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Climate change impacts and farm-level adaptation: Economic analysis of a mixed cropping–livestock system

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ABSTRACT

The effects of climate change on agricultural profitability depend not just on changes in production, but also on how farming systems are adapted to suit the new climatic conditions. We investigated the interaction between production changes, adaptation and farm profits for a mixed livestock–cropping farming system in the Western Australian Wheatbelt. Crop and pasture production was simulated for a range of plausible rainfall, temperature and CO_2 concentrations for 2030 and 2050. We incorporated the results of these simulations into a whole-farm bio-economic optimisation model. Across a range of climate scenarios, the impact on farm profit varied between −103% and +56% of current profitability in 2030, and −181% and +76% for 2050. In the majority of scenarios profitability decreased, and the magnitude of impacts in negative scenarios was greater than the upside in positive scenarios. Profit margins were much more sensitive to climate change than production levels (e.g., yields). Adaptive changes to farm production under extreme climate scenarios included reductions in crop inputs and animal numbers and, to a lesser extent, land-use change. The whole-farm benefits of these adaptations were up to \$176,000/year, demonstrating that estimating the impact of climate change without allowing for adaptation can substantially inflate costs. However, even with adaptation, profit reductions under the more negative scenarios remained large. Nevertheless, except for the most extreme/adverse circumstances, relatively minor increases in yields or prices would be sufficient to counteract the financial impacts of climate change (although if these price and/or productivity increases would also have occurred without climate change then the actual cost of climate change may still be high).

1. Introduction

The effect that climate change has on the productivity and economic viability of agriculture will depend on how much it is possible to adapt to reduce the change's impact (Lobell, 2014). Therefore, estimates of the economic impact of climate change will likely be overstated if adaptation is not allowed for. Nonetheless, in many existing projections of climate change impacts adaptation is not considered (White et al., 2011).

We investigate the impact of climate change, allowing for adaptation, in the Wheatbelt region of Western Australia. In this region the agricultural growing season is limited by moisture availability and as the region is predicted to warm and dry with climate change (e.g., Moise and Hudson, 2008; Turner et al., 2011) the dryland agriculture practiced there is potentially vulnerable. Climate change may already be affecting the region: average growing-season rainfall (May to October) has declined by more than 10% since the 1970s (Ludwig et al., 2009). Interestingly, despite this, farms in the region experienced high yield and productivity growth in the 1980s and 1990s (Islam et al., 2014). However, more recently, average yields appear to have stabilised (Stephens et al., 2012; Turner et al., 2011).

Studies of the economic impacts of climate change that incorporate agricultural adaptation need to encompass: (a) the impacts of climate change on the production of outputs in various possible production systems, and (b) an economic assessment of the impact of these production changes and the options for adaptation that are available to the farmer. Aspect (a) is often addressed using detailed plant and/or animal simulation models, and there have been a number of studies of this type for the case-study region (Anwar et al., 2015; Asseng et al., 2004; Asseng and Pannell, 2013; Farre and Foster, 2010; Ludwig and Asseng, 2006; Ludwig et al., 2009; Moore and Ghahramani, 2013; van Ittersum et al., 2003).

Aspect (b) has been much less thoroughly researched for the study area. There are two main approaches that can be used to investigate it. The first is to identify packages of adaptations that are of interest and then simulate the economic consequences of each package (e.g.,

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Crimp et al., 2012; Ghahramani et al., 2015). An advantage of this approach is that the modeller has complete control over which adaptations are simulated, allowing transparent analysis of particular strategies that are of interest. Deciding which packages of adaptations to simulate can be problematic though (White et al., 2011), particularly in complex mixed farming systems such as those found in the case-study region. The modeller may not be able to anticipate which of the many potential combinations of adaptations are most likely to be worth assessing.

The second approach is to use optimisation to automatically assess all of the available combinations of adaptations. The obvious advantage is avoiding the need for numerous simulations to identify the adaptations that best meet the farmers' economic objectives (Klein et al., 2013). However, the analysis may be less transparent than under the simulation approach, and the objective function used in the optimisation model may not match that of all farmers.

In this study, we utilise process-based simulation models for the first phase, and extensively modify an existing bioeconomic whole-farm optimisation model for the second. We judged that the very large number of production options available in our case-study region means that the advantages of the optimisation approach outweigh its disadvantages. Also, previous analyses of climate change impacts on the case-study region have tended to consider impacts on a solitary crop or enterprise in isolation. Our use of a whole-farm model allows the simultaneous consideration of impacts on all elements of a typical farming-system in the region. Amongst other things, this allows adaptation in the form of changing land use to be represented in our study (Reidsma et al., 2015).

Our aim is to explore potential impacts of future climate change on production and profitability in the West Australian Wheatbelt. Specifically we address the following questions: 1) What is the impact on farm production and profits under a range of realistic climate scenarios over the next 15 to 35 years?; 2) Which currently available adaptations are most effective in moderating any adverse effects or exploiting positive effects, and to what extent do they improve farm profits?; Finally, 3) What increase in prices or yields would be needed to maintain profits equivalent to the no-climate-change scenario?

2. Methodology

2.1. Study area

The Western Australian Wheatbelt region accounts for approximately 40% of the wheat and 11% of the wool exported by Australia (around 5% and 7% of the wheat and wool traded internationally—ABARES, 2013). Our study area is the central part of this Wheatbelt region, around the township of Cunderdin (Fig. 1). This area has a Mediterranean-type climate with long, hot and dry summers and cool, moist winters. Historically annual rainfall is between 330 and 400 mm, approximately 75% of which falls during the May to October growing season.

