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Modelling the effects of climate change on the profitability of Australian farms

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Abstract
Recent shifts in the Australian climate including both higher temperatures and lower winter rainfall have had significant effects on the agriculture sector. Despite these recent trends, there remains uncertainty over the future climate and its potential impacts on Australian farm businesses. In this study, a statistical model of Australian cropping and livestock farms is combined with downscaled temperature and rainfall projections for 2050, to simulate the effects of climate change on farm profits. These future projections are compared against both a historical reference climate (1950 to 2000) and recent conditions (2001 to 2020). The results provide an indication of 'adaptation pressure': showing which regions, sectors and farm types may be under greater pressure to adapt or adjust to climate change. Future scenarios produce a wide range of outcomes, with simulated change in average farm profits (without any long-run adaptation or technological advance) ranging from −2 to -32% under RCP4.5 and −11 to −50% under RCP8.5, compared with a decline of 22.3% under observed post-2000 conditions (all relative to 1950 to 2000 climate). In contrast with the recent observed changes, projections show relatively moderate effects in south-eastern Australia, but relatively stronger effects for livestock farms in northern Australia.

Keywords Climate change · Agriculture · Farm · Simulation · Economics

1 Introduction

Recent droughts across eastern Australia in 2018–2019 and 2019–2020 had dramatic effects on farm businesses (Martin and Topp 2019; Hughes et al. 2019) adding to longstanding concerns around the emerging effects of climate change on Australian agriculture.

In addition to higher temperatures, Australia has experienced significant changes in rainfall over the last 20 to 30 years. In particular, average winter rainfall has declined in southern Australia, while summer rainfall has increased in north-western Australia (CSIRO

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and BoM 2020). These rainfall trends are at least partly related to global warming atmospheric changes (Cai et al. 2014; Cai and Cowan 2013; Cai et al. 2012).

These changes have already had large effects on Australian agriculture. Hochman et al. (2017) estimate that changes in climate have reduced Australian wheat yields by around 27% since 1990. Hughes et al. (2017) found that changes in climate have negatively affected the productivity of Australian cropping farms since 2000, while Kingwell et al. (2014), Islam et al. (2014) found similar effects for farms in south-western Australia. These studies also find evidence of adaptation, including improvements in farming practices and migration of cropping activity helping to offset climate effects (Chancellor et al. 2021; Hochman et al. 2017; Hughes et al. 2017; Kingwell et al. 2014).

Given the difficulty in separating global climate change from natural variability, there remains uncertainty over what these trends will mean for Australian farmers over the long term. Estimating the future effects of climate change on farms, therefore remains an active area of research (see Pearson et al. 2011; Hertel 2018; Blanc and Reilly 2017; Wang et al. 2022). Estimates of farm climate change impacts are important both in informing local adaptation responses and as an input to global assessments of agricultural supply and demand under climate change (see IPCC 2019).

Historically, Australian and international research on this subject has focused heavily on assessing effects on crop yield via 'process-based' bio-physical simulation models (Wang et al. 2022). Recent studies of Australian wheat yields include Ghahramani et al. (2015) and Wang et al. (2019) who both apply the APSIM model (Keating et al. 2003). Although crop yield modelling remains dominated by process-based approaches, statistical crop yield models are also common. Recent reviews (Lobell and Burke 2010; Lobell and Asseng 2017; Moore et al. 2017) show both methods generate similar responses to climate change, at least after accounting for CO_2 fertilisation effects (which are excluded from statistical models).

In Australia in particular, less research has focused on whole-of-farm outcomes particularly farm profits. This is important in the context of Australian broadacre farms, which undertake a wide range of interrelated crop and livestock activities. Further, a focus on farm profits can provide a meaningful picture of climate change 'adaptation pressure', since changes in profits are ultimately what motivate farmer adaptation responses.

Most Australian studies of farm-scale outcomes have applied process-based models to case-study farms (often using the *AusFarm* framework, building on the APSIM model, see Ghahramani et al. 2020; Ghahramani and Bowran 2018; Thamo et al. 2017; Ghahramani and Moore 2016; Rodriguez et al. 2014). These studies generally find negative effects of climate change on Australian farm profits on average (Ghahramani and Bowran 2018; Ghahramani et al. 2020) with a wide range of potential outcomes, with this variation due mostly to uncertainty over rainfall projections.

Bio-physical models are subject to some well-established advantages and limitations (see Blanc and Reilly 2017; Antle 2019). In particular, these models often have limited spatial and industry coverage, with studies usually focusing on a small number of representative farm businesses/locations. Further, while they contain highly detailed environmental processes their representation of farmer behaviour and decision making tends to be more simplistic.

Internationally, farm bio-economic models have been commonly applied to measure agricultural outcomes of climate change (particularly in Europe see for example Louhichi et al. 2010; Blanco et al. 2017). These models draw on economic theory (profit maximisation and partial equilibrium) to represent farm management as a mathematical programming problem usually at a regional (rather than farm location) scale. Larger scale bio-economic models (linked to bio-physical models) are often used for global integrated assessments of agricultural supply and demand (see Nelson et al. 2014).

As with crop yields, statistical approaches to modelling farm-level economic outcomes have also emerged. One approach involves development of reduced-form statistical models, given panel data on farm economic outcomes and linked weather data (see Blanc and Reilly 2017; Fisher et al. 2012; Deschênes and Greenstone 2012; Segerson and Dixon 1999). Another involves hybrid or 'econometric process' models, which link farm panel data with outputs from bio-physical simulation models (see Antle et al. 2014; Antle 2019). This hybrid approach has previously been applied to examine climate change effects on Australian broadacre farms (Nelson et al. 2010)[1].

Such statistical models capture the responses of farms as observed under real world conditions, simultaneously taking into account both bio-physical and socio-economic factors (i.e. the behaviour of farm managers). They also can provide both farm-scale detail and broad spatial coverage, supporting the simulation of national and sector wide outcomes of relevance to policy makers.

In this study, a new statistical model of Australian farms *farmpredict* is applied to simulate the potential effects of climate change on the profits of Australian farms. *farmpredict* is a data-driven reduced-form model of Australian broadacre (extensive cropping/livestock) farms, which simulates the effects of weather conditions and prices on the production and financial outcomes of individual farm businesses. This micro-simulation model combines farm panel data with site specific temperature and rainfall data to estimate non-parametric statistical models. The model provides detailed farm-scale estimates of output and revenue; input use and costs; and changes in farm inventories and farm profit, with national coverage of the Australian broadacre (extensive cropping and livestock) industries.

Downscaled climate change projections for rainfall and temperature (produced by the CSIRO and BoM 2015) are applied to the *farmpredict* model. Farm outcomes are simulated under projected 2050 climate (for a range of greenhouse gas pathways and general circulation models) and compared to the historical reference period 1949–1950 to 1999–2000. For contrast, results are also presented for the recently observed climate (2000–2001 to 2019–2020).

Given the reduced-form statistical approach, the results of this study do not account for the positive effects of long-run adaptation, technological advance or CO_2 fertilisation. Further, the scenarios also do not account for potential long-run changes in global supply and demand of agricultural commodities and related effects on world prices, or the effects on Australian farms of domestic or international climate change mitigation policy.

