern Cross	119.3281	−31.2319	WA	Calcareous loamy earth	012074	348	16.3	0
Cummins	135.7253	−34.2661	SA	Clay loam over red clay	018023	397	15.4	0
Minnipa	135.1500	−32.8361	SA	Red sandy loam over light clay	018052	322	16.7	0
Waikerie	139.9806	−34.1778	SA	Sandy loam	024018	275	16.2	0
Lameroo	140.5175	−35.3288	SA	Sandy loam	025509	382	15.9	0
Naracoorte	140.7402	−36.9564	SA	Sandy loam over brown clay	026023	555	15.0	0
Emerald	148.1617	−23.5267	QLD	Black vertosol	035027	619	17.4	80
Dalby	151.2639	−27.1839	QLD	Grey vertosol–cecilvale	041023	668	15.7	80
Goondiwindi	150.3075	−28.5481	QLD	Grey vertosol	041038	656	17.0	150
Roma	148.7897	−26.5719	QLD	Brown vertosol	043030	620	16.6	80
Condobolin	147.2283	−33.0664	NSW	Sandy clay over medium clay	050052	472	15.4	50
Gilgandra	148.6600	−31.7100	NSW	Loam over a clay loam	051018	574	15.1	50
Walgett	148.1223	−30.0372	NSW	Grey vertosol	052088	481	16.7	80
Moree	149.8383	−29.4819	NSW	Black vertosol	053048	606	15.7	80
Wellington	148.8000	−32.8000	NSW	Sandy clay	065028	613	14.5	50
Cootamundra	148.0236	−34.6411	NSW	Sandy loam over	073009	677	13.9	0
Narrandera	146.5500	−34.7500	NSW	Medium clay over heavy clay	074082	456	15.1	50
Birchip	142.9156	−35.9825	VIC	Clay loam	077007	373	15.0	0
Swan Hill	143.5533	−35.3406	VIC	Sandy clay loam	077042	350	15.4	0
Dookie	145.7036	−36.3717	VIC	Sandy loam	081013	592	13.1	0
Ararat	142.9500	−37.2833	VIC	Sandy clay loam over heavy clay	089000	605	13.1	0
Colac	143.6614	−38.2794	VIC	Heavy clay	090022	680	13.5	0
Hamilton	142.0636	−37.6486	VIC	Rennick Peries' soil description (personal communication)	090173	636	13.5	0

Table 2
Attributes of sowing metrics and maximum simulated top-dress *N* input rate. Day1 and Day 2 are days of year defining sowing window. N rates are without bias correction.

Locations	Reference cultivar	Earlier cultivar	Later cultivar	Day1	Day 2	Sowing density (plants m^{-2})	Optimized N rate in baseline (kg ha^{-1})	Optimized N rate in adapted 2030 (kg ha^{-1})
Dalwallinu	Mace	Axe	Endure	121	153	100	60	80
Mullewa	Mace	Axe	Endure	121	153	100	60	30
Esperance	Mace	Axe	Endure	105	166	150	60	120
Cunderdin	Mace	Axe	Endure	105	166	150	75	100
Northam	Mace	Axe	Endure	105	166	150	60	80
Katanning	Mace	Axe	Endure	105	166	150	15	20
Lake Grace	Mace	Axe	Endure	105	166	100	20	20
Southern Cross	Mace	Axe	Endure	105	166	100	60	60
Cummins	Wyalkatchem	Axe	Yitpi	123	176	150	60	120
Minnipa	Gladius	Axe	Bolac	123	176	100	5	5
Waikerie	Gladius	Axe	Bolac	123	176	100	3.8	4
Lameroo	Gladius	Axe	Bolac	123	176	100	80	40
Naracoorte	Scout	Axe	Bolac	123	176	100	37.5	150
Emerald	Gregory	Spitfire	Eaglehawk	123	176	100	20	20
Dalby	Gregory	Spitfire	Eaglehawk	123	176	100	20	80
Goondiwindi	Gregory	Spitfire	Eaglehawk	123	176	100	60	60
Roma	Gregory	Spitfire	Eaglehawk	123	176	100	25	25
Condobolin	Gregory	Lincoln	Wedgetail	116	173	100	60	60
Gilgandra	Gregory	spitfire	Eaglehawk	123	176	100	80	80
Walgett	Gregory	spitfire	Eaglehawk	123	176	100	50	50
Moree	Gregory	spitfire	Eaglehawk	123	176	100	120	120
Wellington	Gregory	Lincoln	Wedgetail	117	173	150	90	120
Cootamundra	Gregory	Lincoln	Wedgetail	115	173	150	75	150
Narrandera	Gregory	Lincoln	Wedgetail	115	173	100	120	120
Birchip	Yitpi	Axe	Bolac	123	176	100	60	60
Swan Hill	Yitpi	Axe	Bolac	123	176	100	10	40
Dookie	Yitpi	Axe	Bolac	123	176	150	120	120
Ararat	Bolac	Derrimut	Revenue	123	176	150	150	200
Colac	Bolac	Derrimut	Revenue	123	176	100	200	150
Hamilton	Bolac	Derrimut	Revenue	123	176	150	150	150

*Sites in Western Australia may need deep sowing in order to protect from heat stress in early sowing.

regions. Since many Australian farmers are already applying financially optimized N fertiliser (Carberry et al., 2013), we modeled a financially optimized N fertilizer policy in which 20 kg ha^{-1} of N was applied at sowing, and a second application (optimized top-dressing) was made at Zadoks stage 30 (Zadoks et al., 1974). A set of simulations with differing N top-dressing rates was carried out and the rate that maximized the long-term average gross margin for each location × cultivar × sowing date × climate combination was selected for each location. In this analysis, therefore, current practice means the combination of a typical cultivar and sowing date window with a financially optimized, fixed N fertilizer rate (Table 2).

Elevated atmospheric CO_2 concentrations in 2030 are expected to affect plant growth rates. APSIM simulates crop growth via radiation-use efficiency, transpiration efficiency and the critical nitrogen concentration, which are modified by atmospheric CO_2 concentration using leaf-level mechanistic equations (Cammerer and Farquhar, 1981; Reyenga et al., 1999). The APSIM response functions have been reported to reproduce the effect of elevated atmospheric CO_2 in FACE experiments well (Asseng et al., 2004; Tubiello et al., 2007b). In APSIM, yield has a linear response to elevated atmospheric CO_2 consistent with the FACE experiments (Olesen and Bindi, 2002).

Gross margins for each year were calculated using a fixed farm gate price of wheat (AUD$ 225/tonne), nitrogen fertiliser cost (AUD \$ 1.33/kg N), and the cost of growing the crop using 10-year average data from the Australian Bureau of Statistics (Australian Bureau of Statistics, 2012).