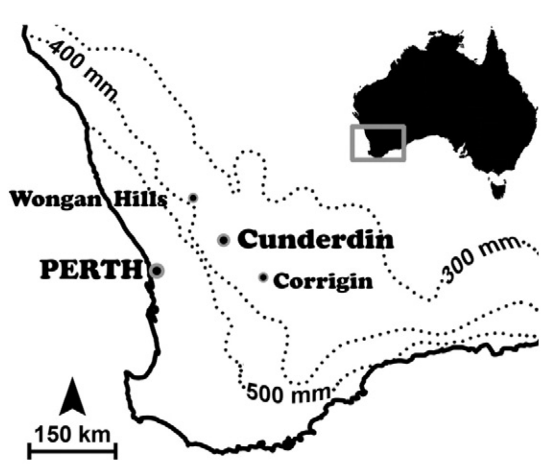

Fig. 1. Our Central Wheatbelt study area is centred on the Cunderdin Township. Precipitation isohyets are based on historical observations.

Farms in the area are commonly 2000–4000 ha, of which 65–85% is typically sown to annual crops in May and June; the remaining areas are pastured, supporting sheep for meat and wool production. Farming systems are solely rain-fed, and after harvest in December, the remaining crop residues are utilised in-situ as dry fodder. Once this feed supply is exhausted, livestock receive a grain-based supplementary ration until adequate green pasture becomes available after the onset of winter rains (Rowe et al., 1989).

2.2. Farm-level modelling

The economic impact of climate change was evaluated using MIDAS (Model of an Integrated Dry Land Agricultural System—Kingwell and Pannell, 1987; Morrison et al., 1986). MIDAS has been used extensively to explore the impacts of innovations, policy changes and environmental degradation on mixed cropping–livestock farms (e.g., Doole et al., 2009; Kragt et al., 2012; Monjardino et al., 2010; Robertson et al., 2010). MIDAS is deterministic, based on an 'average' weather-year in the study area (although the region's Mediterranean-type climate is semi-arid, historically, the variability in this climate has been relatively low, making the steady-state modelling framework of MIDAS justifiable—Kingwell, 2011).

MIDAS uses a linear-programming algorithm to maximise farm net return subject to resource, environmental, and managerial constraints, including machinery capacity and the availability of land, labour and capital. MIDAS contains approximately one thousand activities, including: a range of rotations with different sequences of crops and pasture for each soil type; feed supply and utilisation by different classes of livestock; different crop sowing dates (and yield penalties for delays to sowing); cash flow recording and; machinery and overhead expenditures. MIDAS captures biological and technical relationships at the farm-level, particularly interdependencies between enterprises such as the benefits of nitrogen fixation, the yield-enhancing (e.g., disease-break) effects of crop rotation, the value of crop residues as animal feed, the effects of cropping on subsequent pasture growth and the effect of weed burdens for subsequent crops.

For this study the Central Wheatbelt MIDAS used in recent studies (Kragt et al., 2012; Thamo et al., 2013) was updated to reflect changing trends by increasing the capacity and value of machinery. Farm size was also increased to 3200 arable hectares. The MIDAS farm contains eight different soil types with varying production characteristics, as farms in the study area typically contain a mix of soil types (for descriptions of, and areas assumed for each soil type see the Supplementary Material). Land-uses represented in the model include rotations of wheat (*Triticum aestivum*), barley (*Hordeum vulgare*), oats (*Avena sativa*), lupins (*Lupinus angustifolius*), canola (*Brassica napus*), and annual legume-based pastures. The annual net return we report represents the pre-tax profit after deducting variable costs, as well as non-cash costs like depreciation, and fixed overheads like household expenses and hiring of professional services. For the present study we added the option of retiring land from production, the rationale being if climate change renders agricultural production unprofitable, a producer's optimal response may be to 'retire' from production their least productive land to minimise their losses. Unlike the temporary fallowing of land, land retirement is purely a loss-minimisation activity that neither generates income nor incurs costs (overheads associated with maintaining the farming enterprise as whole are still incurred).

The predicted impacts of changes in climate and atmospheric CO_2 levels (hereafter called 'climate scenarios') on farm production were incorporated into MIDAS. This was done by using biophysical simulation models (described in Section 2.4) to estimate the effect of a given climate scenario on agricultural production, and then based on these results, the growth potential of crops and pastures in MIDAS were scaled.

2.3. Climate projections and scenarios

In the most recent comprehensive climate projections for the study region, Hope et al. (2015) collated the results of over 40 Global Climate Models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) ensemble of climate models (this ensemble underpins the Intergovernmental Panel on Climate Change's Fifth Assessment Report). Compared to the 1986–2005 period, Hope et al. (2015) predicted with high confidence that annual rainfall in the study region will decrease, with June to November (the agricultural growing season in the study region) rainfall in the study region projected to change by −15% to +5% by 2030, and −45 to −5% by 2090. They also predicted that average temperatures will increase (in the order of 1.2–4.0 °C by 2090, equally across all seasons). These projections are consistent with earlier studies, and indeed, decreases in rainfall and increases in temperature already observed in the study region in recent decades (Delworth and Zeng, 2014; Hennessy et al., 2010; Moise and Hudson, 2008).

Although the direction of climatic changes predicted for the study region is relatively clear, particularly in the long-run, the magnitude of these changes is less certain. This uncertainty arises because of variation between the results of different GCMs, limitations of GCMs in general, and uncertainty about future global emissions (Asseng et al., 2013; Hennessy et al., 2010).

To reflect this uncertainty we therefore considered a wide range of changes in climatic parameters and atmospheric CO_2 concentrations in our analysis. A similar factorial approach has been used in other climate change studies of the study region (e.g., Ludwig and Asseng, 2006; van Ittersum et al., 2003). In total we considered 72 climate scenarios: the factorial combination of three CO_2 levels, three temperature increases and four rainfall reductions for each of the years 2030 and 2050 (Table 1). The magnitude of these changes was chosen because they were consistent with the trend of projections from the literature, yet deliberately broad enough to capture a wide range of climatic possibilities, allowing us to explore the sensitivity of the agricultural system to changes.