In effect, the model results simulate how current day farmers, facing current technology and prices would perform under a shift to 2050 climate conditions (relative to a long-run historical climate). As such, the study does not attempt to estimate long-term changes in agricultural land use or supply. Rather, the results provide an indication of current adaptation pressure: identifying which regions, sectors and farm types may be under greater pressure to adapt or adjust to climate change.

[1] An alternative statistical approach involves the estimation of hedonic models of farm-land prices using cross-sectional rather than panel data, referred to as a 'Ricardian' approach (Mendelsohn et al. 1994).

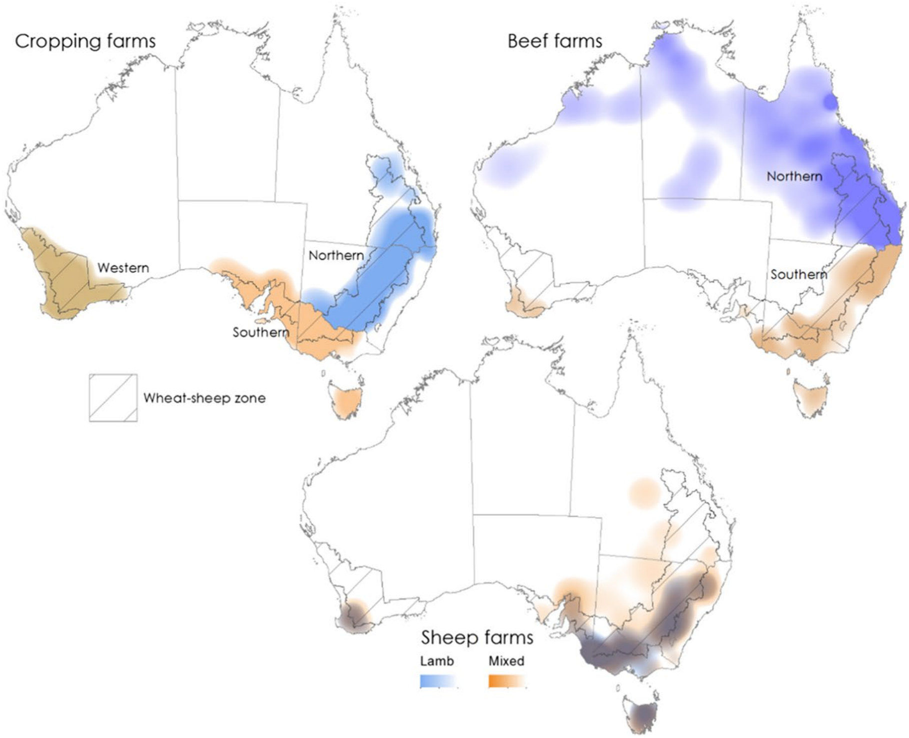

Fig. 1 Broadacre farm industry/region groups

2 Method

2.1 Study focus: Australian broadacre farms

Broadacre (extensive cropping and grazing) farms produce Australia's main agricultural export commodities including wheat, beef, lamb and wool. Australian broadacre farms occupy around 450 million hectares of agricultural land (around 60% of Australia's land mass). The industry generates a total annual production of around \$30–35 billion AUD (of which 70–90% is typically exported).

Cropping activity occurs mostly within the Australian 'Wheat-Sheep zone' (Fig. 1), with livestock tending to dominate in the coastal 'high-rainfall' zones (where rainfall is often too high for extensive cropping) and the more in-land 'Pastoral' zones (where rainfall is generally too low for cropping). Australian broadacre farms are highly diverse, both in terms of their production systems and sizes. Central Australia is dominated by large grazing farms, some over 1 million hectares in size each, while coastal areas are populated with large numbers of smaller properties (of 500 hectares or less).

The Australian Agricultural and Grazing Industry Survey (AAGIS) collects detailed physical and financial information for around 1600 broadacre farms across Australia annually (ABARES 2021). The survey is designed to provide representative coverage of all Australian broadacre farming regions and industries, including extensive cropping, livestock (beef and sheep) and mixed farming types. The survey uses a rotating sampling

Table 1 Summary statistics for sample farm observations by industry group

Industry group	Sample	Area '000 ha		
		5th percentile	Mean	95th percentile
Beef-Northern	1317	0.3	21.3	863.1
Beef-Southern	738	0.1	0.8	15.3
Sheep-Lamb	540	0.3	1.5	18.0
Sheep-Mixed	1005	0.3	1.7	60.7
Cropping-Northern	993	0.2	2.2	18.4
Cropping-Southern	1216	0.4	1.8	9.1
Cropping-Western	503	1.1	5.0	18.4
All farms	6312	0.2	2.4	212.6

strategy leading to an unbalanced panel data set (with farm businesses in the sample for an average of 3.4 years).

In this study farms sampled in AAGIS between 2015–2016 and 2018–2019 are taken as the basis for all model simulations. This sample consists of 6312 observations (2251 distinct farm businesses/locations) providing representative coverage of the broadacre farming sector including both broad spatial coverage (multiple locations/regions) and cross-sectional coverage (multiple farm types/sizes, see Table 1). The model simulations take farm characteristics (e.g. land area, capital and opening stock holdings and other controls) as observed in the survey data during these years. All model results are generated at the individual farm business level, but for reporting purposes the results are aggregated into seven key farm industry/region groupings (shown in Fig. 1 and defined in full in the Appendix).

2.2 A micro-simulation model of Australian broadacre farms

farmpredict is a data-driven micro-simulation model of Australian broadacre farming businesses based on AAGIS data. The model involves two main components: a statistical model estimated from historical farm-level data, and a simulation model which takes the statistical model and applies a range of feasibility constraints, accounting rules and other assumptions to produce scenario results (Fig. 2).

The model simulates production of six crop outputs, four livestock outputs and seven stock (inventory) holdings including livestock numbers and on-farm crop and wool storage (Table 2). These production outcomes are then combined with input and output prices to simulate farm financial results including various measures of profit. In this study, we use the AAGIS *profit at full equity* measure.

2.2.1 The statistical model

The core of *farmpredict* is a statistical model estimated from historical data. A sample of 40,269 farms (drawn from the AAGIS over the period 1988–1989 to 2018–2019) is used to estimate the model, with each farm linked (via point location geocoding) to spatial climate data obtained from the Bureau of Metrology (BoM). The theoretical structure of the statistical model follows that of a 'reduced-form' economic multi-product framework (see Mundlak 2001) in which output supply $\boldsymbol{Q}_{it}$ and input demand $\boldsymbol{V}_{it}$ (for farm i in year t) are functions of exogenous factors including: farm 'fixed inputs' $\mathbf{K}_{it}$ (i.e. land and capital),

