GETTING REAL:

Real Options Analysis of land use change in a world of price, yield and climate uncertainty.

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OCTOBER 2016

A thesis submitted to The University of Adelaide in fulfilment of the requirement for the degree of Doctor of Philosophy

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ABSTRACT

The de-carbonisation of electricity generation systems will be vital in mitigating the worst effects of global climate change. This will involve the substitution of fossil fuel based generation with renewable and carbon neutral energy sources such a photovoltaics, wind and biomass. Internationally, the use of biomass to produce electricity has maintained a market share of approximately 2% of total global generation over the past 20 years (Evans et al., 2010). However, for the biomass share of electricity generation to increase, dedicated biomass crops will likely be necessary on land currently used for traditional agricultural production. Understanding the returns required by landholders from alternative land uses such as biomass is an important first step in determining a) the viability of such an industry in any particular region and; b) how policy setting can facilitate new industries and land use change.

The economics of land use change from agriculture to agro-forestry based biomass production has been broadly examined in Australia. However, these studies have largely employed discounted cash flow analysis (DCF) to determine the profitability of biomass enterprises. Discounted cash flow analysis is an established way to value land use and management investments which accounts for the time value of money. However, it provides a static view and assumes passive commitment to an investment strategy when real world land use and management investment decisions are characterised by uncertainty, irreversibility, change, and adaptation. Real options analysis (ROA) has been proposed as a better valuation method under uncertainty and where the opportunity exists to delay investment decisions, pending more information. When uncertainty and flexibility are considered, the rates of return required for investing in a new land use can be substantially higher than suggested by DCF calculations. This has obvious implications for investors and policy makers alike. However, while investments in biomass agro-forestry are characterised by uncertainties, risk and large upfront (mostly sunk) costs, the application of ROA to this land use change question in Australia has been scarce.

A previous limitation to the uptake of ROA has been model complexity and dimensionality. Established analytical methods demand advanced mathematical skills of the practitioner and can only be applied to limited range of problems, as solutions only exist for rather simple situations considering limited sources of uncertainty. However, investments in alternative land uses, unlike investment questions in financial markets (to which established analytical methods were designed to be applied), will involve multiple sources of uncertainty such as commodity prices, spatially varying risks like crop yields and emerging risks such as climate change. This poses challenges to the application of ROA to these types of investment questions. Newer Monte Carlo simulation methods

provide opportunity to investigate land use change problems where investment decisions are likely to involve multiple sources of uncertainty, spatially variable risks such as crop yields and long investment horizons.

This research aimed to adapt a Monte Carlo based ROA simulation model to investigate [1] the effect of multiple uncertainties on the investment decision to switch land use from agriculture to biomass agro-forestry in a climatically diverse region of southern Australia, [2] Understand the effect of spatially varying yield uncertainty across the study area, [3] explore the role potential climate change may have on the returns required to encourage land use change to biomass agro-forestry and [4] provide mapped estimates of viable areas for biomass agroforestry at a range of price points across the study area.

The results show that the consideration of price and yield uncertainty adds substantially to the returns required to trigger land use change from wheat to biomass when compared to results from the DCF analysis. Results indicate that uncertainty over returns to agroforestry, high upfront (largely sunk) costs, and loss of flexibility associated with agroforestry provide the landholder with a valuable option to delay reforestation and wait for uncertainties to resolve. Our results showed that for the lower Murray study area, the value of this option can be substantial, ranging from 1.45 – 2.32 times the present value of expenditures (DCF break-even point).

Landholders often cite the lack of certainty of government policies, and the longevity of incentive schemes as barriers to investment in reforestation. This research investigated the effect of incentive payments and incentive payment uncertainty on returns required to trigger land use change. This research found that a \$25/t CO_2-e carbon payment reduced the trigger price substantially but that this impact varied spatially. While the effect of an uncertain carbon payment policy was to increase the conversion trigger returns when compared to a fixed carbon payment, the effect of added uncertainty was found to be small. The small effect of payment uncertainty reflects that the additional payment acted more as an additional top up payment, not a main source of revenue from conversion to biomass. This highlights a need to understand the role of incentive payments in the overall revenue stream created from any land use change. For example, when a large proportion of revenue from land use change is reliant on government policy, not market demand, policy risks are higher.