The climate scenarios were generated by 'changing' the historic weather (herein this historic weather—meteorological data observed from 1957 to 2010 at Cunderdin and a constant concentration of 390 ppm atmospheric CO_2—is referred to as the 'base-case' climate). So for instance, for the scenario of 525 ppm CO_2/20% rainfall reduction/2.5 °C increase (or '525/−20/2.50'), the atmospheric CO_2 level in the biophysical simulation models was set to 525 ppm, all rainfall observations in base-case dataset were reduced by 20% (changing the intensity but not regularity of rainfall), and the maximum and minimum temperature observations were increased by 2.5 °C.[1]

2.4. Simulating the biophysical impact of climate change and incorporating the results into MIDAS

The effect of climate and CO_2 change on crop yields and pasture growth was simulated with the models Agricultural Production Systems Simulator (APSIM, ver 7.5) (Holzworth et al., 2014; Keating et al., 2003) and GrassGro® (ver 3.2.6) (Moore et al., 1997) respectively. Both of these biophysical models have been extensively applied to the study area, including for climate change research (e.g., Anwar et al., 2015; Asseng et al., 2013; Ghahramani et al., 2015; Moore and Ghahramani, 2013). These models were calibrated for the eight soil types in MIDAS under base-case climatic conditions. To incorporate the predictions of these simulation models into MIDAS, the yield of crops and growth of pastures in MIDAS were scaled based on their relative difference between the base-case scenario and the given climate scenario predicted by the biophysical simulation models. This meant the relative change in crop yield-potential or pasture growth-potential predicted by the biophysical models for each soil type, with each climate scenario was emulated in MIDAS. MIDAS was then run like normal, to select profit maximising land uses, management strategies and input levels for each scenario.

Currently, APSIM lacks the capacity to simulate the effect of elevated CO_2 on many crops other than wheat. Consequently, in our analysis the impact of CO_2 increases on barley, oats, lupins and, to a lesser degree, canola, was based on APSIM's results for wheat. Additional details on this, how we took into account the potential for climate change to impact pasture growth differently at different times of the year and/or different stocking rates, and the parameterisation of the biophysical models in general can be found in the Supplementary Material.

Table 1
Factorial combinations of the following changes in climate and CO_2 were investigated for 2030 and 2050.

Years	CO_2 (ppm)	Rainfall reduction (%)	Temperature increase (°C)
2030	425	0	0.50
	450	−5	1.25
	475	−10	2.00
		−15	
2050	475	0	1.00
	525	−10	2.50
	575	−20	4.00
		−30	

2.5. Prices

MIDAS was configured with 2013 prices, except for the more volatile fertiliser, grain and livestock prices that were instead set to five year (2009–2013) average prices in real terms (these prices are listed in the Supplementary Material). No systematic, longer term changes in prices (and/or productivity) were implicitly considered, meaning our analysis is contingent upon the assumption that farming productivity and prices of inputs and commodities are not changed fundamentally in the future.

2.6. MIDAS validity

MIDAS has been extensively tested in Western Australia for around 30 years since its creation by Morrison et al. (1986). It has been frequently updated to reflect changes in prices, costs, resources, farming systems and technologies. Although, as an optimisation model, the sort of validation strategies used for simulation models are not applicable, wide exposure and critique of results by experts have established that results and behaviour of the model are realistic and well aligned with actual farms in the region. The model naturally has limitations. Perhaps most importantly for this study, it represents farming under average and deterministic weather and price conditions. This means that interactions between climate change and seasonal variability/risk, such as the role of enterprise diversification in building more resilient, stable farming systems (e.g., Kandulu et al., 2012), could not be considered in the present analysis.

A comparison of profits, yields and land uses predicted by MIDAS and the results of empirical farm surveys is available in the Supplementary Material. It shows that the proportion of the farm cropped, sheep numbers, profit and yields predicted by MIDAS under base-case climate are broadly consistent with common practice in the study area.

[1] With the evaporation rate and vapour pressure deficit derived endogenously within each biophysical simulation model, changes in these two parameters due to the changes in temperature were also taken into account. However, this required that the vapour pressure in the meteorological dataset be recalculated exogenously (Allen et al., 1998) after the temperature was scaled.

3. Results

3.1. Impact of climate change on profitability

The analysis indicates that farm profitability is sensitive to changes in annual rainfall, temperature and CO_2 even after allowing for the most beneficial adaptations (Figs. 2 and 3). Of the 36 scenarios selected to represent the range of possible circumstances for 2030 (Fig. 2), six result in profit increasing by more than 10% relative to the base case, four give profits within 10% of the base case, and 26 result in profits falling by more than 10%. The potential for losses is much greater than the potential for gains; there are 13 scenarios in which the loss of profits is greater than 50%, generally where temperature is highest and/or rainfall is lowest.

Not all of these scenarios are equally likely. At the lowest CO_2 concentration, relatively low changes in temperature and rainfall are more likely, increasing the chance that the impact on profit will be moderate, or even positive. At the highest CO_2 concentration, more extreme changes are relatively likely. Although they are offset to some extent by the benefits of high CO_2 for plant growth, overall the more likely effects on profit at high CO_2 are highly negative.

The 36 scenarios modelled for 2050 reflect the potential for larger changes in temperature, rainfall and CO_2 by that time (Fig. 3). The possibility of a positive impact on profits is less likely than for 2030, with only four of the 36 scenarios resulting in profit increases above 10%. By contrast, there are now 30 scenarios that produce profit decreases greater than 10%, including 24 where the profit falls by more than 50%.

Fig. 3 reveals that there are interactions between rainfall, temperature and CO_2 changes. The greater the rainfall reduction, the less responsive profits are to temperature or CO_2 concentration. Conversely, the greater the temperature increase, the less the impact of rainfall reductions or CO_2 increases.