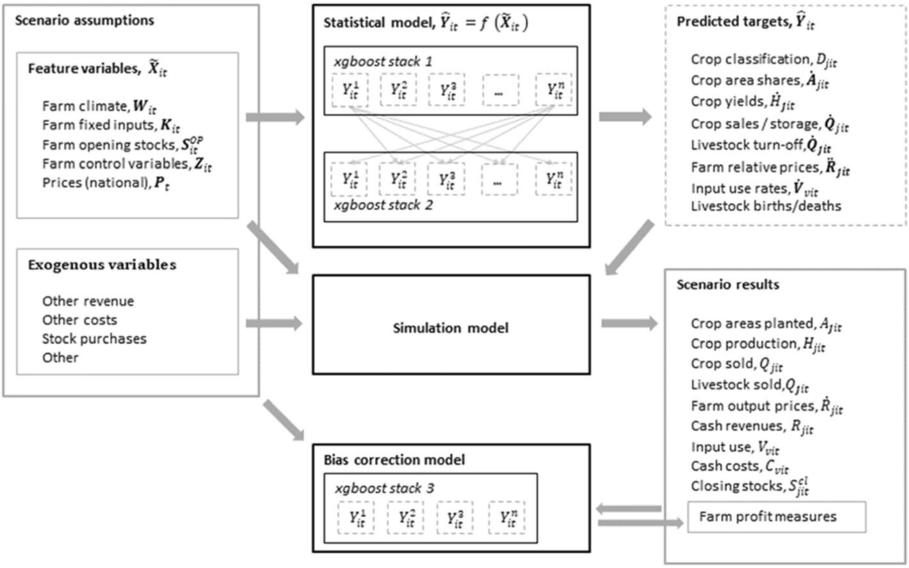

Fig. 2 An overview of the *farmpredict* model

Table 2 Farm output, variable input and stock types

Outputs	Variable inputs	Stocks
Beef cattle	Electricity	Beef cattle
Sheep	Fertiliser	Sheep
Lamb	Fuel	
Wool	Chemicals	Wool
Wheat	Shearing labour	Wheat
Barley	Materials & services	Barley
Canola		Canola
Sorghum		Sorghum
Legumes		
Misc. grains		

opening farm stocks $\mathbf{S}_{it}^{op}$ (i.e. grain and livestock holdings), input and output prices $\mathbf{P}_t$, weather conditions $\mathbf{W}_{it}$ and other controls $\mathbf{Z}_{it}$ (i.e. farm and farmer characteristics).

The dependent variables in this model extend beyond farm outputs and inputs to include other intermediate aspects of farm production and stock dynamics. The dependent (target) variables in the model are mostly defined as ratios of farm fixed inputs or other variables as described in Fig. 2 and Table 4 (see Hughes et al. 2022b for full details).

In contrast with more traditional multi-product models (which rely on parametric econometric methods), *farmpredict* adopts a non-parametric machine learning approach. This machine learning approach makes use of the *xgboost* regression algorithm (Chen and Guestrin 2016; Friedman 2002) combined with multi-target ‘stacking’ (Spyromitros-Xioufis et al. 2016). Hughes et al. (2022b) demonstrate the performance of the model with out-of-sample validation tests, showing significant gains in predictive power relative to a linear benchmark model and traditional econometric models.

Table 3 Climate variable measures

Name	Description	Units
rain	Rainfall volume	mm
tmax	Average maximum temperature	°C
tmin	Average minimum temperature	°C
fr2	Exposure to frost (days below 2°C)	days
gdd	Heat accumulation (growing degree days)	°C
hgdd	Exposure to high temperature extremes	°C
gni	Rainfall volatility (Gini coefficient)	index
pci	Precipitation Concentration Index (PCI)	index
hail	Exposure to hail storms	index (0–1)

Data on hail storms were obtained from the BoM Severe Storms Archive

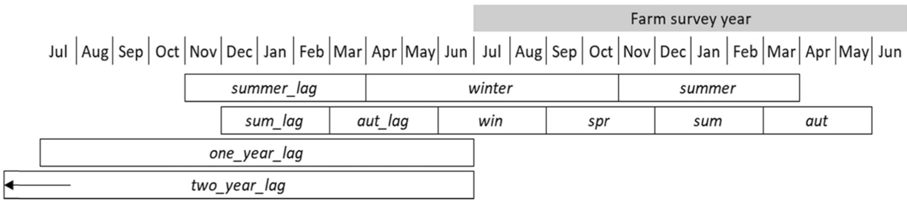

Fig. 3 Climate variable time periods

The statistical models include a wider range of different climate variables, across multiple climate measures (Table 3) and time periods/seasons (Fig. 3) of relevance to Australian broadacre farms. For example, daily rainfall and temperature data at each farm location are aggregated into winter and summer crop growing season values (i.e. April to October, and November to March respectively) along with a range of shorter seasonal values and longer-term lags (Fig. 3). For each of these, a range of climate measures are considered including rainfall volume, average maximum and minimum temperatures and exposure to upper and lower temperature extremes (Table 3).

As would be expected, growing season rainfall (via its effect on crop yields) is identified as a key driver of climate effects in the model. However, the statistical models identify a wide range of relationships, with climate impacting: crop planting and storage decisions; input usage (particularly fertiliser and fodder); livestock turn-off, birth and death rates; and farm prices received (via quality effects on livestock and crop outputs). Temperatures play an important role in many of these responses, proving particularly important for livestock birth and death rates (see Appendix Tables A7 and A8 for more detail on climate relationships in the model).

2.2.2 Simulation model

Model scenarios are defined by data for the predictors $\tilde{\mathbf{X}}_{it}$. For each scenario, predicted values for the target variables $\hat{\mathbf{Y}}_{it} = f\left(\tilde{\mathbf{X}}_{it}\right)$ are obtained from the statistical models. The simulation model then combines these predictions with a range of assumptions including feasibility constraints (i.e. stocks, outputs, inputs, prices must all be positive) and farm accounting rules to

Table 4 Variable definitions

Variable	Description
D_{jit}	Crop classification, = 1 if crop j planted on farm i in year t
A_{jit}	Area of crop j planted (ha)
$\dot{A}_{jit}$	Proportion of farm total crop land planted to crop j,
H_{jit}	Quantity of crop j produced (harvested) (tonnes)
$\dot{H}_{jit}$	Yield for crop j, H_{jit}/A_{jit} (tonnes/ha)
Q_{jit}	Quantity of output j sold on farm i (tonnes or no. of livestock)
$\dot{Q}_{jit}$	Proportion of stock holdings sold for output j,
R_{jit}	Revenue for output j ($)
$\ddot{R}_{jit}$	Relative farm price received for output j,
P_{jt}, P_{vt}	Price indexes for outputs j and variable inputs v
C_{vit}	Cost for variable input v ($)
$\dot{V}_{vit}$	Quantity index for variable input v relative to a farm size index (F_{it}),
$S^{op}_{jit}, S^{cl}_{jit}$	Opening and closing quantities of farm stocks (tonnes or no. of livestock)

produce final results. A summary of this process is provided below (with variable definitions in Table 4, and Fig. 2), for further detail see Hughes et al. (2022b).

For each farm i and crop j, crop area, production, sales and closing stocks are simulated as:

$$\hat{H}_{jit} = \hat{D}_{jit}\overline{A}_{it}\hat{\dot{A}}_{jit}\hat{\dot{H}}_{jit} \tag{1}$$

$$\hat{Q}_{jit} = \hat{\dot{Q}}_{jit}\left(S^{op}_{jit} + \hat{H}_{jit} + S^{np}_{jit}\right) \tag{2}$$

$$\hat{S}^{cl}_{jit} = S^{op}_{it} + \hat{H}_{jit} - \hat{Q}_{jit} + S^{np}_{jit} \tag{3}$$

where $\overline{A}_{it}$ is the total cropping land area and S^{np}_{jit} are net crop purchases (which are assumed exogenous).