A factorial simulation experiment was conducted in which the factors were climate (2 scenario × 2 sensitivity × 6 GCMs), location (30), and adaptation options (11 sowing offsets × 4 levels fertilizer × 3 cultivars). Because of the large size of these simulations, we used the Condor cycle-harvesting software (Department of Computer Science, University of Madison–Wisconsin; http://research.cs.wisc.edu/htcondor) to conduct simulations using up to 10,000 processors across the CSIRO network.

2.4. Adaptation options

Adaptation to climate change requires changing current practices to generate better results under the prevailing climate. It can include reducing risk and vulnerability and building the capacity to cope with climate impacts while seeking opportunities (Tompkins et al., 2010), such as reducing the current gap between realised and potential production.

Here we assessed 3 incremental adaptation options that can have substantial potential benefits under moderate climate change for many cropping systems (Crimp et al., 2012). These included varying the input nitrogen fertiliser, the sowing dates and the choice of crop variety maturity type (Howden et al., 2007). These options provide opportunities to enhance the system's efficiencies toward the efficiency frontier (Keating et al., 2010) by increasing water use efficiency. We identified the financially optimal combination of the above options at each location under historical and projected climate to determine the management resulting in the best financial output averaged over time. Management was optimised for the historical climate in order to make comparison of historical and future without exaggeration. The adapted packages of management policies were chosen to be those that maximised the long term average gross margin. Note that because the optimal adaptation is a fixed strategy, it will not necessarily produce the best financial outcome in any individual year. Farmers are not ever able to realise the best outcome for an individual year as the seasonal weather is never able to be accurately predicted.

For the baseline period we applied the reference sowing window shown in Table 1 and financially optimal N input for each site presented in Table 2**.** For baseline and each projected climate for 2030, sowing windows were progressively varied by 10-day increments from a maximum 50 days earlier to 30 days later than the reference dates. We considered three cultivars at each site (earlier-flowering, reference, and later-flowering cultivars as presented in Table 2) and re-optimized the N top-dressing rate for each combination.

Historically in Australia, sowing of cereal crops has taken place after the occurrence of planting rainfalls which usually occurs in mid-autumn. However, the high climate variability in Australia means that these rainfalls may occur substantially earlier or later than the average, requiring flexibility in planting dates. Hence there is usually a sowing window for each site and planting rules based on accumulated rainfall and on stored soil moisture which can have important impacts on crop yields (French and Schultz, 1984; Hunt and Kirkegaard, 2012). The scenarios of rainfall change indicate possibilities of both drier conditions during the planting window and also a shift of the initial planting rains to earlier in the year. The potential impacts of less rainfall would likely be a decrease in the number of days suitable for sowing, resulting in later sowing which would then require shorter-season varieties (Crimp et al., 2012). If the sowing window comes earlier, then using longer-season cultivars may become favoured along with changes in agronomic practice such as deeper sowing depth to protect the seed against heat stress.

Higher N input rates could produce more reliable yield responses, but these are not always profitable. Here we used financially-optimized N input rates as many Australian commercial wheat producers already aim to have base-N applications at financially-optimized rates (Carberry et al., 2013). We evaluated different levels of top-dressed N in the baseline at each sites to select an optimized profitable rate based on maximizing long term average gross margins. Estimated top-dress N rate was used as a base for modelling under future climate change, however, again different rates (upper and lower than baseline's optimized base-N) evaluated in combination with other adaptation options.

2.5. Upscaling

A multipurpose model based survey estimation methodology (Bardsley and Chambers, 1984; referred to as the BC methodology) was used to upscale the simulation results to a national scale. This is the same methodology as used by the Australian Bureau of Agricultural and Resource Economics and Sciences to produce estimates from its national broadacre farm survey (ABARES, 2003). Simulation results for the 30 case study sites are expressed on a per-hectare wheat area harvested basis. In the BC method a weight (w_i, dimensionless) is computed for each case study unit, *i*. To achieve this, units are categorized into a typology, in this case the ABARES (Australian Bureau of Agricultural and Resource Economics and Sciences) farm survey regions (Fig. 1), from which covariates can be calculated for upscaling. These covariates are the mean wheat yield (x_1) and wheat price (x_2) averaged over the base time period 1980–1999 and estimated from ABARES's farm survey. All financial values were deflated by the consumer price index (CPI) and expressed in 2007 AUD. Corresponding national estimates of these quantities were obtained for the farm survey from ABARES's Agsurf website[1] (X_1 for total broadacre wheat production, and X_2 for total broadacre wheat receipts). The weights are approximately calibrated to these totals, i.e. $\Sigma_i w_i x_{ji} := X_j$, where j indicates either production of wheat ($j = 1$) or receipts ($j = 2$). In addition we imposed a calibration constraint on the weights for

[1] website: http://apps.daff.gov.au/AGSURF/.

total broadacre wheat area sown (X_0). Note that $x_0 = 1$ for all the case study sites. The weights calculated by the BC method are referred to as case weights because they can be applied to any other variable (y_i) to produce a total broadacre estimate for that variable:

$$\tilde{Y} = \sum_i w_i y_i \tag{1}$$

The weights are interpreted as the relative number of hectares of broadacre wheat that each case study site i represents for estimation. The calibration implies that $w_i\, x_{ji}$ is the amount each site represents of X_j in estimation. The BC-weights are model based in the sense that they rely on the fit of a linear model to the data to produce an accurate estimate of Y:

$$y_i = b_0 x_{0i} + b_1 x_{1i} + b_2 x_{2i} + e_i, \tag{2}$$

where e_i is a random error term with mean zero and variance proportional to some size measure (we used average capital value per hectare). For example, when y_i is the average wheat yield over 1980–1999 computed from APSIM, the R^2 for the model fit is over 95%. This indicates that the BC-method will produce an accurate estimate of national average yield per unit area and total national simulated wheat production for the base time period. Regardless of the variable, y, Eq. (1) will be an unbiased estimator of the population total of y as long as Eq. (2) is satisfied (Bardsley and Chambers, 1984). However, assumptions made in the APSIM modelling stage imply that this may not necessarily be an accurate estimate of the total national real wheat production (as derived from ABARES's farm survey). In fact, it over-estimates the amount by approximately 24%. Thus all estimates produced from APSIM-derived variables need to be bias-corrected to compensate for modelling assumptions that differ from reality. Bias correction factors were computed for ABARES regions and applied equally to all sites within each region (Table 3). Two factors were computed, one for wheat production and the other for wheat receipts. For each region, r, these bias correction factors were calculated as the ratios of the region level estimates of the ABARES wheat production variable using Eq. (1) (or wheat receipts variable) and the corresponding APSIM variable. The wheat production bias correction factor, f_{pi}, was applied to all production variables simulated from APSIM, whereas the wheat receipt bias correction factor, f_{fi}, was applied to all simulated financial estimates such as gross margin. The bias corrected estimate is then a simple modification of expression (1):

$$\tilde{Y} = \sum_i f_i w_i y_i \tag{3}$$

where f_i is either the production or financial bias correction factor depending on the type of variable (income or yield) being upscaled as described above. Note that wheat receipts bias correction is done separately to the production bias correction.

