A real options analysis of Australian wheat production under climate change

Todd Sanderson[1], Greg Hertzler[2,3], Tim Capon[4,5] and Peter Hayman[6]

[1] School of Economics at the University of Sydney, Sydney, New South Wales, Australia

[2] University of Pretoria, Pretoria, South Africa

[3] Research Affiliate with the Faculty of Agriculture and, Environment at the University of Sydney, Australia

[4] Commonwealth Scientific and Industrial Research Organisation (CSIRO), Black Mountain, Australian Captial Terrotory, Australia

[5] Research Affiliate with the School of Economics at the, University of Sydney, Adelaide, South Australia, Australia

[6] South Australian Research and Development Institute (SARDI), Waite Research Precinct, Adelaide, South Australia, Australia

Email: Todd Sanderson (todd.sanderson@sydney.edu.au)

[†] We would like to gratefully acknowledge the National Climate Change Adaptation Research Facility in supporting the research leading to this paper and the contribution of two anonymous journal referees.

A significant portion of the world's agricultural systems currently operate at the extreme end of the climate conditions that are considered to be suitable for crop and livestock production. Under these conditions, even moderate climate changes are anticipated to drive substantial transformational changes to agricultural systems. Transformations require new investments and infrastructure and can leave some assets stranded. These transformations can be partially or wholly irreversible and hysteresis effects can make switching difficult and mistakes costly to reverse. This paper demonstrates how a real options decision framework, “Real Options for Adaptive Decisions” (ROADs), can be used to investigate how uncertainties about the climate affect the adaptation and transformation of agricultural systems. By building upon recent developments in the mathematics of stochastic optimization, we extend traditional economic analyses of agricultural investment decisions based on net present values to better represent

incomplete knowledge and uncertainty. We report results from a case study in South Australia that describes the transition pathways farmers might follow as their industries are transformed in response to climate change.

Key words: real options, climate change, adaptation, wheat production

1. Introduction

Agricultural systems are adaptations to the prevailing climate (Gornall *et al.* 2010). Over time, producers have improved their understanding of the specific characteristics of the climate that affect agricultural production and they have responded accordingly, by making decisions informed by historical experience. Climate change presents a challenge to decision-makers because decision-making in agricultural systems is calibrated to the parameters of the current climate. For example, Australian agricultural systems, such as broad-acre wheat production, have evolved to suit a highly variable climate but there is an expectation that this variability is bounded. Future decisions to switch between broad-acre cropping and alternative agricultural systems will be governed by interactions between changing levels of climate variability and other agro-ecological and economic factors.

The location of the thresholds where farmers decide to switch between cropping and grazing has changed with technology and commodity values, but is sensitive to climatic factors (Ryan *et al.* 2009; Nidumolu *et al.* 2012). The impacts of climate change will be most acute at the margin of the Australian wheat belt, where cropping already gives way to extensive grazing. Moving away from high rainfall cropping systems near the coast, there is a transition as average rainfall steadily decreases until the margin between wheat-dominant cropping and extensive grazing systems is reached further inland. The effect of climate uncertainty and variability on the decision thresholds at this margin thereby provides useful case studies of the adaptation of agricultural systems to climate change.

The decisions made by farmers in response to climate change are the central determinants of its impact on agricultural productivity. Although the majority of previous research has focused on the biological and agricultural science dimensions of climate change, understanding the consequences of uncertainty for decisions about agricultural production is vital for understanding the resilience of Australia’s agricultural systems to climate change and to assess the options available for climate adaptation. Past research has provided some understanding of the range of possible climate scenarios, but without linking this research to an analysis of farmers’ adaptation decisions we cannot understand the potential transformation of wheat-dominated agricultural production with climate change.

The adaptation actions of farmers and rural communities can take various forms, such as (1) adjusting practices and technologies, (2) changing production systems, and (3) re-locating production (Howden *et al.* 2010; Rickards and Howden 2012). The second and third actions represent choices between alternative production regimes in the agricultural systems that will be affected by climate change. A switch from one regime to another can be irreversible or only partially reversible. Switching production regimes may require investments into production techniques (i.e. equipment or knowledge), as well as processing and infrastructure. Old technology may have a salvage value or problems with stranded assets. These complications throw up barriers to adaptation, with broader implications for rural communities and regional economies. In this study, we model barriers to adaptation using real options.

This article proceeds as follows. Section 2 outlines our approach to the real options analysis of agro-economic systems. We describe recent developments in stochastic optimization that help bridge the gap between understanding the biophysical impacts of climate change and understanding how these impacts might translate into decisions about agricultural production.

We further develop the real options framework presented by Hertzler (2007) that we call Real Options for Adaptive Decisions (ROADs). Section 3 applies this methodology as an illustration to a case study region in South Australia, using a spatial-temporal approach (Ford *et al*. 2010; Hayman *et al.* 2010; Nidumolu *et al.* 2012) to model transitions in farming regimes driven by climate changes. Section 4 presents the results, Section 5 discusses these results and the use of the method in application to agricultural climate change adaptation, and Section 6 concludes the article.

2. A practical approach to real options analysis

Real Options is the name given to the modern analytical method for modelling the value of flexibility and the timing of action in decision-making under uncertainty (Dixit and Pindyck 1994; Copeland and Antikarov 2001). Simulation and scenarios testing approaches generally seek to understand the effects of risk whereas the real options approach seeks to explicitly show how decision-makers can manage risk. It does this by examining the trade-offs between acting sooner versus retaining the option to act later, by taking into account the value of flexibility and the value of new information that can help to resolve uncertainty. This approach extends traditional economic analyses of agricultural investment decisions based on simple cost-benefit analysis and net present values (NPV) to better represent incomplete knowledge and uncertainty. Taking option values into account is especially important for climate adaptation because many adaptation decisions have consequences that are costly to reverse, or even irreversible.