Livestock production is simulated as:

$$\hat{Q}_{jit} = \hat{\dot{Q}}_{jit}\left(S^{op}_{jit} + \hat{S}^{b}_{jit} - \hat{S}^{d}_{jit} + S^{np}_{jit}\right) \tag{4}$$

where $\hat{S}^{b}_{it}$ and $\hat{S}^{d}_{it}$ are simulated livestock (beef and sheep) births and deaths and S^{np}_{jit} are net livestock purchases (which are assumed exogenous).

Closing stock holdings are then generated for each livestock (beef cattle and sheep) and crop type, in the case of livestock closing stocks are defined:

$$\hat{S}^{cl}_{jit} = S^{op}_{it} - \hat{Q}_{jit} + \hat{S}^{b}_{jit} - \hat{S}^{d}_{jit} + S^{np}_{jit} \tag{5}$$

Revenue for each output is then simply:

$$\hat{R}_{jit} = \hat{\ddot{R}}_{jit}P_{jt}\hat{Q}_{jit} \tag{6}$$

While farm costs are simulated as:

$$\hat{C}_{vit} = \hat{\hat{V}}_{vit} F_{vit} P_{vit} \tag{7}$$

Given the final estimates of revenue, cost and changes in stock values for each farm, the model then generates a range of farm financial indicators in keeping with AAGIS accounting rules. Here, farm profit can be defined broadly as total farm revenue less, total costs plus the value of net changes in stocks:

$$\hat{\pi}_{it} = \sum_j \hat{R}_{jit} - \sum_v \hat{C}_{jit} + \sum_j \hat{\hat{R}}_{jit} \left(\hat{S}^{cl}_{jit} - S^{op}_{jit} \right) \tag{8}$$

where $\hat{\hat{R}}_{jit}$ are the simulated prices for stock j. More specifically, this study uses the AAGIS measure of *farm profit at full equity* which includes further adjustments for imputed depreciation, family labour costs and financing costs (see Hughes et al. 2022b).

2.3 Commodity prices

Farm input and output commodity prices are held fixed at recently observed (2015–2016 to 2018–2019) levels, consistent with related studies (see Ghahramani et al. 2020). While there are ongoing efforts to project long-run global agricultural commodity prices, much uncertainty remains. Based on an ensemble of models, the IPCC (2019)) generally project higher real food prices by 2050, with increases of 1–29% (median 7%) for cereals and smaller (median 1%) increases for animal sourced foods. The latest medium-term forecasts from the OECD/FAO (2020) and World Bank (2020) suggest limited real change (and some slight decreases) for most agricultural commodity prices to 2030 and 2035. In practice, there remains much uncertainty over global commodity prices to 2050 for reasons beyond climate change including potential technology and consumer preference changes.

While global prices are assumed to be fixed at current levels, grain (wheat, barley and sorghum) output and fodder input prices are adjusted in the model simulations to account for the effects of climate on domestic Australian grain and fodder markets. While prices for most broadacre commodities are determined in world markets (and are largely unaffected by Australian climate conditions), price gaps emerge between Australian and world prices of grain in years of widespread drought, as constraints on importing can lead to domestic shortages (see Hughes et al. 2022a). These price spikes tend to lessen the financial impacts of drought on cropping farms (as net producers of grain and fodder) and exacerbate them for livestock farms (as net consumers).

Following, Hughes et al. (2022b), a statistical model is applied to simulate the potential impact of future climate scenarios on Australian grain and fodder prices. These results assume fixed world prices for grain (as observed between 2015–2016 and 2018–2019) but allow for variation in Australian-world price spreads.

2.4 Technology

Farm technology/productivity is held fixed at recently observed (2015–2016 to 2018–2019) levels. As such, the model scenarios reflect how farms with recent technology would respond to projected future climate conditions, excluding any future long-term adaptation/technological advancement. However, by default, the *farmpredict* model does take into account typical short-run adaptation of farm managers (as reflected in the historical model training data) in response to annual climate variability including for example changes in crop areas planted, livestock turn-off and birth rates and input usage.

2.5 Climate scenarios

Climate projection data are taken from the Climate Change in Australia portal (CSIRO and BoM 2015). Specifically, this study makes use of rainfall and temperature projections downscaled using the delta change method with quantile scaling (CSIRO and BoM 2015). Daily time-step data are obtained for a 24-year sequence centred on 2050.

CSIRO and BoM (2015) provide this data for 8 of the 40 Global Circulation Models (GCMs) in CMIP5 (Coupled Model Intercomparison Project 5) selected partly for their skill in representing historical Australian climate data. In this study, 6 of these 8 GCMs are included (*ACCESS1.0*, *CESM1-CAM5*, *CNRM-CM5*, *GFDL-ESM2M*, *HadGEM2-CC*, *CanESM2*) with *NorESM1-M* and *MIROC5* omitted due to their low skill for historical Australian rainfall (see CSIRO and BoM 2015). The CSIRO and BoM (2015) data include two representative concentration pathways (RCPs) for each GCM: *RCP4.5* (where greenhouse gas concentrations reach around 500 ppm CO_2 equivalent by 2050) and *RCP8.5* (where concentrations reach around 600 ppm by 2050). Daily time-step rainfall and temperature projection data are matched to each of the 2251 farm study locations and translated into the climate variables (growing season rainfall etc.) required for *farmpredict.*

One concern with statistical models is that projected climate data may fall outside the range of historical data on which the models were trained on. In the Appendix, we show that on average only 0.06 to 0.09% of the observations in these projection scenarios lie outside of the training data ranges. Note that while climate variables (particularly temperatures) often move outside of historically observed values at a given point location, statistical models can still generalise from farms in other locations where such conditions have been observed.

Selecting an appropriate reference period is complicated given the dramatic shifts in Australian rainfall observed in recent decades (and uncertainty over the relative influence of climate change and natural variability). To account for this, we contrast our future climate scenarios against both a long-term historical reference period of 1949–1950 to 1999–2000 and to the more recent period 2000–2001 to 2019–2020. We refer to the four climate scenarios in our study as *Historical (1950 to 2000)*, *Recent (2001 to 2020)*, *Future (2050 RCP4.5)* and *Future (2050 RCP8.5).*

Tables A1, A2 and A3 in the Appendix compare the four climate scenarios for average winter (April to October) rainfall and average summer (November to March) rainfall and maximum temperatures for key farm groups (as defined in Fig. 1).

For most farms, reductions in winter rainfall over the *Recent* period relative to the *Historical* are larger than the mean projections for 2050 (−16.3% on average compared with mean −5.3% under *RCP4.5* and −12.2% under *RCP8.5*). As BoM and CSIRO (2020) note, observed changes in rainfall to date have tended to track the dry end of the projected range (particularly in southern Australia). Under the driest GCM scenarios included in this study, declines in winter rainfall on Australian farms of 21.4% (*RCP4.5*) and 30.6% (*RCP8.5*) are projected. For Western Australian cropping farms, projections show a higher level of agreement, with reductions in winter rainfall projected under most GCMs.