Future climate change is anticipated to be the principal source of risk affecting long term economic viability of rain-fed agricultural systems. This research specifically modelled land use change from agriculture to biomass production in a spatially explicit framework across a broad region accounting for impacts of climate change on yield variability. The effect of climate change on trigger returns shows substantial spatial heterogeneity not only between high and low rainfall areas as one would intuitively expect, but within similarly classified areas. In broad terms climate change reduced returns required for land use change to biomass in low and medium rainfall zones (-76%) and increased them in the higher rainfall areas (25%). The results of this research show that even under severe climate change comparatively small areas are economically viable for conversion to biomass under $200/ DM t (930,986 ha), and it is not until prices exceed $200/DM t that significant areas become profitable for conversion to biomass (up to 2,738,463 ha).

On an energy equivalence basis, to be competitive with an oil price of AU$41/barrel (current at the time of writing) biomass would have to be priced at less than AU$130/DM t. Similarly, to be competitive with coal at AU$68/t, the energy equivalent price of biomass would have to be less than AU$52/DM t. Whether or not these prices are ultimately achievable is speculative, however, for substantial biomass industry development to occur in the study area, the synchronisation of products and services derived from mallee (oil, biomass, charcoal and carbon) and the development of markets will be paramount.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Courtney Regan

April 2016

ACKNOWLEDMENTS

When I first started along this road it was hard to believe I would ever be at the point where I was writing this section. But after chipping away little by little I find myself, obligatory coffee in hand, sitting at my computer (who I affectionately call old Bertha; a fine example of artificial intelligence who has tried to give me a heart attack on more than one occasion) wanting to thank all of those people that have helped me in my continuing journey to become an educated and enlightened human being. I hope the following does you all justice.

I firstly need to thank my wonderful parents. For constantly sacrificing to give their child the best possible chance in life. You have supported me beyond measure and have believed in me when no one else did, not even myself. If I have achieved anything, it is because you believed I could, and eventually it was infectious. If I am ever so blessed as to become a parent, I have the best examples to follow. Thank you.

I want to acknowledge my primary supervisor Professor Wayne Meyer, who gave me this opportunity. Thank you Wayne for that, I have thoroughly enjoyed our long talks on the future of science and especially our discussions on our shared passions of bees and agriculture. It is always great to know there are kindred spirits in the world.

I wish to thank my other supervisors Dr. Brett Bryan, Associate Professor Bertram Ostendorf, Dr. Jeff Connor and also Dr. Zili Zhu. When I turned up in your office I was pretty unsure and overly ambitious. Thank you for moulding that naive lump of clay in to something resembling an academic. You have all provided me with an outstanding example of how one builds integrity and respect in a career. I sincerely hope I can work with you in future and keep learning from you, you are all amazing at what you do.

To my friends, who are numerous because I am very popular, thanks for the fun we've had during this time, it has kept me sane. A special mention needs to go to the Wizard Council. So to you all thank you! There are, however, a few names among that list that need special mention. Thank you Nick Koch for being my never wavering friend, for being a constant in my life for so many years and for your brave honesty. You are like a brother to me. To my brother Myles and Lintern Fairbrother. You both gave me the confidence to start this thing, assured me I could do it, supported me and guided me through the toughest parts. I will have your advice, Lintern, chiselled on my grave "just keep turning up like an A*#@hole". Although I think that advice originated with Ramesh!? To Ramesh Raja Segaran, you are one Zen mofo. On so many occasions your advice, help, calm and friendship saved me from a nervous breakdown. Thank you brother, I don't know if I can ever repay the favour!

To all the folks in the Davies building, it has been a great privilege to work with you all. You are all doing such amazing work, many of you in a crazy language that isn't your own and so far from the supports that I know I have needed. I don't know how you do it but you have my greatest respect and admiration and you are a constant source of inspiration.

Lastly but by no means least. To my dearest Chevaun. Without your love, support, humour and constant encouragement I would have fallen by the wayside long ago. We have walked a hard road together over the past few years and it seems that our paths now diverge. No amount of thank you can express the gratitude I have for having had you in my life. There will always be a part of my heart that belongs to you. My sincerest wish is that someday we again can be friends. Thank you. XX

LIST OF PUBLICATIONS

Regan, C.M., Bryan, B.A., Connor, J.D., Meyer, W.S., Ostendorf, B., Zhu, Z., Bao, C., 2015. Real options analysis for land use management: Methods, application, and implications for policy. Journal of Environmental Management 161, 144-152.