The ROADs approach to real options analysis allows us to understand the timing of adaptation decisions, modelled as changes from one production regime to another. For example, Figure 1 represents a farmer currently in an agricultural production regime which is primarily concerned with wheat cropping.

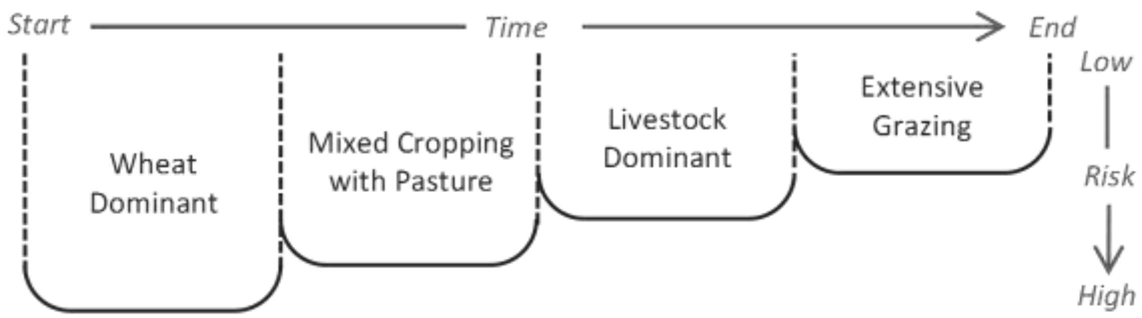


Figure 1: One of many possible sequences of regime transition with climate change

As the climate changes, wheat production may decline and the farmer could switch to a regime with wheat grown in some years and pasture in others. With more adverse climate changes, this farmer might even switch to a regime of extensive grazing. Within each of these broader regimes there is the possibility to adapt by making smaller changes to farming practices, such as adopting improved techniques or adopting new crop varieties. Adaptations at any scale, however, can be both costly and risky, and farmers may be hesitant to adapt immediately especially when there are costs associated with switching to a new regime, or reversing a previous switch.

The timing of switches depends on the risks and uncertainties associated with the alternative regimes. A producer might choose to switch immediately, or never, depending on how the climate is expected to change and the variability associated with that change. The ROADs framework allows us to model the timing of decisions by calculating the values associated with various aspects of climate adaptation decision problems. These include option values, the costs of switching back after a mistaken decision to switch, and the time remaining before growers can be expected to switch from one regime to another. Examining these costs and benefits provides one approach to understanding the resilience of alternative agricultural production regimes to climate changes.

2.1 Implementing a real options analysis for adaptation to climate change

The first step in understanding the implications of climate change for a given system is to understand that system. In this paper we are interested in understanding the implications of climate change on wheat dominant agricultural systems and the thresholds for transformations to other agricultural systems. This means that we need to be able to characterize both the wheat dominant agricultural system and alternative agricultural systems. For each alternative, a time series of seasonal profits or gross margins is used to estimate stochastic differential equations. In their most basic form, differential equations relate the variations in the state variable *dx* against the current position of the state variable *x*. An important characteristic of any system is the extent to which *x* can change year to year and whether or not there exists a tendency for *dx* to tend towards a value of zero, that is, for the system to approach some kind of equilibrium.

There are two common stochastic differential equations for which transition probabilities are known, these being Geometric Brownian Motion and the Ornstein-Uhlenbeck process. In real options analyses, Geometric Brownian Motion is frequently employed due to the existence of the well-known Black-Scholes analytical solution for the option prices. Even though an equivalent analytical solution is not available for the Ornstein-Uhlenbeck process it is possible to calculate solutions using finite-difference algorithms (Miranda and Fackler 2002). The two stochastic processes, however, have very different properties and their application to a particular context needs to be carefully considered. If we defined an Ornstein-Uhlenbeck process over some variable of interest, say gross margins x_t, the corresponding stochastic differential equation would be

(1) $$dx_t = b\{\mu - x_t\}dt + \sigma dz_t$$

The presence of the known transition probability makes it possible to estimate this process from time series data using Maximum Likelihood Estimation (Tang and Chen 2009) for the unknown parameters b, μ and σ, where b is the rate of reversion to the long-term mean μ, and σ is the variability. The Ornstein-Uhlenbeck process displays the important property of linear reversion (Doob 1942). Geometric Brownian Motion, unlike an Ornstein-Uhlenbeck process, has no tendency to revert to a mean and is undefined for negative values of *x*. Most agronomic systems may be approximately described by an Ornstein-Uhlenbeck process as those systems tend towards some mean over a sufficiently long period of time.

After estimating the parameters which characterise the dynamics of the alternative systems, the option values, location of regime thresholds and the expected times of transition between regimes may be calculated. These are estimated using standard option pricing equations (Hertzler 1991; Dixit and Pindyck 1994):

$$(2) \qquad \frac{\partial w}{\partial t} - rw + \frac{\partial w}{\partial x} b\{\mu - x\} + \frac{1}{2}\frac{\partial^2 w}{\partial x^2}\sigma^2 = 0$$

$$(3) \qquad w\big(T, x(T)\big) = V\big(x(T)\big)$$

In equation (2), *w* is the option price, *x* is the gross margin, *r* is the interest rate and parameters *b*, σ and μ are from the Ornstein-Uhlenbeck process in equation (1). The first term in equation (2) is the shadow price of time. The second term is the opportunity cost of retaining the option instead of selling it and putting the money in the bank. The third term is the value of an expected change in the gross margin. In this term, a shadow price multiplies the expected change to give a negative cost or a positive benefit. The fourth term is the risk premium. In this term, a shadow price for risk multiplies the variance. Together, the last two terms are the risk-adjusted capital gains from retaining the option. If the capital gains exceed the opportunity cost, the option price will increase. Otherwise it will decrease.