Table 3
Bias correction factors and upscaling weights. The factor f_{pi} is for APSIM production variables and f_{fi} is for APSIM financial variables.

State	Location	w_i	f_{pi}	f_{fi}
NSW	Walgett	334159	0.750	1.231
	Moree	334159	0.750	1.231
	Condobolin	330938	0.610	0.929
	Gilgandra	330938	0.610	0.929
	Wellington	330938	0.610	0.929
	Cootamundra	265973	0.530	0.835
	Narrandera	265973	0.530	0.835
VIC	Birchip	606406	0.865	1.403
	Swan Hill	606406	0.865	1.403
	Dookie	171876	0.483	0.791
	Ararat	15915	0.476	0.711
	Colac	15915	0.476	0.711
	Hamilton	15915	0.476	0.711
QLD	Dalby	124244	0.844	1.585
	Emerald	122543	0.592	0.980
	Goondiwindi	122543	0.592	0.980
	Roma	122543	0.592	0.980
SA	Cummins	258242	0.496	0.749
	Minnipa	258242	0.496	0.749
	Waikerie	289663	1.085	1.636
	Lameroo	289663	1.085	1.636
	Naracoorte	42333	0.601	0.893
WA	Esperance	518840	0.636	0.956
	Cunderdin	518840	0.636	0.956
	Northam	518840	0.636	0.956
	Katanning	518840	0.636	0.956
	Dalwallinu	449160	0.648	0.959
	Mullewa	449160	0.648	0.959
	Lake Grace	449160	0.648	0.959
	Southern Cross	449160	0.648	0.959

3. Results

3.1. Climate

Projected long term average rainfall for 2030 (averaged across all scenarios) decreased at all 30 sites between −10.4% (Cunderdin in Western Australia) and −2.2% (Naracoorte in South Australia) compared to the baseline. Growing season rainfall (Apr–Oct) at all 30 locations decreased between −12.0% (Mullewa in Western Australia) and −4.8% (Colac in Victoria) (Fig. 2c). For sites with annual rainfall less than 500 mm there was a similar decline in Apr–Oct rainfall relative to the annual rainfall. Across locations and averaging over climate scenarios and GCMs, there is a decline in projected May rainfall, which is in general the sowing time. However, projected rainfall in April increased in 57% of locations by up to 8%, providing an opportunity for early sowing. April is also projected to have one of the smaller increases in mean maximum temperature (Fig. 2b).

3.2. Validation and bias correction

Modeled results for individual sites in the baseline period (Figs. 3 and 4) upscaled to the ABARES regions and compared with ABARES farm survey results during 1980–1999. Simulated yields for the ABARES regions were over-estimated while gross margin is roughly in agreement with the survey results once they were upscaled (Fig. 5a and b). The yield over-estimation occurs because simulations were conducted under optimized N input rates (in reality all are not optimized) and ideal farm system management without accounting for effects of pests and diseases. To adjust, bias correction factors f_i (Section 2.5) were applied to the baseline and future scenarios when the site scale simulation results were upscaled.

3.3. Impact and adaptation at local scale

Enhancing system efficiency of the baseline period (AY) could increase yields across sites up to 79% (Emerald, Queensland) with a median of 15% compared to HY (Fig. 4). In the baseline, gross margin increased by optimal adaptations (AG) across sites in range between 1% (Lake Grace, Western Australia) and 216% (Emerald, Queensland) with a median of 20% compared to HG (Fig. 3).

By applying current practice in 2030, relative yield compared to the baseline varied between −37% (Walgett, New South Wales) and +19% (Cootamundra, New South Wales) with a median of −1% (Fig. 4). Adaptations could offset the impact of climate change on yield across sites up to +76% (greatest in Emerald, Queensland) with a median of +15% compared to the baseline without adaptation in the baseline. This offset by adaptation in terms of gross margin was up to 208% (Emerald, Queensland).