Regan, C.M., Connor, J.D., Bryan, B.A., Meyer, W.S., Ostendorf, B., 2016. Spatial real options analysis: informing better incentive policy for motivating biomass agroforestry in agricultural land. Land Use Policy. Submitted, manuscript ID LUP_2016_139.

Regan, C.M., Connor, J.D., Raja Segaran, R., Meyer, W.S., Bryan, B.A., Ostendorf, B., 2016. Climate change and the economics of biomass energy feedstocks in semi-arid agricultural landscapes: A spatially explicit real options analysis. Journal of Environmental Management. Submitted, manuscript ID JEMA-S-16-01136.

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CHAPTER ONE

INTRODUCTION

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1 Introduction

Since the development of the United Nations Framework Conventions on Climate Change (UNFCCC), adopted at the Rio Earth Summit in 1992, the depth of scientific understanding regarding the effect that human activity is having on the Earth's climate systems has grown enormously (IPCC 2014). The scientific evidence is overwhelming, human activities are having a measurable effect on the planet's climate systems (Stern, 2007). Evidence suggests that most of the observed increase in global average temperatures (0.61°C) since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations (IPCC, 2007). In order to mitigate the worst effects of climate change, the Kyoto Protocol was developed under the auspices of the UNFCCC. The main aim of the Kyoto Protocol is to contain emissions of the main greenhouse gases in ways that reflect underlying national differences in emissions, wealth and capacity (Grubb, 2004). The Australian Government, under Prime Minister Kevin Rudd, ratified the Kyoto Protocol in 2007, thereby committing Australia to limiting its emissions to 108% of their 1990 level over the 2008-2012 period (Howarth and Foxall, 2010).

Australia's total greenhouse gas emissions account for less than 1.5 percent of global emissions, however due to a heavy reliance on coal for electricity generation, Australia is among the top five largest polluters on a per capita basis (Schiermeier, 2014). In order to meet its Kyoto Protocol commitments, the Australian Government introduced a range of climate change mitigation policies – including the Mandatory Renewable Energy Target (MRET) and the Carbon Farming Initiative (CFI). The MRET is designed to ensure that 20 per cent of Australia's electricity generation comes from renewable sources by 2020 (Valentine, 2010), and it is hoped the CFI will encourage landholders to generate carbon offset credits though the creation of carbon sinks, primarily on agricultural and pastoral lands (Van Oosterzee, 2012). A third important component of Australia's climate change mitigation policy and a key driver of demand for carbon credit supplied by the CFI, was the emissions trading scheme (ETS). Successive Australian federal governments have dismantled the ETS. However, despite this, significant interest remains in using agricultural land as carbon sinks (Evans et al., 2015) and as a source of renewable energy (Bryan et al., 2010c), while simultaneously addressing many environmental issues in Australian agricultural regions .

The development of landscapes for agricultural production has resulted, in many instances, in environmental degradation which has limited not only the agricultural productive capacity, but also the resilience of ecosystems broadly (Vitousek et al., 1997). The large scale clearing of perennial native vegetation in favour of annual crops and pastures has resulted in widespread degradation of biological, land and water resources (Bryan et al., 2013; Millar and Roots, 2012). In the face of declining natural capital, long standing approaches to landscape and ecosystem management are gradually being replaced by paradigms that accept that landscapes are complex social–ecological systems (Parrott and Meyer, 2012). In addition, society is demanding that landscapes be managed to produce a range of ecosystem services separate from food and fibre including carbon, water, biodiversity, energy and amenity. New economies and markets are emerging that are placing transformational pressure on the landscape (Bryan et al., 2013). Indeed, these pressures are being felt within traditional agricultural commodity markets with consumers increasingly demanding credence attributes such as food safety, animal welfare and environmental protection (Chang and Kristiansen, 2006). Less intensive, more diverse farming systems are often considered by consumers to be more environmentally responsible, provide higher standards of animal welfare and each linked to safer food (Viegas et al., 2014). Despite the recognition of the need to manage landscapes as a mosaic of land uses, providing multiple services, there are considerable (and evolving) challenges to achieving these objectives.