Across all 72 scenarios, if there is either a greater than 2.5 °C temperature increase or greater than 20% rainfall reduction, then regardless of what happens to the other climate parameters, farm profit falls compared to the base-case. If changes in climate are minor, then the implications for farm profit can be quite positive due to CO_2 increases and the beneficial impacts of small increases in temperatures. On the other hand, if the more extreme negative climate outcomes are realised in the 2050 scenarios, the consequences for farmers, in the absence of effective and novel adaptations, would be substantial, even after accounting for the positive effects of CO_2.

3.2. Impacts on production versus profit

Profit margins are inherently sensitive to production levels because a certain level of production needs to occur to cover production costs. Hence the impact of climate change on profitability is proportionately larger than the impact on the amount of food and fibre produced by the farming system. To illustrate, Fig. 4 shows changes in net production and profit for five selected climate scenarios (these scenarios were selected because they show the effect of changes ranging from small to large, as may be associated with different CO_2 levels). As the scenario becomes more severe, annual net return falls more rapidly than does production. Although severe climate change reduces the productivity of both crops and pasture, the relative reductions in the production of animal-derived outputs are disproportionately large.

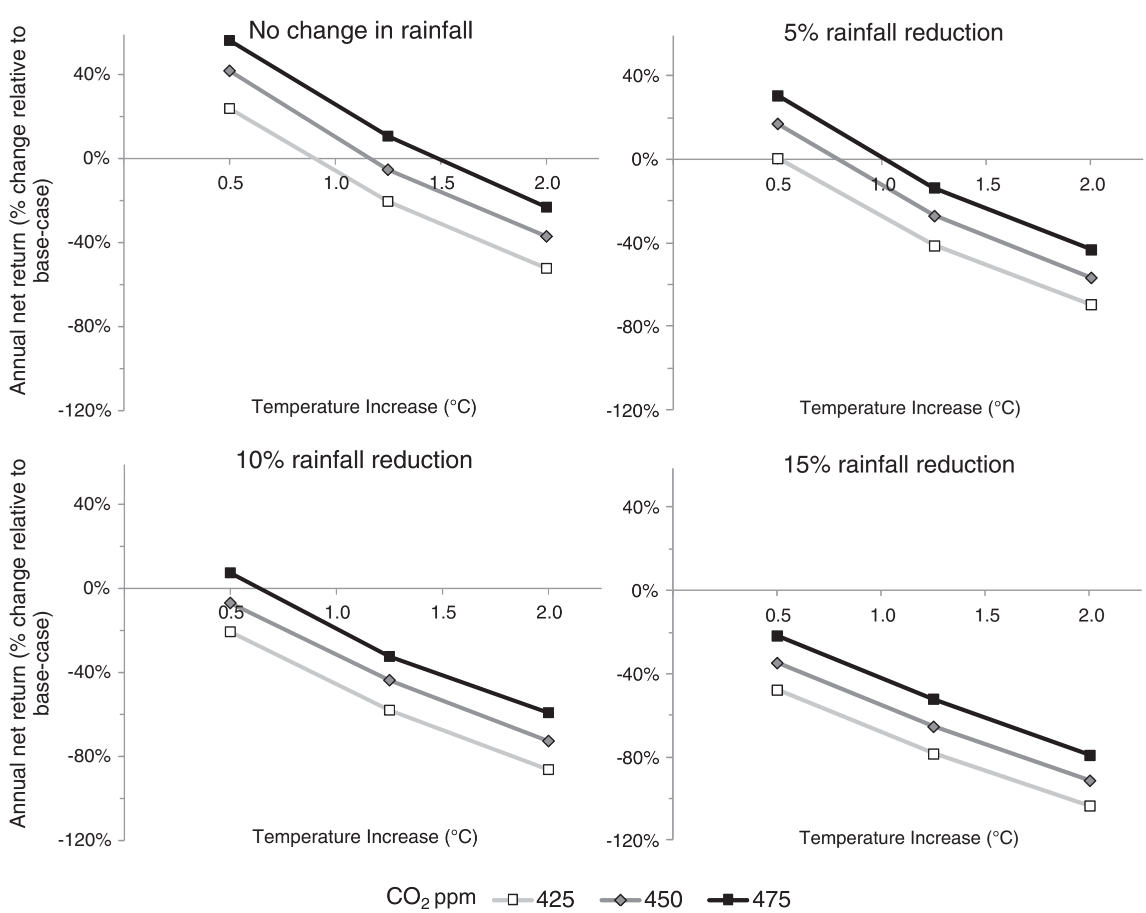

Fig. 2. Percentage change in net return relative to base-case net return (of $208,000) for the 36 climate scenarios for 2030.