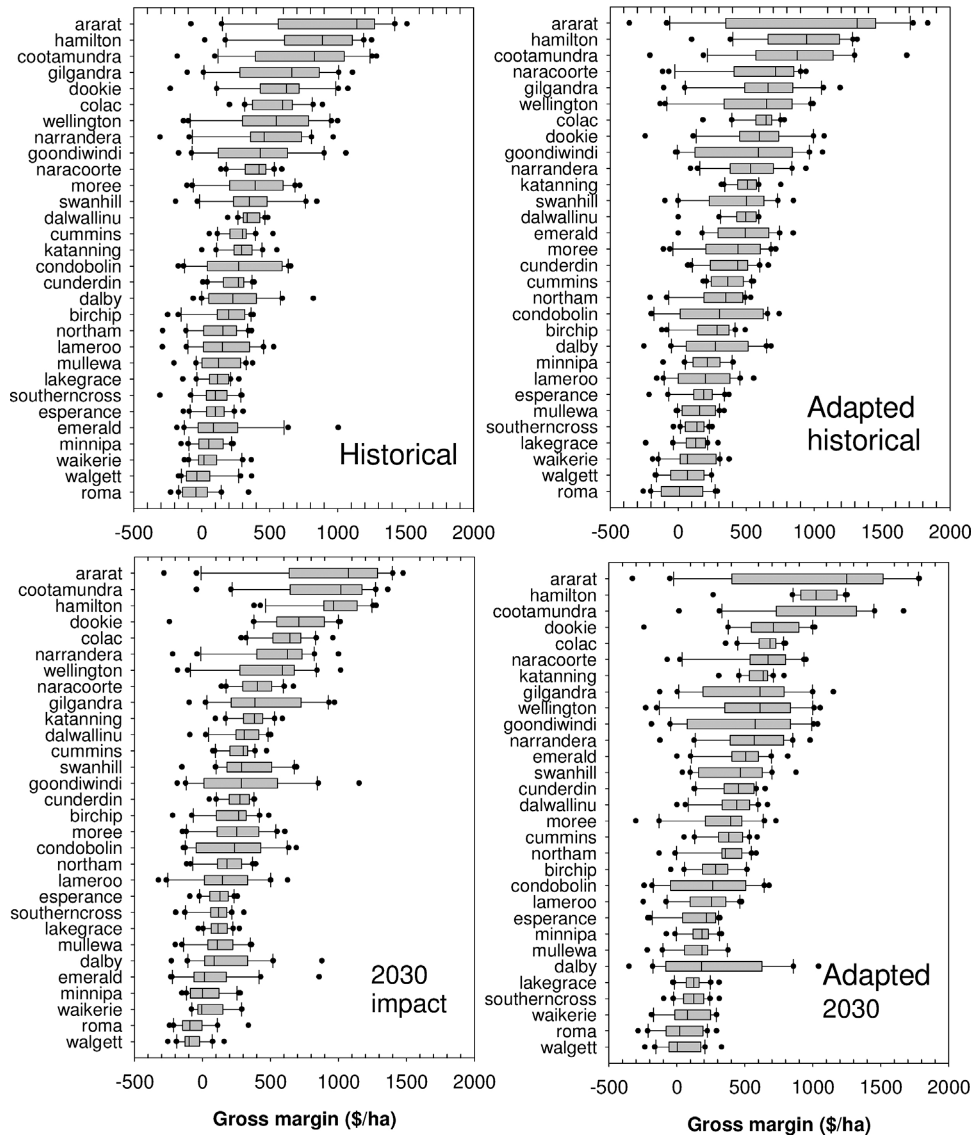

Fig. 3. Variability of annual gross margin (AUD$/ha) in historical period (1980–2010) and projected climate for 2030 (averaged among GCMs and scenarios) under current and optimal management (adaptations). Results are not bias corrected. Those optimal adaptation options selected that resulted in the greatest gross margin over 1980–1999 and projections for 2030, however, optimal adaptations may result in smaller gross margin compared to the baseline in an individual year (e.g. Ararat).

3.4. Impact and adaptation at cross-regional (national) scale

By applying adaptation options to the baseline, yield (tonnes/ha) and gross margin (AUD$/ha) changed by +17% and +33%, respectively, at the EF.

Under projected climate for 2030 (averaging over scenarios, sensitivities, and GCMs) and without enhancing current efficiency of the farm systems, yield and gross margin over the entire wheatbelt were projected to decline by 1% compared to the baseline, i.e. a 0.15 million tonne decline in production. With current cost and prices this will result in AUD$ 32 M p.a. lower gross margin compared to the baseline.

Yield and gross margin per unit area of the wheatbelt increased by applying the adaptation options in both the baseline and 2030 climate while inter-annual variability (1980–1999) increased (Fig. 5c and e).

As shown in Fig 5c–f elevated atmospheric CO_2 has a significant effect on yield and gross margin both with and without enhancing system efficiency. In 2030, the modelled fertilisation effect of the elevated atmospheric CO_2 closely compensates the effect of changes in rainfall and temperature (Fig. 4c–f).

3.5. Changes in adaptation practices

In the baseline, earlier sowing and later sowing would increase gross at 80% and 7% of sites, respectively. These became 83% and 3% for future climate without the effect of elevated CO_2, while elevated CO_2 had little impact with 80% and 7% for early and late sowing respectively.

For the baseline climate, later or earlier maturity cultivars became more useful for achieving the EF in 40% and 13% of sites, while in 2030 late and earlier cultivars were used to reach the EF in 37% and 13% of sites.

In the baseline, there was capacity to increase financially optimized N fertilizer rate at 43% of sites to attain the EF, where management was associated with changes in cultivar and sowing window. In 2030 this opportunity was identified at 50% of sites.

For the whole wheatbelt, as shown in Tables 4 and 5, optimal N fertilizer rate for the EF increased WUE by 20% in the baseline and

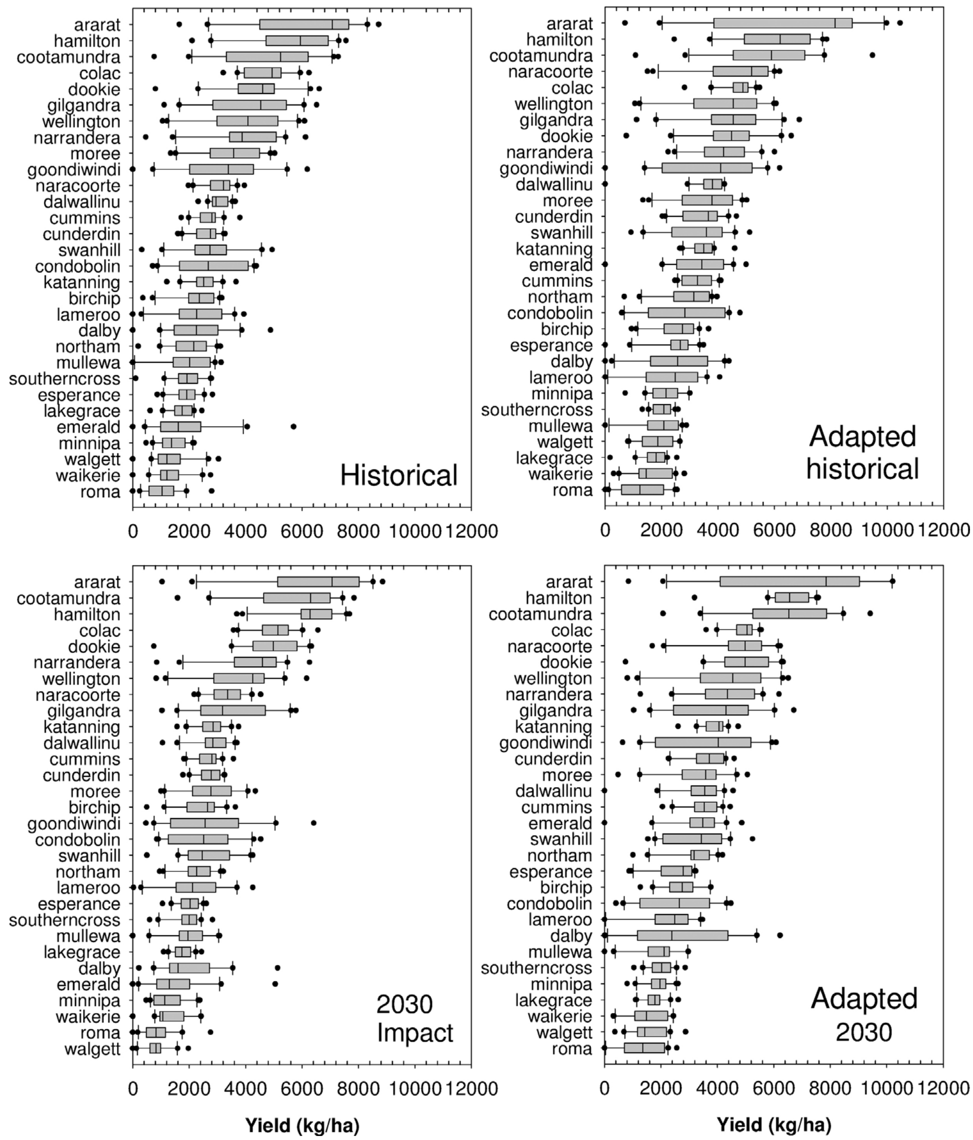

Fig. 4. Variability of annual yield (kg ha^{-1}) in historical period (1980–2010) and projected climate for 2030 (averaged among GCMs and scenarios) under current and optimal management (adaptations). Results are not bias corrected. Those optimal adaptation options selected that resulted in the greatest gross margin over 1980–1999 and projections for 2030, however, optimal adaptations may result in smaller yield compared to the baseline in an individual year (e.g. Ararat).