Australian dryland agriculture is inherently risky, with Australian farmers experiencing a much higher level of financial risk than any other developed country (Hutchings, 2013).There is clear evidence that shows that farm business margins are declining with total Australian farm debt rising exponentially since 1965 (Reserve Bank of Australia, 2009).This situation is not sustainable. For growers to adopt strategies for sustainable land management, returns from alternative land uses must be greater or at the very least comparable to those from traditional agricultural production (Lyle et al., 2009). Climate variability, and its predicted increase as a result of climate change, pose substantial additional economic risks to farmers which may limit their ongoing access to credit for continuing traditional agricultural production as well as their ability to respond to global challenges such as food security and environmental problems (Kandulu et al., 2012). Traditionally, landholders have employed enterprise diversification as a way to manage the impact of climate variability on returns (Kingwell, 2006). New markets for services such as carbon sequestration, biodiversity, water quality and the production of biomass for the purpose of electricity generation from well adapted *Eucalyptus* species, may serve as a valuable diversification option for landholders as change occurs in societal expectations, increased financial pressure and increasing climate risk (Bryan et al., 2010a; Bryan et al., 2010c).

Internationally, the use of biomass to produce electricity increased by an average of 13 TWh per year between 2000 and 2008 and has maintained a market share of approximately 2% of total global generation over the past 20 years (Evans et al., 2010). However, for the biomass share of electricity generation to increase, dedicated biomass crops will likely be necessary on land currently used for traditional agricultural production. In order to address the economic competiveness of new forestry industries in Australia, economic analyses have been conducted on both the viability of carbon forestry (Crossman et al., 2010; Paterson and Bryan, 2012; Polglase et al., 2011; Polglase et al., 2013) and biomass with a range of climate futures and spatial extents (Bryan et al., 2010c; Rodriguez et al., 2011; Ward and Trengove, 2004). In the case of biomass, research has indicated that large areas would be more profitable if used for biomass than traditional agriculture (Bryan et al., 2008a) while the areas available for biomass may increase given the effects of climate change (Bryan et al., 2010c).

While the biomass industry in Australia is largely undeveloped, evidence from other countries suggests that despite the potential profitability of land uses such as BEG, there is an observed friction between land use change behaviour and economic theory (Musshoff, 2012). Indeed, low investment rates have been a puzzling phenomenon in a range of agricultural technologies (Hüttel et al., 2010) including irrigation technology (Carey and Zilberman, 2002), conservation interventions (Winter-Nelson and Amegbeto, 1998), perennial crops and pastures varieties (Richards and Green, 2003; Tozer and Stokes, 2009) and precision agriculture technology (Tozer, 2009). Classical investment theories, such as discounted cash flow analysis (DCF), assume complete markets and information symmetry (Hüttel et al., 2010). As such, if a project has a positive net present value (NPV), a rational investor should be expected to invest. However, research to explain observed investment inertia has found landholders intuitively value the option to wait for uncertainty to decrease before making investment decisions (Ihli et al., 2013). This poses a problem for studies that have used DCF analysis to determine revenues at which landholders would change land use from conventional agriculture to alternative land uses. Primarily, DCF does not account for uncertainty in key variables such as commodity prices and does not value the flexibility to wait for more information. Experimental studies (Ihli et al., 2013; Maart and Musshoff, 2011) show landholders make investments later than would otherwise be optimal under DCF rationale. This has important implications for policy made using estimates derived from DCF. Revenues at which DCF indicates land use conversion would be more profitable than current land use, and the revenues at which a landholder would actually change land use, can be very different. Consequently, time taken to achieve land use conversion may be far greater than anticipated and far more costly. This is likely to have a significant effect on the prices required to encourage land use conversion. It also means that forecasting land use change for environmental restoration by policy makers and natural resource managers is quite uncertain.