Increases in Australian summer rainfall have been observed over the last 20 years in some regions, particularly in parts of western and northern Australia (BoM and CSIRO

2020). However, on average, Australian farmers have seen limited change in summer rainfall over the *Recent* period, with some slight increases amongst western Australian cropping farms. Projections suggest declines in summer rainfall by 2050 for most farming groups (−7.4% and −10.8% under the mean *RCP4.5* and *RCP8.5* projections on average). Climate models project increases in average summer maximum temperatures for farmers of +0.5 to +1.2°C and +1.3 to +2.0°C under the *RCP4.5* and *RCP8.5* scenarios respectively.

3 Results

Simulated changes in farm profits are presented in Table 5, Figs. 4, 5 and 6 (with regional level profit results presented in the Appendix). Note these tables and charts present averages of farm-scale estimates, and results can vary considerably at the farm level even for farms within a given region or industry (particularly with respect to farm size, see Table 7). For future scenarios the mean, minimum and maximum across the 6 GCMs are presented.

Under the *Recent (2001 to 2020)* scenario, simulated farm profits are 23% lower on average compared to the *Historical (1950 to 2000)* period (Table 5). Recent climate effects have been felt most strongly amongst cropping farms particularly in south-western and south-eastern Australian (Table 5, Fig. 6).

Climate projections for 2050 show a wide range of outcomes across the 6 included GCMs. Simulated changes in average farm profits under the *Future (2050 RCP4.5)* scenario range from −31.9 to −2.0%, while *RCP8.5* ranges from −49.9 to −10.7% (Table 4).

Western cropping farms show the largest mean reductions in average farm profits under the future scenarios (−55.9 to −5.1% under *RCP4.5* and −68.1 to −7.3% under *RCP8.5*). This mainly reflects projected declines in winter growing season rainfall in this region and the resulting effects on crop yields (Table A10 in the Appendix) and revenue (Table 5).

Beef farms in northern Australia also show significant reductions in average profit under the *Future 2050* scenarios (−22.1 to −3.0% under *RCP4.5* and −54.5 to −16.3% under *RCP8.5*). These changes are driven by projected declines in winter and summer rainfall along with increases in maximum temperatures. As discussed in Hughes et al. (2022b), the climate response of livestock farms in the *farmpredict* model depends more heavily on temperature compared to cropping farms, explaining why simulated livestock farm profits are considerably worse under *RCP8.5* than *RCP4.5*.

Table 5 Percentage change in average farm profits relative to *Historical (1950 to 2000)*

Industry group	*Historical* ($)	*Recent*	*Future (RCP4.5 2050)*			*Future (RCP8.5 2050)*		
			Min.	Mean	Max.	Min.	Mean	Max.
Beef-Northern	152,815	−3.1	−22.1	−11.7	−3.0	−54.5	−27.6	−16.3
Beef-Southern	20,968	−22.5	−26.6	+0.5	+10.3	−63.8	−18.0	−2.7
Sheep-Lamb	108,234	−14.9	−16.6	−5.8	−0.1	−31.6	−12.9	−5.6
Sheep-Mixed	58,817	−26.7	−37.3	−13.2	−6.3	−66.3	−28.1	−15.9
Cropping-Northern	212,491	−36.2	−23.7	−9.8	−3.6	−43.1	−20.1	−4.8
Cropping-Southern	179,423	−21.7	−27.7	−3.3	+11.5	−30.8	−8.5	+4.1
Cropping-Western	437,227	−26.8	−55.9	−31.6	−5.1	−68.1	−50.5	−7.3
All farms	129,187	−22.6	−31.9	−13.1	−2.0	−49.9	−25.6	−10.7

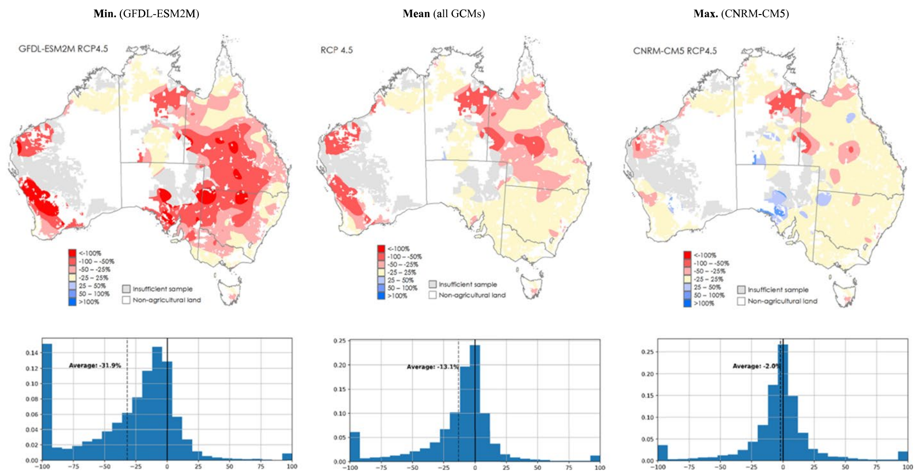

Fig. 4 Percentage change in farm profits under the *Future 2050 (RCP4.5)* scenario relative to *Historical (1950 to 2000)*

In south-eastern Australia, future scenarios show a very wide range of potential outcomes, due largely to differences in rainfall across the 6 GCMs. For cropping farms in the southern region (Vic., SA, Tas.), changes in average simulated profits under *Future (2050 RCP8.5)* range from −30.8 to +4.1%. Under *Future (2050 RCP4.5)*, increases in farm profits for southern cropping farms are observed under the most favourable climate scenarios (+11.5% under CNRM-CM5) due to projected increases in winter rainfall.

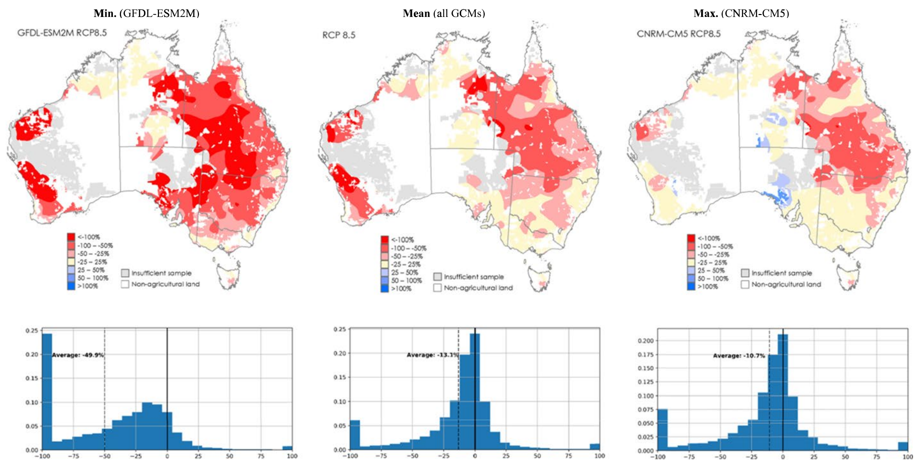

Fig. 5 Percentage change in farm profits under the *Future 2050 (RCP8.5)* scenario relative to *Historical (1950 to 2000)*. Based on farm-level scenario results calculated using a symmetric percentage change metric: $\left(\frac{Y_{ia}-Y_{ib}}{(|Y_{ia}|+|Y_{ib}|)/2}\right)$, where Y_{ia} is average annual profit for farm i under the *Future 2050 (RCP4.5)* scenario, and Y_{ib} average annual farm profits under the *Historical (1950 to 2000)* scenario