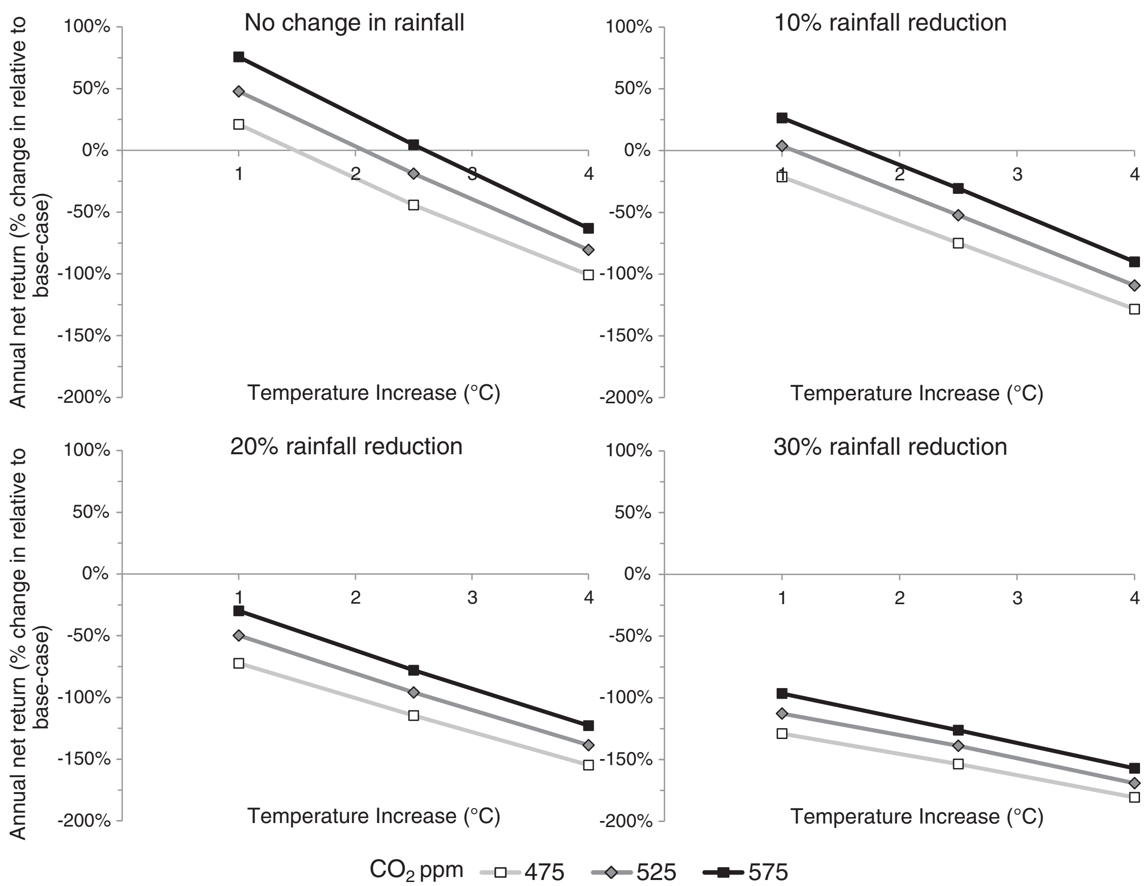

Fig. 3. Percentage change in net return relative to base-case net return ($208,000) for the 36 climate scenarios for 2050.

3.3. Adaptation to climate change

For the same five climate scenarios, Table 2 shows the optimal set of changes or adaptations from those strategies that are presently available in the model. These strategies include altering land-uses (crop types, crop and pasture areas, rotational sequences, allocation of land uses to soil types, retiring land) and/or management (fertiliser rates, livestock numbers, and feeding strategies). The impact that each climate change scenario has on crop and pasture production (that is, the bio-physical changes driving the adaptation) is difficult to show in Table 2 because changes in yield or growth are occurring not only due to climate change, but also due to adjustments in land use and management.

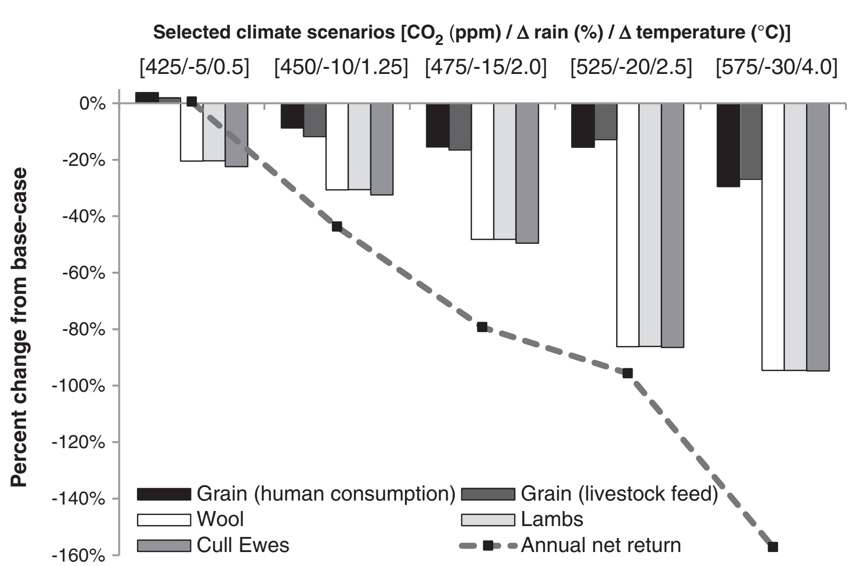

Fig. 4. Reductions in profitability are disproportionately larger than reductions in the amount of food and fibre (tonnes of grain and wool, or in the case of livestock, number of head) produced.

Table 2
Optimal farm plan with average commodity prices and a base-case climate, and how it changes under selected climate scenarios.

	Units	Base-case 390/0/0.0	Change from base-case with selected climate scenarios [CO_2 (ppm)/Δ rain (%)/Δ temperature (°C)] 425/−5/0.5	450/−10/1.25	475/−15/2.0	525/−20/2.5	575/−30/4.0
Net return	$'000/yr	**208**	1	−91	−165	−200	−327
Crop area	ha	**2548**	65	10	0	112	165
Pasture area	ha	**652**	−65	−230	−220	−332	−385
Retired land	ha	**0**	0	220	220	220	220
Cereal area	ha	**1362**	28	4	0	48	261
Lupin area	ha	**545**	0	0	0	0	0
Canola area	ha	**641**	37	6	0	64	−96
N fertiliser[a]	t	**91**	5	−17	−21	−26	−50
Winter sheep	dse	**2545**	−553	−809	−1249	−2198	−2410
Extra feeding[b]	t	**132**	5	−13	−44	−108	−125
Soil Type 1	Rotation	**PPPP**	PPPP	Retired	Retired	Retired	Retired
Soil Type 2	Rotation	**WNWL**	WNWL	WNWL	WNWL	WNWL	WNWL
Soil Type 3	Rotation	**WNWL**	WNWL	WNWL	WNWL	WNWL	WNWL
Soil Type 4	Rotation	**WNWL**	WNWL	WNWL	WNWL	WNWL	WNWL
Soil Type 5	Rotation	**NWBL**	NWBL	NWBL	NWBL	WNWL	WNWL
Soil Type 6	Rotation	**PPPW**	42% PPPW 58% PPNWW	91% PPPW 9% PPNWW	PPPW	PPNWW	PWW
Soil Type 7	Rotation	**PPNWW**	PPNWW	PPNWW	PPNWW	PPNWW	PWW
Soil Type 8	Rotation	**WNWL**	WNWL	WNWL	WNWL	WNWL	WNWL

W: Wheat B: Barley N: Canola L: Lupin P: Pasture dse: dry sheep equivalents.
[a] Total use of synthetic nitrogen (applied to cereals & canola only).
[b] Amount of supplementary grain fed to livestock.