A more recent valuation method, Real Options Analysis (ROA), has been proposed as a better model for explaining investor behaviour under conditions of uncertainty. ROA was adapted from methods for pricing financial derivatives and has been broadly applied to forestry applications including optimal harvest and rotation (Gjolberg and Guttormsen, 2002; Insley, 2002; Plantinga, 1998; Saphores, 2001; Thorsen, 1999). In an agricultural context, ROA has been applied to organic farming (Irene and Konstadinos, 2009; Kuminoff and Wossink, 2010; Tanner Ehmke et al., 2004), adoption of precision agriculture (Tanner Ehmke et al., 2004; Tozer, 2009), expansion of agricultural enterprises (Hinrichs et al., 2008; Odening et al., 2005; Tozer and Stokes, 2009), the adoption of genetically modified crops (Nadolnyak et al., 2011) and adaptation to climate change (Hertzler, 2007; Sanderson et al., 2016). Fewer examples of ROA application to environmental land issues exist. Several studies have applied ROA to the growing of biomass for electricity generation on agricultural land (Musshoff, 2012; Wolbert-Haverkamp and Musshoff, 2014a, b). Despite its insight, the complexity of ROA methods has meant that adoption has been sporadic, even in corporate settings (Regan et al., 2015) and several major sources of uncertainty influencing investment behaviour have remained largely unaddressed.

Climate variability is the principal source of risk affecting long term economic viability of rain-fed agricultural systems (Kandulu et al., 2012). In addition, primary production is not only sensitive to annual changes but also to seasonal distribution of rainfall (Iglesias and Quiroga, 2007). Previous ROA studies have often used invariant yield data (Musshoff, 2012; Reeson et al., 2015; Wolbert-Haverkamp and Musshoff, 2014a), or have accounted for production variability in stochastic processes modelling returns to agriculture (Isik and Yang, 2004; Sanderson et al., 2016). As a result temporal climate variability has been largely ignored as a major source of uncertainty influencing landholder decision making.

Research using conventional economic analysis has incorporated spatial heterogeneity in primary productivity to understand the distribution of *cost-effective* land use change (Bateman, 2009; Bryan et al., 2008a; Crossman et al., 2011; Polglase et al., 2008a) and have found that underlying landscape heterogeneity is likely to influence the timing and location of land use change. The inclusion of heterogeneity in the biological drivers of primary productivity, until recently, has received scant attention in the ROA literature. However, the acknowledgement of differing production risk profiles across the landscape and their inclusion into ROA modelling could help understanding of the contribution of a variety of sources of uncertainty to the observed reluctance to switch land use. The relative contribution of different sources of risk to investment inertia is also likely to differ spatially. This is important for policy makers to understand as any incentives offered to promote land use change need to address the source(s) of uncertainty responsible for reluctance to invest, and also that the effects of uncertainty will likely differ across a region.

In addition to commodity price and yield risks, climate change is expected to pose new risks to agricultural production and as such presents opportunities for landholders to participate in emerging economies by modifying their current land use. In an Australian context, several studies (Hertzler, 2007; Nelson et al., 2013; Sanderson et al., 2016) have used ROA to understand how climate change may affect land use investment decisions and timing. However, none have done this in a spatially explicit environment. The effects of climate change are likely to occur along a spectrum that includes both the benign and the catastrophic (Dobes, 2010). Modelling (IPCC, 2014; Suppiah et al., 2006) suggests spatial heterogeneity in climate change effects across the Australian wheat belt (Potgieter et al., 2013). The implication of this is that not only is climate change likely to affect the returns required to trigger land use change, but that the distribution of effects will vary spatially. The inclusion of these risks in a spatially explicit environment is important to generate more precise estimates of the returns land holders will require to switch land use, regional net return values and potential land conversion patterns (Yemshanov et al., 2015) under a range of climate futures.

With this background the aim of my research is to establish the potential of ROA for landholders and policy makers to better account for multiple sources of uncertainty in land use and land use change decision making. By incorporating key stochastic uncertainties associated with land use, natural resource managers can gain valuable insight into how uncertainties affect cost associated with transitioning land use away from predominantly agricultural use to multi-functional landscapes providing a range of ecosystem services.