37% in 2030 without considering the effect of elevated CO_2, and 25% in 2030 with considering the effect of the elevated CO_2 (Table 4 and 5). The effect of elevated CO_2 could support a greater rate of optimized top-dressed N for the whole wheatbelt at the EF. However, optimized N rate at the EF did not exceed that of the baseline (Table 4 and 5). In optimally adapted systems of 2030, N input rate, sowing day, and cultivar changed at 23%, 50% and 17% of sites, respectively, compared to the optimal adapted systems under the baseline climate.

3.6. Effect of changes in rainfall, temperature, and elevated CO_2

Changes in yield across locations and years were non-linearly related to the changes in mean rainfall and temperature projected for 2030 (Fig. 6). Without considering the fertilisation effect of CO_2, adaptation options had an increasing benefit for seasonal temperature increases up to +0.9 °C, with positive effects up to +1.1 °C (Fig. 6a), contrary to the results of Porter et al. (2014) in a more global analysis. Under the effect of elevated CO_2 the response pattern did not change, but the fitted line for relative changes shifted up (Fig. 6a). Increasing system efficiency by adaptation options at locations and years produced a slight decrease in yield sensitivity to rainfall (Fig. 6b) with relative yield increasing at lower seasonal rainfall. Without adaptation, changes in yield were spatially and temporally less sensitive to changes in rainfall than to changes in temperature (Fig. 6a and b). However, over the long term, sites presented a diverse response in yield, indicating the importance of climatic or biophysical factors other than annual rainfall and temperature, perhaps including the seasonal pattern of rainfall. Overall, elevated CO_2 did not change the pattern of interactions but shifted the system to a more productive one, more so at moderate temperature increases and rainfall decreases (Fig. 6).

At the national scale, the simulated fertilisation effects of the elevated atmospheric CO_2 on yield are predicted to be large enough to not only offset the negative impacts of changes in rainfall and temperature but also to increase yields without enhancing current efficiency (Fig. 7, Table 4 and 5). In 2030 and

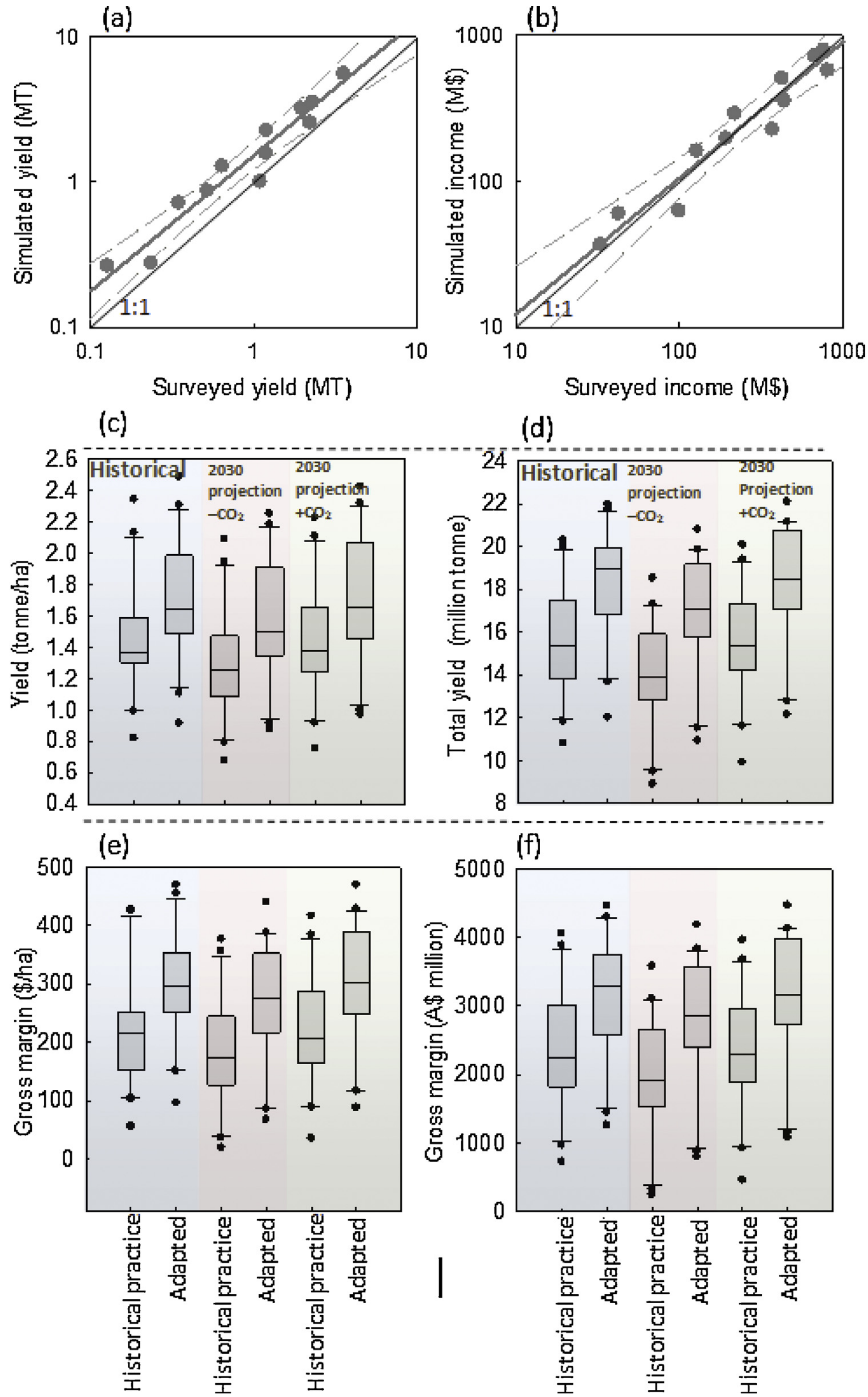

Fig. 5. Model validation and variability of year to year wheat yield at the national scale, including historical and projected impact and adaptation. (a–b) Validation of simulation results by comparing long-term average (1980–1990) simulated yield and income with those from ABARES's farm survey (Fig 2). After bias correction (Eq. (3)) the points in both sub-figures will lie on the 1:1 line. From c to f: Variability of upscaled yield and gross margin over 1980–1999 and projections in 2030 (c) Yield per unit area (tonne/ha), (d) total yield (million tonne), (e) gross margin per unit area (tonne/ha), (f) total gross margin (AUD$ million). $-CO_2$ and $+CO_2$ are atmospheric CO_2 concentration in baseline level and projected for 2030 (averaged for A1FI and A2).

at the national scale, the effect of CO_2 is to increase median yield and gross margin by 11% and 20% if current practices are maintained. However, this effect declined to 9% and 12% for yield and gross margin at the EF (Fig. 6 b, c, e, and f). In 2030, compared to the baseline, under the fertilisation effect of elevated CO_2, the efficiency frontier of the total wheatbelt shifted up by 1% (Fig. 7f) and increased between 0% and 13% at 53% of individual sites.