However, data showing how the average yields and pasture growth would be affected by each climate scenario in the absence of confounding changes in land use and management is available in the Supplementary Material (Section A4).

3.3.1. Changes in the farming system

Across these selected scenarios, impact on farm profit ranges from a slight increase with modest changes to the climate of the study area—which may be more likely in the shorter term—to dramatic reductions in returns with more substantial changes in climate that may be more indicative of the study area in the longer term (Table 2). The economically-optimal set of land uses is not highly sensitive to climate change. Across the scenarios in Table 2 there is a slight trend toward increased cropping (usually cereals) and transition away from pasture. The main changes in land use are on Soil Types 6 and 7, which have relatively high clay contents and so are vulnerable to rainfall reductions (e.g., Farre and Foster, 2010; Ludwig and Asseng, 2006). Despite the negative returns in many scenarios, only Soil Type 1, which has low fertility, is ever retired in the optimal solution. This indicates that production is still covering variable costs on most of the soil types, albeit by a small margin in some cases. Therefore the negative net returns reflect that income from production is not sufficient to cover fixed costs and the farmer's personal expenses. Clearly this would not be sustainable in the long run.

Within a given land use, adaptation through changes in management is important—more so than changes in land use. The optimal size of the sheep flock is reduced substantially—by up to 95% in the most extreme climate scenario (Table 2). This leads to reductions in the amount of extra feeding required to sustain livestock in the period prior to the commencement of the growing season. For cropping land-uses, reduced nitrogen applications are the main management response to climate change, reflecting the reduced yield response to fertiliser under less favourable growing conditions. Although enhanced CO_2 can increase the nitrogen fertiliser requirements of crops (e.g., Howden et al., 2010), in the scenarios where yields are substantially reduced (despite elevated CO_2), the optimal rate of fertiliser instead declines.

Results from a sensitivity analysis on grain and livestock prices (available in the Supplementary Material) show that the general pattern of results is not altered. At higher or lower prices, the most favourable adaptations to climate change are adjustments in livestock numbers and fertiliser rates, rather than changes in land use. Land retirement is more prevalent under low crop/high livestock prices, but under all price scenarios only soils less suited to cropping are retired from production.

3.3.2. Benefits of adaptation

To illustrate how much difference the adaptations described in the previous section make, Table 3 shows the change in annual farm profit (relative to the base-case) under different climate scenarios. The first column shows results when the model is free to adapt in any way that increases returns (the profit change is the same as in Table 2 as 'full adaptation' is the default setting used in our analysis). Moving across the columns from left to right involves progressively greater restrictions on which adaptations are allowed, and economic returns accordingly decrease. Results show that in this case study, land-use change (including land retirement) makes a relatively minor contribution to profit. On the other hand, comparison between the last two columns suggests that adaptations in management (livestock stocking rate and fertiliser rates) are much more beneficial, especially under the most extreme climate scenario. However, even under full adaptation the costs of climate change remain high.

3.4. Maintaining profitability

In the results presented above, it is assumed that current output prices and farming technologies remain unchanged in the future. However, climate change that resulted in changed levels of agricultural production around the world would inevitably lead to altered prices. Also, ongoing agricultural research has the potential to increase production levels under any given climate scenario. Because these potential future changes are highly uncertain, we take a break-even approach, asking the question: what percentage change in either output prices or production levels would be required to return the farm to base-case profitability? For the purpose of this analysis, all output prices or production levels are assumed to change by the same percentage, with the model allowed to select profit-maximising management in response. Table 4 shows that with the exception of the most extreme climate scenario, the price or production increases required to maintain profitability are less than 18%, and of a magnitude which could plausibly occur as a result of market adjustments or successful research.

Table 3
The effect of varying levels of adaptation to climate change.

Selected scenarios CO_2 (ppm)/ Δ rain (%)/Δ temperature (°C)	Change in net return ($'000/year) compared to base-case			
	Full adaptation (changes to both management & land-uses)	Full adaptation minus the ability to retire land	Ability to adapt management but not land-uses	No adaptation (of management nor land-uses)
425/−5/0.50	1	1	1	−1
450/−10/1.25	−91	−95	−95	−107
475/−15/2.00	−165	−169	−169	−195
525/−20/2.50	−200	−203	−204	−252
575/−30/4.00	−327	−331	−344	−503

4. Discussion

Given the high level of uncertainty about the details of future climate change, the plausible range of financial outcomes for farmers in the case-study area is very wide. In both the medium term (2030) and the longer term (2050), financial outcomes from the modelled scenarios range from moderately positive to highly negative. Results suggest that the more extreme climate scenarios would likely see sizeable reductions in the economic activity generated by agriculture in the study area. Though adaptation with existing strategies was beneficial in these scenarios, the impacts of climate change remained substantial.

There are, however, grounds to hope that, at least some of the negative financial outcomes indicated for the more adverse climate scenarios could be offset by conceivable changes in prices or technology. In relation to prices, population growth and increases in wealth are expected, particularly in developing countries, contributing to increased demand for food (e.g., Spence, 2011). On the supply side, depending on the spatial pattern and severity of climate change globally, there may be reductions or increases in supply. Results in Table 4 suggest that a modest rise in agricultural prices resulting from these factors would offset much or all of the impact of climate change (assuming the costs of inputs did not change).