In equation (3), *V* is the payoff function. Unlike financial options, the options to exit and enter are perpetual options and can be held indefinitely or exercised at any time. The exercise time chosen by the farmer is *T*. If the option price exceeds the payoff function, the farmer will retain the option. If the payoff function exceeds the option price, the farmer should have already exercised the option. The optimal exercise time is when the option price falls to just equal the payoff function. The payoff function is highly nonlinear with a kink. It is specified as

$$(4) \qquad V = \begin{cases} \chi[x(T) - k]; & \chi[x(T) - k] > 0 \\ 0 & \chi[x(T) - k] \leq 0 \end{cases}$$

In equation (4), χ is equal to +1 for the option to enter and -1 for the option to exit. The parameter k is either the annual cost of plant and equipment or the annual salvage value per hectare.

Of course, the entry and exit decisions are even more complicated than this. When our representative farmer enters a regime, the option to enter is destroyed but a new option is created—the option to exit. The farmer anticipates this will happen before deciding to enter. In other words, the payoff function for the option to enter also includes the value of the option to exit. To go further, upon exiting, the option to exit is destroyed and the option to enter another regime is created. The option value of the next regime must be included in the option value to exit from this regime, and so on in a sequence of regimes.

To solve all this, we have to assume there is a last regime and a complete exit from farming with the money put in the bank. We solve for the exit from this last regime using the payoff function in equation (4). For the entry into earlier regimes, we use a different payoff function:

$$(5) \qquad V = w_f\left(x_f(T_f)\right) + \begin{cases} \chi[x(T) - k]; & \chi[x(T) - k] > 0 \\ 0 & \chi[x(T) - k] \leq 0 \end{cases}$$

In equation (5), w_f is used to denote the value of future options, which is added to the terminal value for the current regime. In this way, a sequence of regimes is modelled.

The farmer may switch between regimes at any time T. In other words, we must find the optimal stopping time. Unfortunately, the option prices are poorly behaved. The discount rate fights to reduce the option prices. Uncertainty and the nonlinear payoffs fight to increase the option prices. At the optimal time, the fight is most intense, creating waves in the option prices. There are many local maximums and minimums and the usual method of differentiating with respect to T will not work. Instead, finding the optimal stopping time requires a global search algorithm. There are no analytical solutions for the sequence of entry and exit options as farmers switch from one regime to another. Instead, the search algorithm employed in ROADs (Hertzler 2012a) has four steps:

> *Step 1*: For each decision problem (e.g. decision to enter wheat), create a table with one dimension for all the possible gross margins (e.g. -$1000 to $2000/ha) and the other dimension for all the possible times (0 to 50 years). Then, solve the option pricing equation (2) for all possible times and gross margins, in other words, for all cells in the table. This creates a table of option values for each gross margin at each time.
>
> *Step 2:* For a particular gross margin, search the table in the time direction for the largest option value. Record this option value and the corresponding time, which is the expected time until the regime transition.
>
> *Step 3:* Repeat Step 2 for all possible gross margins and create a table with three columns: one for gross margins, one for the largest option values and one for expected times.
>
> *Step 4:* Plot the largest option values (y-axis) against the range of gross margins (x-axis) and compare with the associated terminal values from equation (4) or (5). Identify the gross margin where the largest option price is equal to the terminal value. At this gross margin, the decision-maker will choose to exit the current regime and enter another.

2.2 Estimating probabilities of regime change

The use of an Ornstein-Uhlenbeck or Geometric Brown Motion process also allows for direct estimation of the probabilities of crossing regime thresholds. In this case, the Ornstein-Uhlenbeck process in equation (1) has the transition density function

$$(6) \qquad f(s,x,t,y) = \left\{\frac{b^{0.5}}{\pi^{0.5}\sigma\left(1-e^{-2b(t-s)}\right)^{0.5}}\right\} e^{-b\left\{\frac{\left[(y-\mu)-(x-\mu)e^{-b(t-s)}\right]^2}{\sigma^2\left(1-e^{-2b(t-s)}\right)}\right\}}$$

In this equation, *f* is the probability density function, *s* is the present time, *x* is the present gross margin, *t* is some time in the future, and *y* is a random gross margin which can occur at time *t*.

As time *t* gets large, the transition density converges to the invariant density

$$(7) \qquad f(y) = \left\{\frac{b^{0.5}}{\pi^{0.5}\sigma}\right\} e^{-b\left\{\frac{(y-\mu)^2}{\sigma^2}\right\}}$$

If parameter *b* was set to 0.5, this would be the more familiar normal density. The transition probability distribution is the integral of the density,

$$(8) \qquad F(s,x,t,y) = \int_{-\infty}^{y} f(s,x,t,v)dv$$

If *y* in equation (8) is set equal to the threshold for switching, then *F* is the probability of being below the threshold and 1-*F* is the probability of being above the threshold. As time *t* gets large, the transition probability distribution also converges to an invariant probability distribution,

$$(9) \qquad F(y) = \int_{-\infty}^{y} f(v)dv$$

Similarly, as time *t* gets large, *F* is the equilibrium probability of being below the threshold and 1-*F* is the equilibrium probability of being above the threshold. A companion package for ROADs called TRIPs (Hertzler 2012b) has been developed to manage the calculation of these transition probabilities. The following section illustrates an application to model the implications of climate change in the Australian wheat belt.