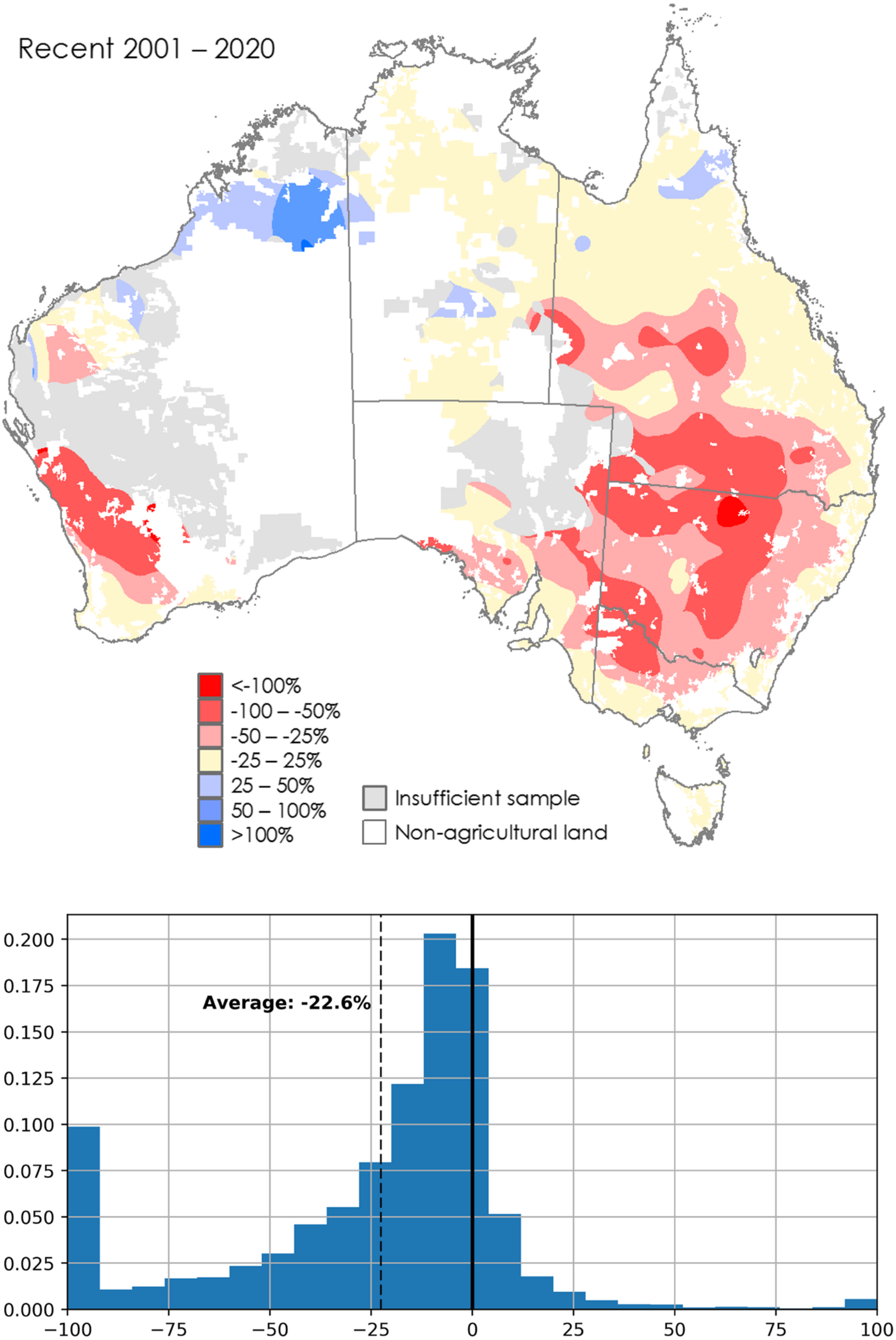

Fig. 6 Percentage change in farm profits under the *Recent (2001 to 2020)* scenario, relative to *Historical (1950 to 2000)*. Based on farm-level scenario, results calculated using a symmetric percentage change metric: $\left(\frac{Y_{ia}-Y_{ib}}{(|Y_{ia}|+|Y_{ib}|)/2}\right)$, where Y_{ia} is average annual profit for farm i under the Recent *(2001 to 2020)* scenario, and Y_{ib} average annual farm profits under the *Historical (1950 to 2000)* scenario

Table 6 Average percentage change in farm revenue relative to *Historical (1950 to 2000)*

Industry group	*Historical* ($)	*Recent*	*Future (RCP4.5 2050)*			*Future (RCP8.5 2050)*		
			Min.	Mean	Max.	Min.	Mean	Max.
Beef-Northern	634,004	+2.38	+3.13	+4.65	+6.39	+6.05	+8.23	+13.94
Beef-Southern	256,699	−0.08	+0.15	+0.49	+1.00	−0.00	+0.65	+2.38
Sheep-Lamb	551,558	−0.80	+0.39	+1.04	+1.47	+0.12	+0.68	+1.26
Sheep-Mixed	332,995	−0.80	+0.53	+1.29	+1.79	+0.04	+0.72	+1.43
Cropping-Northern	890,090	−8.89	−5.60	−2.13	−0.27	−9.35	−4.22	−0.51
Cropping-Southern	735,279	−6.23	−9.30	−1.82	+2.57	−10.64	−3.56	+0.54
Cropping-Western	1,636,559	−8.30	−19.49	−11.30	−2.83	−24.37	−17.57	−3.28
All farms	590,105	−4.08	−4.81	−1.71	+0.44	−5.34	−3.03	+0.11

Under *Future (2050) RCP4.5*, simulated impacts for beef farms in southern Australia are modest on average (0.5% mean profit increase). Many southern Beef farms are located in relatively cool and high-rainfall coastal regions (see Fig. 1), where small increases in temperature/declines in rainfall can feasibly be productivity increasing. However, under the more extreme *Future (2050 RCP8.5)*, scenarios simulated changes in average farm profits for southern Beef farms become clearly negative: −63.8 to −2.7%.

While the spatial pattern of the effects varies under each GCM, in general, the largest changes in farm profits are simulated in the northern parts of the western cropping zone (*WA:North and East Wheat Belt* region, Table A9 in the Appendix), along with parts of western NSW (*NSW:Far West*, *NSW:Central West*) and central QLD (*QLD:West and South West*, *QLD:Charleville-Longreach* regions). Similar to recent historical trends and past projection studies, these results generally show larger climate change impacts in more marginal (hotter, lower-rainfall and more in-land) areas. Compared with recent trends (Fig. 6), future scenarios show generally smaller effects in south-eastern Australia and larger impacts in Queensland (see Figs. 4 and 5).