Table 4
Wheat yield and top-dress N input of wheat belt (weighted average) for 1980–1999.

item	Unit	Baseline	Baseline adapted	2030 not adapted −CO2	2030 adapted −CO2	2030 not adapted +CO2	2030 adapted +CO2
Wheat yield	Tonne ha^{-1}	1.56[a]	1.83	1.39	1.69	1.55	1.85
Top-dress nitrogen	kg ha^{-1}	37.00[b]	45.00	27.00	37.00	35.00	45.00

[a] This is 1.54 t/ha in ABARES survey (ABARES, 2003) for the same time period of 1980–1999.
[b] This is 30.00 kg/ha in Angus (2001) for slightly different area and time period.

Table 5
Relative changes in yield, N and water use efficiency metrics (see Moore et al., 2011 for WUE metrics) of wheat belt (weighted average) for 1980–1999. Rainfall is for period of growing season Apr–Oct. Last row is weighted average *N* for all wheat belt.

		Efficiency index	AY Baseline vs. HY Baseline	$-CO_2$, CPY 2030 vs. HY Baseline	$-CO_2$, AY 2030 vs. AY Baseline	$+CO_2$, CPY 2030 vs. HY Baseline	$+CO_2$, AY 2030 vs. AY Baseline	$-CO_2$, AY 2030 vs. CPY 2030	$+CO_2$, AY 2030 vs. CPY 2030
Yield		–	+17%	−16%	+7%	+4%	+23%	+23%	+18%
N		–	+21%	−27%	−18%	−6%	0%	+36%	+29%
WUE	Gross water use efficiency for grain production	Yield/rain	+17%	−8%	−2%	+11%	+13%	+24%	+19%
RCE	Rainfall capture efficiency	(Rainfall/runoff) − 1	0%	0%	0%	0%	0%	0%	0%
SWUE	Soil water use efficiency	Transpiration/(rainfall–Runoff)	+14%	1%	+6%	+2%	+2%	+19%	+14%
TE	Transpiration efficiency	Biomass/transpiration	+3%	−6%	−7%	+8%	+6%	+2%	+1%
HI	Harvest index	Yield/biomass	0%	−2%	0%	+1%	+4%	+2%	+3%

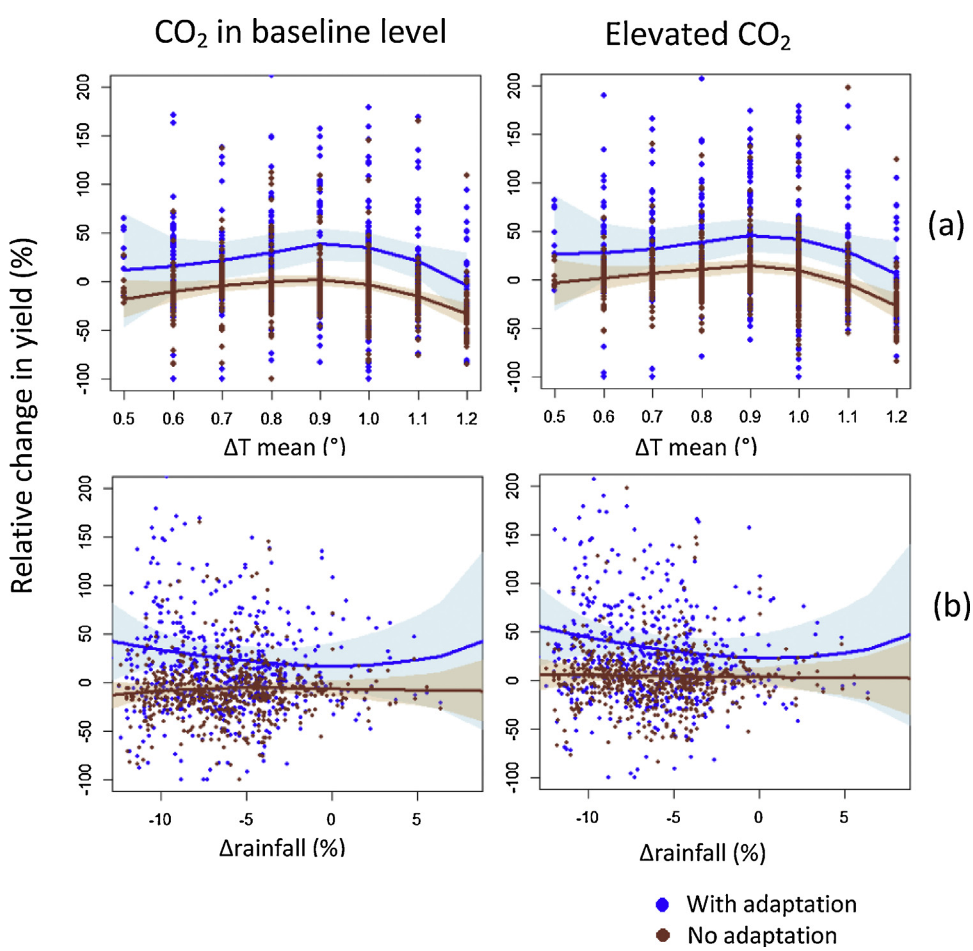

Fig. 6. Yield change in 2030 (averaged over all GCMs, sensitivities, and scenarios) compared to baseline related to the changes in the local climate (Apr–Oct) at each simulated year by location, with and without adaptation and the modelled fertilisation effect of elevated atmospheric CO_2. Effects of changes in rainfall and temperature are not isolated in (a) and (b), respectively. The fitted lines are non-parametric regressions; the shaded areas are the 95% confidence intervals.