3. An application to climate adaptation in the Australian wheat belt

To demonstrate the application of this real options method, a spatial transect was used as an analogue for possible temporal changes (Ford *et al.* 2010; Hayman *et al.* 2010; Nidumolu *et al.* 2012; Ramírez-Villegas *et al.* 2011). This allows us to model the adaptation and transformational processes that might occur in the future at one site by examining the nature of optimal decisions at another site where possible future conditions are currently observed. It is important to note that although spatial transects can be used to represent possible future conditions, one site will never become exactly the same as another site. In particular, there are temporal changes associated with climate change that are not captured by spatial transects, including higher CO_2 concentrations and their interaction with higher temperatures. Even so, the spatial-temporal analogues approach reflects the fact that the location of a farm can be a good predictor of the prevailing farming activity. Figure 2 maps the selected transect across the South Australian wheat belt.

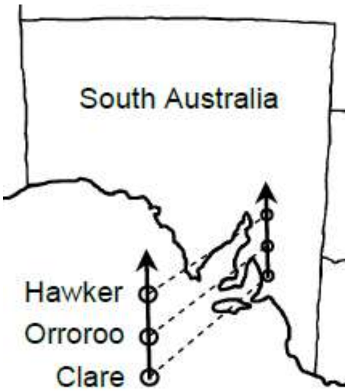


Figure 2: Case study transect

This transect has been deliberately selected to straddle Goyder's line, a line drawn through south-eastern South Australia in the 1860s by George Goyder, the Surveyor-General of South Australia, which demarcates the land suitable for extensive grazing to the north from the land suitable for cropping in the south. This transect ranges from intensive cropping with a high proportion of relatively high risk and high return crops at Clare, through to an increasing proportion of cereals with lower inputs around Orroroo, and then finally to grazing enterprises with opportunistic cropping around Hawker (Hayman *et al.* 2010). Moving from Clare towards Hawker, production conditions become hotter and drier, which reflects the general pattern of climate changes anticipated for the region (CSIRO and BoM 2007). Through the time period for which simulation data were available, 1900-2007, the annual average rainfall at Clare, Orroroo and Hawker was 623, 338 and 310mm, respectively. Average growing season rainfall for Clare, Orroroo and Hawker was 486, 225 and 201mm, respectively.

Since we are interested in the thresholds for transformations to other agricultural regimes, we must seek to understand both the wheat-dominant agricultural system and alternative systems such as extensive grazing. Reducing this illustration to two regimes is not unreasonable given that mixed crop-livestock farming systems have been a major and long standing feature of agricultural land use in Australia (Bell and Moore 2012). For our purposes we can think of wheat-cropping and livestock-grazing, in this case sheep (merino) production, as two alternative production regimes available to a farmer. Accordingly, the decision problems modelled for South Australia consist of switching into and out of wheat cropping and sheep grazing.

Accessing appropriate data is always a challenge, but for present purposes a combination of climate data, farm-level data, and simulation results from APSIM (McCown *et al*. 1996) was used to model the production regimes. Table 1 provides an overview of the data sources and simulations used for each location. APSIM simulations were used to translate historical weather observations into time series of wheat yields and sheep stocking rates. In these simulations, variability in production is driven exclusively by the timing and magnitude of weather events, primarily rainfall, since all other inputs and technologies were held constant by APSIM. Sheep stocking rates were estimated based on the relationship between annual rainfall and biomass growth (Assang *et al.* 2012). These time series of yields and stocking rates were converted into time series of gross margins using data on representative costs and returns from wheat and sheep production (Rural Solutions South Australia 2012).

Table 1: Data overview

Regime	Data Type	Period	Regime Costs		Transition Costs
Wheat cropping	APSIM simulation	1900-2007	Revenue	Wheat $300/t	Entry Cost $309/ha
			Variable Costs	Clare ($/ha): $417 Orroroo, Hawker ($/ha): $85.14 (0-0.2t/ha), 87.42 (0.2-0.6t/ha), $91.84 (0.6-1.2t/ha), $105.26 (1.2-1.8t/ha), $112.75 (>1.8 t/ha)	Exit Salvage $278/ha
Sheep grazing	GSR-Stocking rate calculation	1900-2007	Revenue	Wool 840c/kg, Wethers $95/head	Entry Cost $32/ha
			Variable Costs	SA Farm Gross Margin Guide 2012	Exit Salvage $29/ha

4. Results

The time series of gross margins at each location was modelled using Ornstein-Uhlenbeck stochastic differential equations with the parameters estimated using Maximum Likelihood Estimation based on equation (6). Although, ordinary least-squares could also be used as the errors are not heteroskedastic. Table 2 presents the parameter estimates for each location.

These parameter estimates are used to describe the stochastic production regimes along each transect. In particular, the parameter μ of an Ornstein-Uhlenbeck process, the average state attractor, represents the average gross margin at each location in our models. Moving along this transect, μ is 649.8 at Clare, translating to an average gross margin of $649.8/ha. Notably,

Table 2: Estimated Ornstein-Uhlenbeck SDE parameters for regime gross margins ($/ha)

Location	**Regime**	b	μ	σ	CV
Clare	Wheat	0.916	649.8	203.7	0.232
	Sheep	0.887	471.6	147.9	0.235
Orroroo	Wheat	1.038	481.3	353.9	0.510
	Sheep	0.923	186.6	93.5	0.369
Hawker	Wheat	0.940	328.7	314.7	0.698
	Sheep	0.891	157.6	111.9	0.532

average gross margins decrease to $481.3/ha at Orroroo and $328.7/ha at Hawker as we move along this transect.