Table 7 Average percentage change in farm costs relative to *Historical (1950 to 2000)*

Industry group	*Historical* ($)	*Recent*	*Future (RCP4.5 2050)*			*Future (RCP8.5 2050)*		
			Min.	Mean	Max.	Min.	Mean	Max.
Beef-Northern	399,791	+1.60	+0.95	+2.23	+4.41	+2.70	+4.69	+9.98
Beef-Southern	174,313	+0.74	-0.49	+0.01	+1.42	−0.52	+0.31	+2.75
Sheep-Lamb	326,247	+0.84	+0.08	+0.54	+1.83	+0.11	+0.98	+3.36
Sheep-Mixed	230,312	+1.28	+0.10	+0.67	+2.45	+0.21	+1.50	+5.03
Cropping-Northern	588,016	−3.78	−2.93	−0.52	+0.39	−5.25	−1.71	−0.05
Cropping-Southern	482,816	−3.13	−7.13	−2.50	−0.12	−9.27	−3.84	−1.14
Cropping-Western	1,083,363	−3.38	−9.75	−5.65	−2.29	−13.79	−8.67	−2.28
All farms	386,662	−1.36	−2.35	−1.10	−0.25	−2.50	−1.57	−0.10

Table 8 Average percentage change in farm closing stock value relative to *Historical (1950 to 2000)*

Industry group	*Historical* ($)	*Recent*	*Future (RCP4.5 2050)*			*Future (RCP8.5 2050)*		
			Min.	Mean	Max.	Min.	Mean	Max.
Beef-Northern	1,753,457	−0.72	−3.23	−2.07	−1.07	−7.28	−4.08	−2.92
Beef-Southern	510,187	−0.59	−0.86	−0.00	+0.35	−2.62	−0.74	−0.14
Sheep-Lamb	562,442	−1.54	−3.06	−1.75	−1.28	−4.92	−2.49	−1.62
Sheep-Mixed	527,776	−1.84	−3.87	−1.83	−1.20	−5.79	−2.72	−1.58
Cropping-Northern	434,243	−4.48	−3.95	−1.04	−0.04	−8.70	−3.27	−1.19
Cropping-Southern	273,436	−3.25	−5.74	−1.77	+0.21	−8.03	−2.97	−1.06
Cropping-Western	437,593	−3.92	−7.43	−3.56	−0.59	−10.83	−6.14	−0.96
All farms	650,512	−1.55	−3.24	−1.59	−0.86	−6.34	−3.09	−2.10

In Tasmania, simulation results are highly consistent across the 6 GCMs with relatively modest declines in profit overall, and negative effects appearing to be concentrated in the south of the state. In contrast, extremely wide variation is observed in parts of South Australia. In the *SA: Eyre Peninsula* region, simulated changes in farm profits range from −76 to +41% under the future scenarios (Table A9 in the Appendix).

While not directly comparable (due to differences in climate scenarios, reference periods, farm locations and profit measures), these results are broadly consistent with the recent literature. For example, Ghahramani et al. (2020) simulated percentage changes in farm profits by 2030 of between −74% and +16% (mean -26%) across a range of farm sites in the southern Australian wheat belt (under a 'Hot and dry' RCP8.5 scenario). While Thamo et al. (2017) simulated changes in farm net returns by 2050 of −100 to −160% for farms in the Western Australian wheat belt.

Table 6 and 7 show simulated changes in average farm revenues and costs. As discussed in Hughes et al. (2022b) the effects of hotter and drier conditions on livestock farms tend to be transmitted more through herd (stock) changes (Table 8) due to lower livestock net birth rates (along with some small increase in costs due to higher fodder expenses). Cropping farms show reductions in revenue and costs under most future climate scenarios (due to declines in crop production, see Table A10 in the Appendix).

Table 9 Average percentage change in profit by farm size group relative to *Historical (1950 to 2000)*

Farm size	*Historical* ($)	*Recent*	*Future (RCP4.5 2050)*			*Future (RCP8.5 2050)*		
			Min.	Mean	Max.	Min.	Mean	Max.
Small farms	17,688	−96.0	−130.9	−52.8	−9.4	−197.9	−100.4	−41.5
Medium farms	171,877	−22.6	−32.2	−14.6	−4.1	−49.6	−26.8	−12.2
Large farms	661,259	−11.9	−19.4	−9.1	−2.6	−29.7	−16.2	−7.8

Table 10 Percentage change in average Australian grain and fodder prices by climate scenario relative to *Historical (1950 to 2000)*

Commodity	Recent	Future (RCP4.5 2050)			Future (RCP8.5 2050)		
		Min.	Mean	Max.	Min.	Mean	Max.
Wheat	+6.1	+1.5	+4.0	+13.0	+3.0	+8.3	+26.9
Barley	+7.4	+0.9	+5.0	+19.2	+3.6	+11.7	+40.0
Sorghum	+4.1	+3.1	+6.8	+16.1	+5.5	+12.6	+33.5
Fodder	+7.6	+3.3	+6.2	+14.9	+6.0	+10.5	+24.3

In contrast, increases in revenue are observed for livestock farms due to increases in turn-off. This reflects the 'short-run' nature of the *farmpredict* model where (year opening) livestock holdings are held fixed[2].

The results in Table 6 and 7 also illustrate how small changes in farm revenues and costs can have large effects on profits, particularly for farm groups with low profit margins. This is reinforced by Table 9 which shows changes in profits by farm size. These farm size groupings are based on farm capital holdings relative to farms in the same industry and region group. In general, smaller farms tend to have lower profit margins than larger farms (Boult and Jackson 2019; Jackson et al. 2020), as a result they show significantly higher percentage change in profits under future climate scenarios.

Table 10 presents the average simulated domestic grain (and fodder prices) under each climate scenario. Future scenarios show that increases in average Australian prices for major grain crops (wheat, barley and sorghum) are possible (of between 1 and 40%) with increases in prices for livestock fodder (hay) of between 3 and 24%.

Additional model results are presented in the Appendix. Table A10 in the Appendix presents modelled change in crop yields under each climate scenario, with larger changes simulated for winter crops. In particular, declines in national wheat yields of 2.8 to 24.1% are estimated under *RCP4.5*, compared with 2.7 to 11.9% for sorghum. Table A11 in the Appendix presents changes in livestock birth and death rates, with declines in birth rates (−2.6% to +0.1% for beef cattle under *RCP8.5*) and increases in death rates (+8.2% to +17.2% under *RCP8.5*) typically simulated under future scenarios.

Finally, Table A12 in the Appendix presents estimates of the frequency of drought under each scenario, drawing on drought indicators developed in Hughes et al. (2021). Here, the model predicts the percentage of years that farmers would self-assess their property as being 'in-drought' under each future scenario given contemporary farmer perceptions of drought (Hughes et al. 2021). On average, drought frequency changes from 5.2% under the *Historical* scenario (and 14.7% under the *Recent* scenario) to 8.7 to 11.4% under *RCP4.5* and 10.6 to 39.4% under *RCP8.5*.

[2] Within the model, short-term decreases in livestock holdings (due to higher turn-off and death rates and lower birth rates) are captured in the profit accounting rules by deducting the value these stock losses from farm profits. Explicit consideration of multi-year livestock dynamics remains a subject for future research.