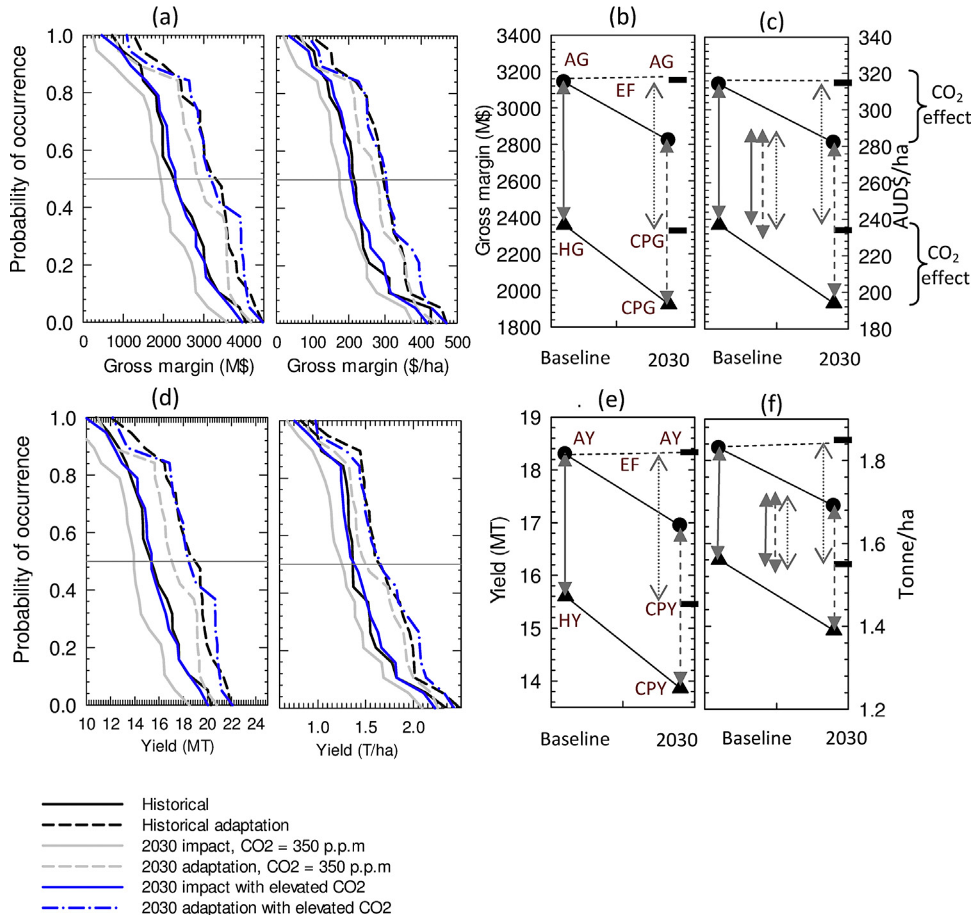

Fig. 7. Gross margin and yield in Australian wheatbelt (a) Probability of occurrences for upscaled gross margin over time (national and per unit area), (b) total gross margin of wheatbelt, (c) average gross margin per unit area, (d) Probability of occurrences for upscaled yield, (e) total yield of wheatbelt, (f) yield per unit area. HG: Historical gross margin, AG: adapted gross margin, CPG: current practice gross margin, HY: historical yield, AY: Adapted yield, CPY: current practice yield, AG and AY with fertilisation effect of elevated atmospheric CO_2. Arrows are to compare gaps in Figs and all are downscaled with the same size ratio.

3.7. Yield

For the baseline period, the increase in AY varied among ABARES regions by between +4% and +54%, while in 2030 it was between 0% and +59% (computed from Fig. 3). In the baseline and on upscaling over the wheatbelt, the median AY (tonne/ha) and AG (AUD$/ha) was 17% and 33% greater than HY and HG. For 2030, the corresponding changes became +19% for AY and +35% for AG.

The probability of occurrence for yield and gross margin varied over time under different climate and management practices with less opportunity to increase yield and gross margin at the upper and lower limits of systems productivity (Fig. 7a and d), which correspond to dry and wet years.

In 2030 and upscaled to the national scale, CPY (with elevated CO_2 effect) changed by −1.0% compared to CPY of the baseline, while AY changed by +1.0% compared to AY of the baseline (Fig. 7 e and f).

There was little change in the yield and gross margin of 2030 compared to the baseline with and without enhancing systems efficiency at national scale (Fig. 7c and f). However, this isn't the case at all individual sites as at 55% of sites a decline was projected in both production and gross margin.

3.8. Increase in water use efficiency

The adaptation options could improve system water use efficiency. In the baseline we predicted +16% and +14%, and +3% changes in wheatbelt's EF from CY in water use efficiency ($kg\,ha^{-1}\,mm$), soil water utilization efficiency (mm/mm), and transpiration efficiency ($kg\,ha^{-1}\,mm$), respectively (Table 5).

To reach the EF in 2030 there would be a need to apply more N (Table 5) to achieve a slightly greater WUE than in the baseline (+2%) if we consider the fertilisation effect of elevated CO_2 (Table 5). Without considering the fertilisation effect of CO_2, there will be a greater need in increasing WUE up to +23% of that in the CPY scenario (Table 5). Elevated atmospheric CO_2 had a positive effect on increasing WUE up to 15%.

The fertilisation effect of the elevated atmospheric CO_2 maintained the opportunity for higher N input rates (financially feasible) at the EF, but at CPY the financially optimal N rate was, on average, $3\,kg\,ha^{-1}$ less than that in the baseline period which resulted in less production (Table 5).

4. Discussion

4.1. Methodological concepts

The adaptation options we evaluated for 2030 were adjustments of current systems with currently available technologies. As 2030 is only 15 years away, applying current technologies could be the most feasible and reliable way to offset the impact of climate change or to explore opportunities to increase production. At the majority of sites, earlier sowing is the main opportunity to enhance farm systems for both the baseline and future. This option is currently being promoted in the Australian wheatbelt as a method to adapt to climate variability and to increase water use efficiency (Hunt and Kirkegaard, 2012). Change of cultivar maturity is an important adaptation option at 17% of sites and has also been suggested as an adaptation to manage changes in the on-farm risk of frost and heat effects during the reproductive stages of growth (Zheng et al., 2012).

The modelled fertilization effects of elevated CO_2 in this paper are consistent with experiments (Tubiello et al., 2002) that have shown positive response of wheat yield to elevated atmospheric CO_2, particularly when water is a limiting factor (Chaudhuri et al., 1990; Kimball et al., 1995).