If the rate of reversion, b, was 0.5, the Ornstein-Uhlenbeck process would become a normally distributed process and the coefficient of variation could be calculated in the usual way as $CV = \sigma/\mu$. In Table 2, the rate of reversion is much larger and the variance has been scaled, $\upsilon = \sigma^2/2b$, so that the coefficient of variation as a measure of relative riskiness of production can be calculated as $CV = \sqrt{\upsilon}/\mu$. The value of CV is estimated for wheat production as 0.232 for Clare, 0.510 for Orroroo, and 0.698 for Hawker. This indicates that wheat production at Clare is the least risky when compared with Orroroo or Hawker, given that larger values of CV imply greater production risk. In contrast, at Orroroo and Hawker, sheep grazing is less profitable than wheat but is also less risky, whereas at Clare, sheep grazing is less profitable than wheat but about as risky.

The real options analysis conducted using the ROADs and TRIPs modules uses the parameters estimated for the Ornstein-Uhlenbeck processes at each location to examine three decision problems, (1) ‘Enter wheat’ with the possibility to exit farming, (2) ‘Exit wheat to enter sheep’, and (3) ‘Exit sheep’. The costs of transition k appearing in equations (4) and (5) are reported in Table 1, for both entry and exit from a particular regime. Table 3 presents the resulting estimates from ROADs of the option value (w), regime threshold (x), expected waiting time at the threshold (T-t), and the estimates from TRIPs of the probability of transition from one regime to another (F).

Table 3: Estimated option values w ($/ha), threshold values x ($/ha), expected waiting times at the threshold T-t (years) and transition probabilities F (%)

Location	**Decision**	w	x	T-t	F
Clare	Enter wheat	320.3	629	0.18	55.50
	Exit wheat to enter sheep	369.0	268	2.19	0.56
	Exit sheep	5.3	29	0.05	0.00
Orroroo	Enter wheat	201.7	509	0.61	40.72
	Exit wheat to enter sheep	253.0	148	2.21	8.73
	Exit sheep	5.5	29	0.14	1.17
Hawker	Enter wheat	113.0	419	0.47	34.71
	Exit wheat to enter sheep	220.6	158	1.01	22.85
	Exit sheep	12.5	19	0.15	5.07

We use the case study to explain how these estimates can be interpreted. At Clare for the first decision 'Enter wheat' we are examining the conditions under which a farmer would exit the current regime, which in this case is akin to money sitting in the bank earning interest, to enter a regime of wheat growing. Each of these regimes has different risks, and the switch will not happen immediately. The results in Table 3 indicate that a farmer will wait until a threshold gross margin (x) of $629/ha is observed before entering wheat production, and is willing to pay an option value (w) in foregone potential earnings of $320.3/ha while they wait. The expected waiting time at the threshold (T-t) of 0.18 years indicates that once a gross margin of $629/ha is observed, a farmer will start wheat cropping within a year. A graphical illustration of this situation is captured in Figure 3, which identifies the threshold gross margin on the x-axis ($629/ha) and the option value on the y-axis ($320.3/ha).

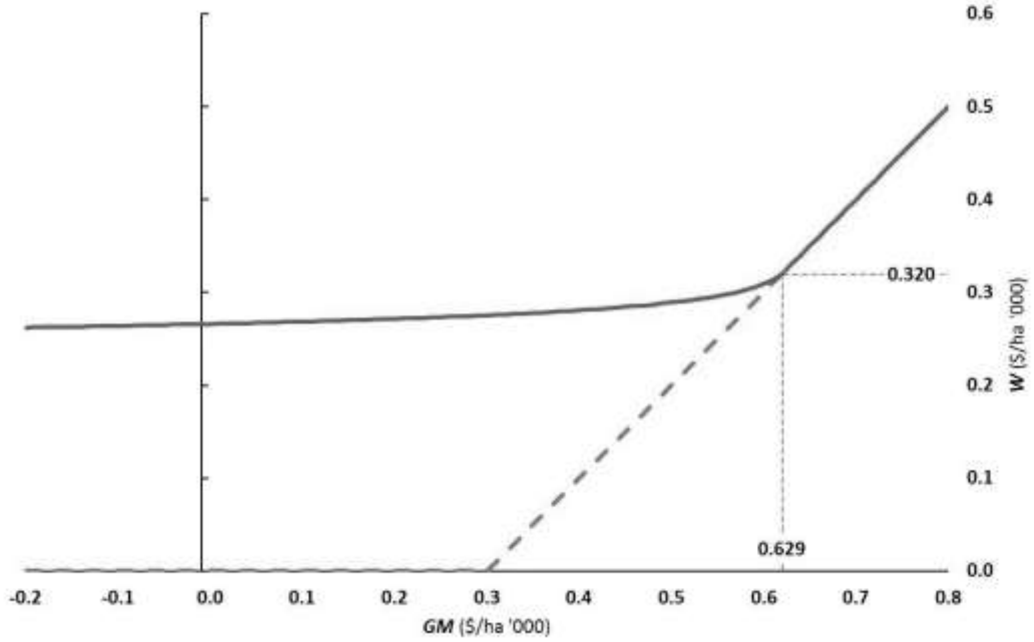


Figure 3: Option value at state threshold – entry into wheat cropping at Clare

With the rapid rates of reversion estimated in Table 1, the transition probability in equation (8) converges to the invariant probability in equation (9) in about 5 years. Figure 4 allows us to estimate the probability of entering wheat cropping within a 5 year period for a given threshold gross margin.