4 Discussion

4.1 Climate change adaptation

As with the previous literature, the results in this study show a wide range of outcomes reflecting uncertainty over projected temperature and rainfall. Of key importance are projections for Australian winter rainfall where there is a high level of disagreement amongst GCMs. While rainfall projections in south-eastern Australia are highly uncertain, recent data (particularly the last 20–25 years) show a strong negative trend, such that observed rainfall is now tracking the extreme dry end of the projected range in key parts of southern Australia (see BoM and CSIRO 2020).

While future projections are subject to much uncertainty, the above results confirm that climate change has the potential to make conditions tougher for Australian farmers. Under the most severe future scenario (*RCP8.5* with the *GFDL-ESM2M* GCM), average Australian farm profits are simulated to decline by 50% relative to the period 1950 to 2000.

Clearly, the impacts of this magnitude would induce strong adaptation responses. Already, there is evidence of significant farmer adaptation in response to the climate shifts in recent decades. This has included significant gains in productivity within the cropping sector with the emergence of a range of new technologies and practices focused on better conserving soil moisture in response to declining in-season rainfall (Hochman et al. 2017; Chancellor et al. 2021; Hughes et al. 2017; Hunt and Kirkegaard 2012). In addition, there is now growing evidence of migration of the Australian cropping zone in response to changes in climate observed to date (see Fletcher et al. 2020; Nidumolo et al. 2012; Hughes and Gooday 2021).

While many of the future scenarios are less severe than the *Recent (2001 to 2020)* period, long-term shifts in climate could still induce stronger adaption responses, particularly where they lead farmers to update their expectations over future climate conditions[3].

Over the longer term, improvements in technology could help offset the effects of climate change. A simple continuation of long-run productivity trends (average annual TFP growth of 1.6% since 1960, Sheng et al. 2013) would be sufficient to prevent absolute declines in Australian farm productivity or production levels by 2050 even under the most severe climate projections. However, there remains uncertainty over the extent to which new technologies will support further adaptation to dry and hot conditions, and also the adjustment costs this adaptation might involve. Further, even with strong adaptation responses, climate change could still reduce Australian farmers' international competitiveness depending on the climate change impacts and productivity trends in other nations.

4.2 Strengths and weaknesses of a statistical modelling approach

A variety of modelling techniques have been applied to estimated climate change impacts in agriculture each with their own strengths and weaknesses. While the statistical approach applied in this study offers both farm-scale analysis and broad regional coverage, the approach is unable to account for longer-term adaptation (or CO_2 fertilisation effects) and so may lead to larger estimated impacts than comparable bio-physical model studies.

[3] Hughes et al. (2021) provide evidence that the recent shifts in climate have already led to some updating in climate expectations by Australian farmers, while Severen et al. (2018) present evidence for US farmers.

Future technological change remains extremely difficult to predict regardless of the modelling approach adopted. However, bio-physical models do have some additional flexibility in accounting for long-term adaptation, since they can simulate adjustment in capital inputs such as land areas, (opening) livestock holdings and equipment (which are typically held fixed in statistical models like *farmpredict*[4]). For example, some recent studies (Ghahramani and Bowran 2018; Ghahramani et al. 2020) considered structural adjustments such as changes in the mix of cropping and livestock activity. These studies show potential benefits, although such adaptations are still typically insufficient to fully offset climate change impacts, particularly under the more severe GCM projection scenarios (Ghahramani and Bowran 2018; Ghahramani et al. 2020).

By their nature, statistical production models also assume that farmer behaviour remains reflective of that observed in the recent past. As such, while these models allow for typical short-term responses of farmers to annual climate variability, they do not account for longer-term responses farmers may make in response to permanent shifts in climate, even those possible with existing technology, such as adoption of management practices or livestock breeds/crop types better suited to their new local climate.

For this reason, some economists have argued in favour of a 'Ricardian' approach (Mendelsohn et al. 1994). While common in the economic literature (Huong et al. 2019; Dall'Erba and Domínguez 2016; Gbetibouo and Hassan 2005), such studies not generally used in integrated assessments of climate change (see Nelson et al. 2014). The Ricardian approach assumes that land prices reflect the expected future profits of farmers operating under the prevailing local climate (as proxied by historical climate data). However, this approach becomes problematic in a modern context where the climate is in transition, and historical data becomes a poor proxy for the 'current' or expected climate in each region[5]. Further, as Quiggin and Horowitz (1999) note, the approach does not account for adjustment costs farmers face in modifying their practices or farm capital, and so will tend to understate the costs of climate change.

Increasingly, global analysis of agricultural climate change impacts involves an 'integrated assessment' approach (see Nelson et al. 2014; IPCC 2019) involving multiple linked models, most commonly bio-physical (crop production) models linked to global bio-economic (land use/supply and demand) models. In future, *farmpredict* could play a role in this type of modelling chain, helping to bridge the gap between purely bio-physical and purely economic models. For example, a key option for future research is to include outputs from bio-physical models (such as *APSIM*, Keating et al. 2003) within the *farmpredict* training data. This hybrid approach (as advocated by Antle 2019) could help to improve model extrapolation and better account for CO_2 fertilisation effects. Further, it could be used to provide inputs (i.e. changes in farm profits) for economic optimisation models simulating long-term changes in land use and/or agricultural supply.

Given the extreme uncertainty surrounding future climates and technology and persistent differences in agricultural model responses (Nelson et al. 2014), projections of long-term agricultural outcomes (both in Australia and internationally) remain highly speculative. Over time, research focus has naturally shifted from predicting the future effects of climate change on agriculture towards also measuring observed impacts. In this modern context, where climate and farming systems are in transition and there is increasing policy attention on adaptation, statistical models like *farmpredict* could have some advantages.

[4] While it remains possible to simulate exogenous changes in capital in models like *farmpredict* (including for example changes in the mix of cropping and livestock activity on farms), accuracy could be limited if this leads to farm structures significantly different to those observed in the historical training data.

[5] Particularly since farmer expectations over the future climate (and therefore current land prices) are already being influenced by climate projection information (see Severen et al. 2018).

Firstly, statistical models based on farm survey data can be useful in measuring the effects of climate changes on farm outcomes to date, and since the models can be easily updated (as each year of new farm data becomes available), they can incorporate the latest industry adaptation responses as they emerge. As such, these models can be effective in tracking the climate transition in the farm sector, with climate projection scenarios then being used more to assess adaptation pressure (i.e. the prevailing direction of change rather than the potential endpoint).

While statistical models like *farmpredict* cannot estimate long-term land use or supply changes (unless coupled with economic optimisation models), they can still provide useful information to support government adaptation policy and industry responses. For example, the ability of statistical models to produce farm-scale results could be leveraged to generate customised reports for farmers, showing the recent and/or potential future impacts of climate change on their farm business (given its specific location, size, structure etc.). These reports could support local adaptation, by translating abstract rainfall and temperature data into actionable information for farm business owners. Similar reports could also be useful in helping the financial sector (farm lenders and insurers) assess the exposure of their portfolios to climate change risk.

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Data availability Data tables (and metadata) containing aggregated (regional level) data have been provided as part of this submission both the historical model data and climate scenario results. Unit record (farm business level) data used by ABARES to estimate the underlying statistical models cannot be published due to confidentiality constraints.

Code availability A copy of the complete model code (for *farmpredict*) can be provided to reviewers on request.

Declarations

Conflict of interest The authors declare no competing interests.

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