Further, crop producers in the region have a strong record of innovation and adoption of superior technologies as they become available (Asseng and Pannell, 2013). Consequently, since the mid-1980s, average yields have approximately doubled, from around one to two tonnes per hectare (Turner, 2011). Table 4 indicates that much smaller percentage yield increases than that would be sufficient to offset the adverse effects of climate change as modelled here. Also, as superior adaptations become available, we may see more extensive changes in land use than indicated in Table 2, as farmers adapt to take advantage of new opportunities.

Of course, price or productivity increases could also enhance profitability without climate change. Therefore whilst price or productivity increases may offset or counterbalance the effects of climate change, they will only reduce the actual true cost of climate change to the extent that they would not have occurred without climate change (Lobell, 2014).

In this study we defined a range of future climate scenarios to explore the consequences of uncertainty about the extent of change in rainfall and temperature. However, uncertainty about the resulting production levels of crops and pastures is even greater, because of uncertainty about the timing of changes within a year. We assumed that temperatures would increase by the same amount for every day of the year, and we changed all historical rainfall observations by the same percentage across the year. In the study area, crop yields are much more responsive to rainfall in May or August than in June or July (Ludwig et al., 2009; Stephens and Lyons, 1998). Hence the rainfall reductions already experienced in the study region since the 1970s have had negligible impacts on yields because they have been concentrated in June and July (Asseng and Pannell, 2013; Ludwig et al., 2009). Assuming uniform changes across an entire growing season has therefore been criticised as likely to overstate the impacts of climate change (Ludwig et al., 2009). On the other hand, it is possible that future rainfall reductions might occur disproportionately in the most sensitive periods.

The results of this study can be compared to several other modelling studies that have been conducted for this same region. Moderate temperature increases had a more adverse effect in our study than in some previous studies (e.g., Asseng et al., 2004; Ludwig and Asseng, 2006). In Figs. 2 and 3, CO_2 increases only improved farm profitability if changes in temperature (and/or rainfall) were minor. In contrast, Ludwig and Asseng (2006) who, like us, also assumed that any changes in climate would be distributed uniformly across the entire year, found that the positive effect of elevated CO_2 would generally compensate for the negative effects of increased temperatures. Although both studies used APSIM, the versions of the model varied. Specifically, unlike Ludwig and Asseng (2006) we did not represent the possibility of reduced waterlogging following climate change. However, such benefits—which are difficult to predict—are more applicable to areas with higher rainfall than the study area (Stephens and Lyons, 1998).

On the other hand, there are other APSIM-based analyses of the Western Australian Wheatbelt that are more consistent with our results: Farre and Foster (2010) found that increased CO_2 often failed to adequately compensate for reductions in rainfall and increases in temperature, and Crimp et al. (2012) also found negligible benefits from increased temperature. It is worth noting that ambiguity about the response of crops to high temperatures (potentially in interaction with CO_2) is a leading source of uncertainty when modelling climate change impacts (Asseng et al., 2013; Boote et al., 2013; White et al., 2011; Yin, 2013).

Our economic, farming-systems approach could also have contributed to our predictions of potentially more severe impacts than other analyses for several reasons. Firstly, other studies for the study region have tended to consider impacts on single enterprises in isolation, ignoring interactions between enterprises. These interactions can affect the viability of the farm-business too: changes in crop growth will also alter the amount of crop residue available post-harvest for livestock fodder, and reductions in the growth of legume crops and pastures will reduce the amount of nitrogen they provide for subsequent non-legume crops. By using the MIDAS model we captured such farming-system changes. Secondly, wheat production—the sole enterprise that other studies have typically considered—is potentially less sensitive to climate change than other cropping enterprises (Anwar et al., 2015). Lastly,

Table 4
Changes in either output prices or production levels required for the farm to maintain the same annual net return as the base-case.

Selected scenarios CO_2 (ppm)/Δ rain (%)/Δ temperature (°C)	Change required in all output prices or output levels to restore base-case profitability[a]
425/−5/0.50	−0.1%[b]
450/−10/1.25	7.1%
475/−15/2.00	13.9%
525/−20/2.50	17.3%
575/−30/4.00	35.7%

[a] Assuming no changes in input costs.
[b] Negative result because net returns increase in this climate scenario.

previous analyses tend to be biophysical, whereas profit is disproportionately sensitive to yield changes.

There is one comparable economic analysis of climate change for the study region (John et al., 2005). They employed the whole-farm economic optimisation model MUDAS. MUDAS differs from MIDAS primarily in representing a probability distribution of season types, rather than a single weather-year with average conditions. They found that climate change could potentially reduce farm profit by more than 50%. Whilst severe, this reduction is less than we found for many scenarios in Figs. 2 and 3. However, John et al. (2005) used less-sophisticated biophysical models to simulate the effects of climate change on plant growth. Also, the farming-system portrayed in their version of MUDAS is somewhat dated compared to present-day conditions (Kingwell and Payne, 2015). For instance, they did not capture recent advances in cropping agronomy (e.g., the breakcrop canola was omitted from their model) and machinery technology. Likewise, labour cost (and availability) has become an increasingly challenging issue in modern times, particularly for animal production (Doole et al., 2009; Kingwell, 2011).

This study did not concentrate on exhaustively representing all possible adaptation options and further work to parameterise a greater range of adaptation options would lead to improved results. Nonetheless, Table 3 shows that adaptation with existing strategies (relatively simple management and land-use changes) can moderate adverse impacts. These strategies are true 'adaptations' in the strict sense of the term (Lobell, 2014) because, whilst they are impact-reducing, they offer no benefit with a base-case climate. Had we not allowed for these adaptations we would have overstated the impacts of climate change by 15–35%. However, many studies fail to allow for any form of adaptation when projecting climate change impacts (White et al., 2011). In some cases this may be because those studies rely on simulation models, for which each adaptation option must be manually specified and solved. Conveniently, optimisation models such as MIDAS adapt automatically. In reality, farmers may not fully identify the optimal adaptations, or may delay their adaptive responses, in which case the losses due to climate change would be increased relative to an optimal set of adaptations. Further, like any whole-farm model, MIDAS is not a perfect representation of any particular farm, so the results should be treated as indicative rather than precise.