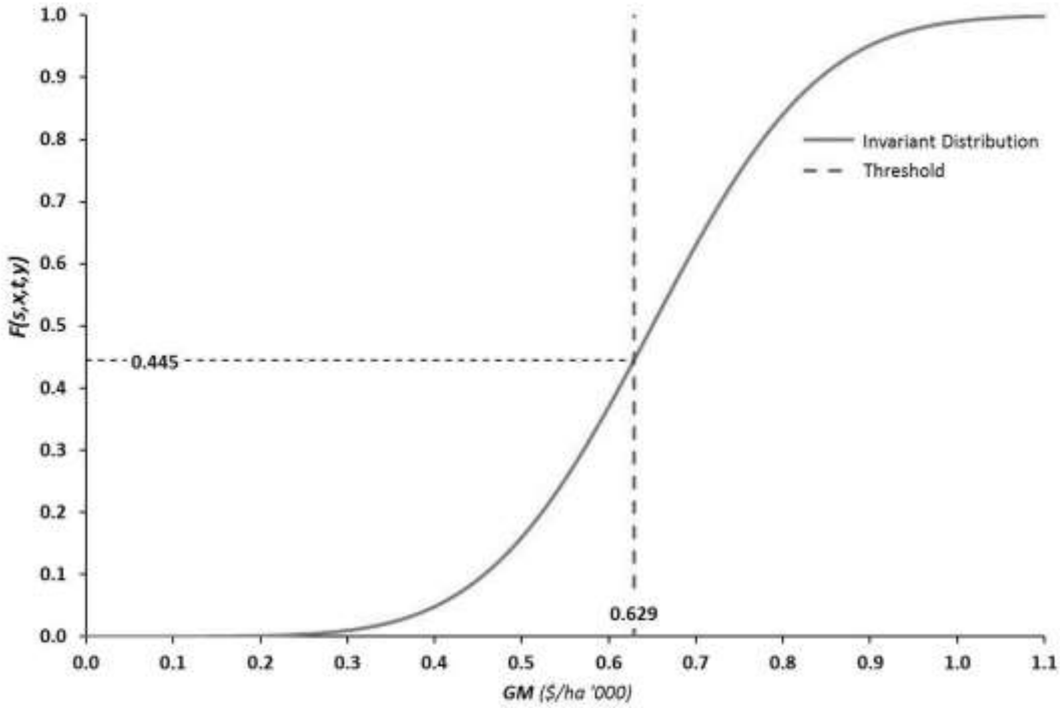


Figure 4: Transition probability – entry into wheat cropping at Clare

The estimated value for the probability of transition (*F*) is 55.5 per cent. This value can be identified in Figure 4 as one minus the probability (44.5%) along the y-axis that corresponds to the threshold gross margin ($629/ha) along the x-axis. That is, the probability of being above a gross margin of $629/ha is 55.5 per cent. This probability indicates the likelihood of entering the wheat production regime sometime in the next 5 years, regardless of the current gross margin.

An examination of the results for the decision to enter wheat production for the two other locations on our spatial transect, Orroroo and Hawker, indicate estimated transition probabilities are 40.72 and 34.71 per cent, respectively (Table 3). Compared to the estimated probability at Clare (55.5%) there is a steady decline in the probability of a farmer entering wheat production. This is consistent with the steady decline in the favourable conditions for wheat production as we move along the transect (Table 2).

Similar patterns emerge for other regime transitions, such as the transition from wheat to sheep production. At Clare, Orroroo and Hawker these transition probabilities are 0.56, 8.73 and 22.85 per cent, respectively (Table 3). Wheat is a profitable albeit relatively risky regime when compared to sheep production. Under these circumstances the probability of a transition from wheat to sheep is consistent with an overall decline is the profitability of the farm. The likelihood of crossing this threshold increases along the transect towards less favourable wheat production locations.

Using this approach to real options analysis in conjunction with a spatial-temporal analogues approach allows us to consider the implications of adverse climate change without relying on particular climate projections. Climatic conditions at Clare may approach conditions at Orroroo or Hawker because there are reasons to anticipate a pattern of warming and drying. For instance, Suppiah *et al*. (2006) report worst case projections of rainfall change based on scenarios in the region of the study transect. Projected change by 2030 in rainfall falls within ranges of autumn -6 to +2 per cent, winter -11 to -1 and spring -20 to -1 per cent. Projected change by 2070 in autumn is -19 to +7, winter is -35 to -3 and spring is -60 to -3 per cent. Given the relatively greater importance that spring growing season rainfall has for crop development, these worst case scenarios look rather dire. The growing season rainfall in Clare is approximately 50 per cent greater than that in Orroroo, and 60 per cent greater than that in Hawker. In the worst case, Clare would experience conditions somewhere between its current conditions and those at Orroroo by 2030, and approximately the current conditions experienced at Hawker by 2070. The implication being that as conditions at Clare became more like current conditions at Orroroo or Hawker, then the likelihood of a transition from a wheat production to a sheep production regime is increased. Of course, these results are not forecasts. They are predicated on the assumption that space is a good analogue for climate change and that climate will change significantly. One region may come to resemble another region but will never become exactly like an analogue along a spatial transect.

Beyond the direct biophysical implications of climate change for farmers there are also important implications for market prices. For instance, commodity prices could also be characterised by a stochastic process. Because our analysis depends upon APSIM results, stochastic prices were not included. We can, however, illustrate possible implications by examining the sensitivity of transition probabilities to changes in the relative prices of outputs. For instance, Table 4 presents estimated transition probabilities from wheat to sheep under conditions of a wheat price $\pm$\$100/T from the \$300/T assumed above, with the price of sheep held constant.