Based on literature, modelling the effect of the elevated CO_2 on wheat production is somewhat uncertain (Tubiello et al., 2000) but mainly for high CO_2 concentrations and large temperature increases (Asseng et al., 2013a). Amthor (2001) in an open-top field chamber experiment reported yield increases in the range of 7% to 30% (and an average of 15%) for 440 ppm of atmospheric CO_2 (close to the future concentration in this work). A similar increase in yield was reported for an experiment in Western Australia with a median of about 15% (Asseng et al., 2013), and by Ainsworth and Long (2005), but both results were without an increase in temperature. In this paper, relatively greater temperature increases in 2030 are mostly predicted for sites that make a small contribution (Fig. 2b) to cross-regional production (~9% in baseline). In addition, considering the fact that overall there is a relatively small increase in temperature across sites (0.2–1.2 °C) this would not have significant effects on the cross-regional and local scale averaging over time (Fig. 4) but may reduce the benefits of adaptation in individual years × locations if temperature increase exceeds 1.1 °C (Fig. 6a).

The upscaling methodology described in this paper is based on the approach used in the ABARES national farm survey (Bardsley and Chambers, 1984; ABARES, 2003). Thus the methodology produces estimates that are consistent with the mainstream Australian agricultural commodity statistics. Not only is it a tried and well tested methodology, it is an approach that can be used when the sample of case study sites is unbalanced relative to the whole population. The upscaling weights approximately calibrate the estimates to totals of the benchmark variables in the base period at the national level. Accurate estimation of the potential value of adaptation relies on a strong linear relationship between the benchmark variables and income (Fig. 5), as well as the bias correction. It is not possible to predict changes in the bias so it was necessary to assume that this component remains fixed in relative terms in the projection period and at the EF.

4.2. Enhancement in N and water use efficiency

The increase in national yield at the adapted yield point (Fig. 7) is associated with improved water use efficiency and increased N input rates (Mueller et al., 2012). Currently in many regions in Australia it is unlikely that producers can increase current yield by increasing N fertiliser rate (van Rees et al., 2014); higher-N systems would not be economically exploitable because many farms are already optimized in term of N supply (Carberry et al., 2013). This is consistent with our results in Tables 4 and 5, as the optimized N input rate at AY in 2030 is modeled to be identical to that of the baseline climate.

The adapted management systems have improved water use efficiency for both baseline and 2030 climate; in 2030 WUE is boosted by elevated atmospheric CO_2 (Table 5). There is likely to be benefits obtained in terms of yield (and consequently profit) from adjustments in planting date and cultivar in the baseline (Hochman et al., 2012; Hunt and Kirkegaard, 2012) and these options are expected to be more useful in the future because they are associated with improved WUE under elevated atmospheric CO_2 (Table 5). We note that further optimizing WUE by tactically adjusting planting date each season (rather than strategically, over the long term, as in this study) would need to be aided by an improvement in seasonal forecasting of rainfall.

Adaptation is expected to decrease failure risk (Challinor et al., 2010), but here our examined options would not be effective in extreme dry years or relatively high rainfall years (Fig. 7a and d). This suggests a requirement for a long term perspective (20 years in this study) on the benefits of adaptation.

4.3. Yield under adaptation

The results indicate the potential to increase yield by 17% and gross margin by 33% in the baseline climate when systems are fully enhanced by the considered adaptation options. In 2030 this potential increase is projected to be 19% and 35%, respectively over an unadapted management. This concept of potential increase in yield is similar to the 'yield gap' approach (e.g. Cassman, 1999; Lobell et al., 2009) although our estimated potential for change is less than yield gaps estimated in the literature for Australia (van Rees et al., 2014). In this paper, potential increase in yield was estimated by feasible options which are economically optimized. Potential yield gaps in the literature, on the other hand, are the prospects for potential productivity increases established between actual farm yield and production attained using optimal inputs, the best agronomy, and an absence of limiting stresses without financial constraints (Carberry et al., 2013). This potential yield is not all financially achievable and this would be valid for our estimated potential as well because of biophysical and economical constraints to increase water and N use efficiencies.

Given the consistency of our modelling results for CO_2 effect with experiments (Ainsworth and Long, 2005; Amthor, 2001; Asseng et al., 2013) we expect that the wheatbelt should realize the benefits of elevated atmospheric CO_2 (Fig. 5) projected here. This will apparently offset potential declines in national wheat production and profitability. As shown in Figs. 5 and 7, without enhancing current efficiencies there would be a decline in production and profit by 2030 at the national scale but not a significant change compared to current levels. There are further opportunities for system-level adaptation via wheat breeding itself as new varieties are gradually adapted to higher temperature conditions and maturity requirements (Chapman et al., 2012).

Losses from pests and foliar disease are not substantial issues in Australian wheat farm systems although control costs can be high (Murray and Brennan, 2009) and in this paper we assumed that this issue will not have changed greatly by 2030. Despite likely resilience of the industry at the national scale and in major production regions, there would be a decline in production/profit at CYP in 2030 in 55% of individual sites which will require local adaption.

Full enhancement of the current system (baseline) with current technology is not expected, and this will remain a future challenge. However, moderately elevated atmospheric CO_2 in 2030 may provide an opportunity for greater yield by enhancing transpiration efficiency while helping to keep N rates at the same level as under the baseline climate (Table 5).

4.4. Future trade constraints

We predicted AG and AY based on current prices and costs, mainly determined by the wheat and N fertiliser prices. Historically there is less effect from variations in N fertiliser cost on optimal management of Australian wheat farms, as the trend in ratio of N fertiliser cost to grain price has been stable (Angus, 2001). There is evidence of crop market sensitivity to climate extremes in key producing regions of the world (Porter et al., 2014). However, for 2030, projections that include the effects of CO_2 changes (without ozone and pest and disease impacts), indicate little increase in global crop price (Porter et al., 2014). In line with the last 50 years or so of agricultural expansion, the World Bank (2014) predicts a moderate decline in the current global price of wheat and N fertiliser up to 2025, in which the ratio of N fertiliser cost to wheat price remains almost stable. Therefore, based on available commodity prices, and acknowledging that there is uncertainty, our predicted AG and AY are not expected to be significantly impacted by changes in the global market.

4.5. Limitations

Despite the consistency of our simulation results with field experiments, it still might not be possible to realize the modelled benefit from elevated CO_2 due to non-modelled interactions e.g. potential plant-pest interactions (Tubiello et al., 1999). Overall this uncertainty can be assumed as small because of the relatively small changes in projected CO_2 for 2030. Probable but unpredictable economic, social and trade shocks are not included in our estimations. This work does not consider improvements in technologies (e.g. new cultivars) and short term negative effects on yield or gross margin from changes in climate.

5. Conclusions

Over the Australian wheatbelt as a whole, the projected yield and the gross margin at 2030 did not change substantially compared to the baseline with current practices. At the national scale, there might be a greater opportunity to increase yield over current levels by applying currently available management options, due to a boost from the moderate elevated atmospheric CO_2 effect on enhanced water use efficiency in 2030. It is expected that production at national scale would be resilient averaged over a long time period (20 years). It should be noted, however, that at 55% of sites a decline was projected in production and gross margin.

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