For two reasons, our results suggest that there is not a clear case for strong pre-emptive adaptation. Firstly, there is a wide range of possible outcomes, given the diverse climate scenarios modelled. Secondly, there are relatively small benefits from adaptation when changes in climate are less substantial (i.e., more representative of changes likely in the near term). Therefore, farmers may be wise to wait and see how climate change unfolds before committing to any particular adaptation. In the meantime, research focused on improving the ability of farmers to adapt in the future and on developing resilient adaptation strategies suitable for a wide range of climatic situations may be advisable (Asseng and Pannell, 2013; Hayman et al., 2012; Howden et al., 2007).

Land retirement was included in the model as a simple strategy for loss-minimisation. In reality, more-nuanced responses may occur. For instance, rather than being fully-retired, land could be planted to hardy perennial shrubs and grazed occasionally on a strategic basis (Monjardino et al., 2010). However, given the relatively low levels of land retirement observed in the results, and that whilst generating more returns than land retirement, more-nuanced approaches would also incur more costs, there is little to suggest that these more-nuanced approaches would substantially improve farm returns.

In none of the climate scenarios we examined in detail did the optimal adaptation strategy involve an increase in the area of pastoral enterprises. In many cases, it fell. This is consistent with empirical evidence that a greater dependence on crop production has been a successful strategy adopted by many farms during the number of challenging years experienced across the study region this century (Kingwell et al., 2014; Kingwell and Payne, 2015; Lawes and Kingwell, 2012). Nonetheless, a recent analysis of the most profitable farming systems in the lower rainfall zone directly east of our study area revealed 80% still included a livestock component, even though livestock generated only a small proportion of farm income (Kirk, 2014).

Moore and Ghahramani (2013) attributed large/disproportionate reductions in stocking rates with climate change to the need to guard against soil erosion. In the study region not all of the pasture biomass grown can be grazed; some must remain unconsumed as groundcover, protecting against erosion. Consequently, any reduction in pasture production results in a relatively larger percentage reduction in the amount of grazable biomass, and therefore, a disproportionally large reduction in livestock profitability. As MIDAS contains constraints for minimum levels of soil cover this is probably the explanation for the reduction in pasture area under adverse climate change. On the other hand, our results also showed that if pasture area was not reduced in response to climate change, profit only decreased slightly. Given that some farmers in the region perceive that livestock production is less risky than cropping, they may consider that the trade-off between risk and return favours retaining livestock in the system, although probably at a reduced stocking rate.

This analysis of climate adaptation is unusual in its integration of simulated results for several crops and pastures within an optimisation framework. There were, however, some limitations encountered when doing this. Crop yields are susceptible to the occurrence of relatively short periods of frost during anthesis or to desiccating events during grain-fill (Barlow et al., 2015; Teixeira et al., 2013). Although the frequency of hot days during grain-fill has increased in the study region (Asseng and Pannell, 2013), the ability of many crop models to capture the impacts of temperature extremes (both spring frost and heat shocks) is currently limited (Barlow et al., 2015). Also, APSIM lacked the capacity to represent the impact of elevated CO_2 on canola and lupin yield. Similar problems with crop models not being as developed for intermediate crops compared to principal crops have been encountered by others (e.g., Kollas et al., 2015); our response was to assumed equivalent-percentage responses to wheat for these crops, as outlined in the Methods and Supplementary Information. Furthermore, when simulating pasture growth, the seed dormancy/germination characteristics assumed in GrassGro reflected those typically exhibited by current pasture populations, and were especially sensitive to rainfall reductions. In reality, evolution (and/or breeding) may result in pasture systems with germination characteristics more suited to future conditions. Rather than relying solely on GrassGro and APSIM, a superior approach would be to utilise the combined predictions of an ensemble of biophysical simulation models (e.g., Asseng et al., 2015). However, the limited range of models—locally-calibrated and capable of simulating the more intermediary crops and annual, self-regenerating pastures—precluded this.

5. Conclusions

Our estimation of climate-change impacts at the system/whole-farm level is unlike most analyses that instead focus on a single crop or enterprise, and thereby ignore the interactions between the various enterprises that can have a large impact on the performance and make-up of a farming system. Unlike some studies, we also allowed for adaptation with existing management strategies when projecting climate impacts, showing that failing to allow for this adaptation would exaggerate estimates of the financial cost of climate change by 15–35%. Of the existing adaptation strategies we represented in our analysis, changes in cropping inputs and livestock stocking rate were predominate, with land-use change playing a more minor role.

Across the climate change scenarios considered for the study region, the uncertainty about profit impacts is high, ranging from moderately positive to highly negative. However, the potential for loss appears much greater than the potential for gain. Although increasing atmospheric CO_2 concentration has a positive impact, under most scenarios it is not nearly enough to offset rainfall and/or temperature changes.

Further, an increase in temperature or a decrease in rainfall by itself can still have severe adverse impacts without the other.

Small changes in production caused much larger changes in profitability. Amongst other things, this means that in all but the most extremely adverse climate scenarios, plausible increases in productivity or prices would be sufficient to restore profitability to pre-climate-change levels. However, if these price and/or productivity increases would have occurred in the absence of climate change then, compared to what otherwise would have happened, the cost of climate change may still be high.

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The views Donkor Addai expresses in this article do not necessarily reflect those of his employer, the Australian Bureau of Agricultural and Resource Economics and Sciences.

Appendix A. Supplementary Material

Supplementary material for this article can be found online at http://dx.doi.org/10.1016/j.agsy.2016.10.013.

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