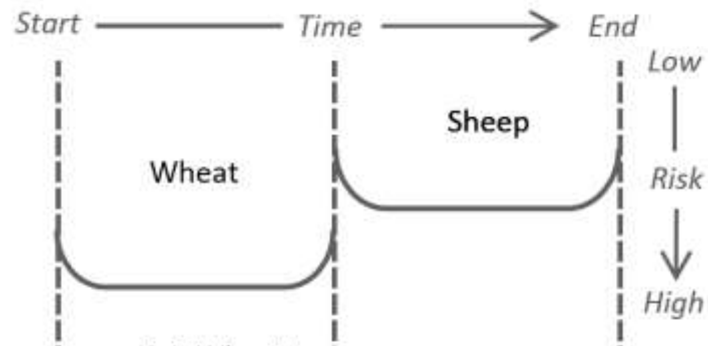
Table 4: Probabilities for transition between wheat and sheep production regimes based on alternative wheat pricing assumptions with sheep prices held constant.

Wheat Price ($/T)	Clare (*F*)	Orroroo (*F*)	Hawker (*F*)
200	32.26%	31.38%	45.27%
300	0.56%	8.73%	22.85%
400	0.00%	2.13%	11.29%

Probabilities indicate that transition out of wheat into the alternative sheep-based production regime is strongly contingent on the price of wheat relative to sheep. For instance, if we take a starting point at Clare with a price of wheat at $200/T, then a change in the climate that approximates current conditions at Orroroo would be more than offset by a $100/T increase in the price of wheat, since this would see a decline in the probability of transition out of wheat from 32.26 to 8.73 per cent. Indeed the same is true for Clare approaching a Hawker-like climate, since an increase in the price of wheat would outweigh the negative consequences of less favourable growing conditions. This demonstrates that a sufficient change to relative prices would mean that wheat production could persist despite adverse climate changes. Farmers will need to adapt to changing biophysical conditions but they will also take changes in the relative prices of commodities into account.

5. Discussion

The impacts of climate change on Australian agriculture will ultimately be determined by the decisions made by farmers. This paper demonstrates how methods for the real options analysis of agricultural production can be extended to account for the value of flexibility in decision-making as agricultural systems transition through alternative production regimes. Option values capture the benefits of retaining flexibility and are estimated in contrast with a counter-factual where there is no flexibility and the decision-maker instead has an obligation to continue in their current production regime. We model stochastic returns by fitting appropriate stochastic processes to gross margins in order to estimate option values, threshold values, and expected waiting times at thresholds. In addition, we use the Ornstein-Uhlenbeck process to estimate the probabilities of regime transitions. We demonstrate this approach by examining possible sequences of transition for Australian wheat production under climate change, for example, as shown in Figure 5 for Clare.



Parameter	Enter Wheat	Exit Wheat to Enter Sheep	Exit Sheep
Option value *w* ($/ha)	320.6	369	5.3
Threshold value *x* ($/ha)	629	268	29
Expected time *T-t* (years)	0.18	2.19	0.05
Transition probability *F* (%)	55.50	0.56	0.00

Figure 5: The sequence of regime transitions at Clare showing the option values, threshold values, expected times, and transition probabilities for each decision threshold.

Option values reflect the nature of risk and returns. For instance, increasing σ in Equation 1 for the decision to ‘Enter wheat’ at Clare but leaving all other parameters the same increases the risk of returns from wheat, thereby increasing the option value and the threshold value for this decision. Likewise, option values increase with the expected value of returns in the prospective regime relative to the current regime. For instance, even though at Clare returns from wheat are not particularly variable (Table 2), the option value to enter wheat is relatively high compared to Orroroo and Hawker (Table 3) because returns from wheat are higher at Clare. Consequently, the transition probability to enter wheat at Clare is quite high (55.5%). In contrast, the high option value for ‘Exiting wheat to enter sheep’ ($369/ha) at Clare reflects the value of delaying entry into the lower returning sheep production regime. The low transition probability (0.56%) reinforces the observation that the high option value reflects the high returns from wheat relative to sheep.

Whilst this paper demonstrates the application of real options analysis to analyse particular sequences of regime transitions, future applications could use similar approaches to help identify optimal adaptation pathways. In theory, the total value of a firm or a farm's assets is comprised of the present value of expected future returns plus the option value of future regimes (Dixit and Pindyck, 1994). In other words, a farm with the flexibility to switch production regimes has a higher value than an identical farm without that flexibility. This implies that a sequence of regime transitions organised from highest total value to lowest total value is an optimal adaptation pathway. For instance, the sequence from Wheat to Sheep at Clare (Figure 5) could be interpreted as an optimal pathway, given that Wheat has higher expected future returns and a higher option value than Sheep (Table 2). However, this assessment of asset value assumes that it is possible to account for all the sources and factors that affect the option value of the firm. In practice, adaptation pathways can be complex (e.g. Wise *et al*., 2014) and further advances in the methodology of real options analysis will be needed to analyse the relative costs and benefits of managing risks and returns given multiple sources of uncertainty and irreversibility (e.g. Mezey and Conrad, 2010).

Real options analysis can provide additional insights for policy makers and private enterprise. It demonstrates that rational decision-makers will tend to delay switching to alternative production systems under uncertainty. It is important for policy-makers to understand that rather than unnecessary delay, a farmer's hesitation to adopt new practices can reflect the value of retaining flexibility. Real options methods can help policy analysts better understand how farmers might adjust their practices to adapt to changing conditions, and future research could extend this analysis to examine how alternative policies might influence the transitions of agricultural systems. For instance, expensive bulk grain-handling infrastructure, such as silos and rail lines, are at risk of becoming stranded assets in regions with a general transition away from wheat cropping. Future applications of real options analysis to adaptation pathways have the potential to help policy makers better understand industry level change by quantifying option values, key thresholds and the associated probabilities of transition among alternative production regimes.

A particular challenge is to move the analysis beyond the direct biophysical implications of climate change for farmers to the implications of climate change for market prices. Farmers adjust their mix of inputs depending on the relative prices of inputs and outputs and their expectations about the growing season. The corollary is that the transformation of Australian agriculture depends upon international prices, which in turn depend upon the transformations of agriculture globally in response to climate change. If global wheat yields decline with adverse climate change wheat prices may rise over time. An increased price for wheat relative to other commodities (wool or sheep meat) may partially, completely or overly compensate for declining yields. We may see farmers enter wheat production as the climate becomes hotter and drier if rising wheat prices more than compensate for the decreased yields and increased risks.

Future research should extend the analysis presented here to examine the simultaneous effects of global climate change on biophysical conditions and market prices. Formal modelling will require extending the ROADs framework to specify yields and prices as separate stochastic processes in the optimization problem. This is not straightforward and would require the development of real options models that can handle multiple stochastic processes. If such technical challenges can be overcome, then this research can be extended to examine broader patterns of industry transition, since alternative production regimes are all dependent on prices in markets for labour, capital, and infrastructure.

6. Conclusion

Climate adaptation can be costly, costly to reverse, or effectively irreversible. This means we need to account for the value of flexibility in decision-making. Real options analysis provides a methodology for comparing the costs and benefits associated with waiting for new information to resolve some of the uncertainty about climate change whilst retaining the option to act later. Although farmers will also have new options available to them in the future, real options analysis helps us understand how climate adaptation depends upon the availability of alternatives. This paper outlines an approach to modelling these alternatives which emphasizes the importance of understanding farmers' decisions for analysing the impacts of climate change on agricultural production.

References

Assang, S., Thomas, D., McIntosh, P., Alves, O. and Khimashia, N. (2012). Managing mixed wheat-sheep farms with a seasonal forecast. *Agricultural Systems* 113, 50-56.

Bell, L. W. and Moore, A. D. (2012). Integrated crop-livestock systems in Australian agriculture: trends, drivers and implications. *Agricultural Systems* 111, 1-12.

Copeland, T. and Antikarov, V. (2001). *Real Options: a Practitioner's Guide*. Texere, New York.

CSIRO and BoM (2007). *Climate Change in Australia*. CSIRO and BoM, Canberra.

Dixit, A.K. and Pindyck, R.S. (1994). *Investment Under Uncertainty*. Princeton University Press, Princeton.

Doob, J.L. (1942). The Brownian movement and stochastic equations. *Annals of Mathematics* 43, 351-369.

Ford, J.D., Keskitalo, E., Smith, T., *et al.* (2010). Case study and analogue methodologies in climate change vulnerability research. *Wiley Interdisciplinary Reviews: Climate Change* 1, 374-392.

Gornall, J.R., Betts, E., Burke, R., *et al.* (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society B* 365, 2973-2989.

Hayman, P., Alexander, B., Nidumolu, U. and Wilhelm, N. (2010). *Using spatial and temporal analogues to consider impacts and adaptation to climate change in the South Australian grain belt*. 15th Australian Agronomy Conference, Lincoln New Zealand, 15-18 November 2010.

Hertzler, G. (1991). Dynamic decisions under risk: application of Itô stochastic control in agriculture. *American Journal of Agricultural Economics* 73, 1126-1137.

Hertzler, G. (2007). Adapting to climate change and managing climate risks by using real options. *Australian Journal of Agricultural Research* 58, 985-992.

Hertzler, G. (2012a). *Real Options for Adaptive Decisions* (Software). University of Sydney, Sydney.

Hertzler, G. (2012b). *Transformations in Probability Space* (Software). University of Sydney, Sydney.

Howden, S.M., Gifford, R.G. and Meinke, H. (2010). Grains. In: Stokes C.J, Howden S.M. (eds), *Adapting Agriculture to Climate Change: Preparing Australian Agriculture, Forestry and Fisheries for the Future*. CSIRO Publishing, Melbourne.

McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D.P. and Freebairn, D.M. (1996). APSIM: a novel software system for model development, model testing, and simulation in agricultural systems research. *Agricultural Systems* 50, 255-271.

Miranda, M.J., and Fackler, P.L. (2002). *Applied computational economics and finance*. MIT Press, Cambridge Mass.

Mezey, E.W. and Conrad, J.M. (2010). Real options in resource economics. *Annual Review of. Resource Economics* 2, 33–52.

Nidumolu, U.B., Hayman, P.T., Howden, S.M. and Alexander, B.M. (2012). Re-evaluating the margin of the South Australian grain belt in a changing climate. *Climate Research* 51, 249-260.

Ramírez-Villegas, J., Lau, C., Köhler, A., *et al.* (2011). *Climate analogues: finding tomorrow's agriculture today*. Working Paper no. 12. CGIAR, Colombia.

Rickards, L. and Howden, S.M. (2012). Transformational adaptation: agriculture and climate change. *Crop and Pasture Science* 63, 240-250.

Rural Solutions South Australia (2012). *Farm Gross Margin Guide*. Government of South Australia, Adelaide.

Ryan, J., Ibrikci, H., Sommer, R. and McNeill, A. (2009). Nitrogen in rainfed and irrigated cropping systems in the Mediterranean region. *Advances in Agronomy* 104, 53-136.

Suppiah, R., Preston, B., Whetton, P., *et al.* (2006). *Climate Change under Enhanced Greenhouse Conditions in South Australia*. CSIRO Publishing, Melbourne.

Tang, C.Y. and Chen, S.X. (2009). Parameter estimation and bias correction for diffusion processes. *Journal of Econometrics* 149, 65-81.

Wise, R.M., Fazey, I., Stafford Smith, M., *et al.* (2014). Reconceptualising adaptation to climate change as part of the pathways of change and response. *Global Environmental Change* (in press).