In addition to the broad aim of the thesis, my research aims to accomplish the following specific objectives and address several key gaps in the ROA literature, specifically:

- ROA methods can be mathematically complex and this has resulted in ROA being technically inaccessible and consequently appearing to be a *black box* to managers. This has inhibited the wide adoption of ROA in land use and management decision making problems. New methodologies are being developed to provide simpler, more heuristic ways of incorporating ROA into land use and management decision making. However these methods have not been widely introduced to natural resource managers. Chapter 3 addresses this by introducing ROA as an alternative valuation method and discusses its use in land use and management decisions. Chapter 3 discusses the merits of various ROA methodologies and their key limitations.
- A key limitation of many ROA methodologies is the failure to account for multiple, interacting sources of uncertainty which are important sources of risk for land holders and influence land use decisions. The effect of multiple sources of uncertainty of returns needed to

encourage land use change has been largely unaddressed in the ROA literature to date. Chapter 3 addresses this gap and proposes ROA combined with Monte Carlo simulation as a promising method that provides a cognitively accessible model with the capacity to include multiple sources of uncertainty into the analysis. To highlight this, the paper applies an ROA simulation model to a stylised land use change problem. The results are reported and their implications for natural resource managers and policy makers discussed.

- Previous studies have applied ROA to land use change questions in one location and have made broad conclusions regarding the effects of uncertainty on land holder decision making. However, considerable geographical variability in production risk is often present, and an understanding of if and how differing locational production risk profiles effect land use change decisions has been lacking. Chapter 4 addresses this gap by applying a simulation-based ROA model to examine the effects of interacting uncertainties on landholder decision making. In addition to commodity price uncertainty, the paper's focus is on the effects of geographically varying risk at several locations across a diverse region of southern Australia. Incentive policies are often employed by policy makers to encourage participation in agro-environmental programs by offsetting establishment costs or attempting to negate variability in returns from alternative land uses. However, given the variability in the production risk, incentive payments are unlikely to have a homogenous effect across any area. Chapter 4 aims to firstly investigate payment policies that include alternative treatments of risk and secondly if the effect of these payments differs geographically. Chapter 4 concludes by discussing the implications of the research for policy makers and natural resource managers.
- Studies using DCF to analyse land use change have frequently done so in a spatially explicit environment in order to better understand the distribution and patterns of possible land use change. The complexity of ROA methods has seen the inclusion of spatial variables largely ignored with only several exceptions. However, simulation based ROA models make the inclusion of spatial variables more feasible. The aim of Chapter 5 was to incorporate spatial complexity into the ROA in order to better understand the distribution effects of multiple sources of uncertainty across a biophysically diverse and heterogeneous agricultural region. Chapter 5 then examined the role of different sources of risk on land holder decision making, and how that differed across the region.
- In addition to price and production risks, climate change may pose an addition source of uncertainty to land holders and exacerbate existing production risks thereby affecting land use change decisions. Previous ROA studies addressing land use and land use change under potential climate change scenarios have relied upon spatial analogues to provide an approximation of future condition. However temporal changes associated with climate

change cannot always be adequately captured using spatial analogues, such as the effect on plant growth of increased CO_2 concentrations. In addition, the effects of climate change on production risks is likely to vary spatially and the severity of effects occur along a spectrum from the benign to severe. Chapter 5 aims to address this by examining the effects of potential climate change futures on the returns required to induce land use change from agriculture to biomass in a spatial framework. The inclusion of spatial variables allows for the chapter to be concluded by quantifying the area economically viable for land use change to biomass at different commodity price points.

The thesis is structured around the specific aims listed above. Chapter 2 provides additional background on the potential of a biomass industry in Australia and the selection of the ROA model. Chapters 3-5 directly related to the specific aims above and the final chapter (6) provides an overall conclusion of my research and recommendations for possible future research.

Publication details of the thesis chapters are as follows. Chapter 2 was published as a critical review in *Journal of Environmental Management.* Chapter 3 has been submitted as an original research paper in *Land Use Policy*. Chapter 4 has been submitted *to Journal of Environmental Management* as an original research paper.

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CHAPTER TWO

FURTHER CONTEXT

CHAPTER TWO

2 Further context

The purpose of this chapter is to provide additional context and background on two foundational settings of this thesis. The first is to outline the recent development of the tree biomass industry in Australia that has arisen largely in response to environmental concerns of soil erosion and groundwater management associated with increasing dryland salinity. Use of the biomass and other value adding products has been part of improving the financial viability of this perennial revegetation activity. The second foundational setting is that of using Real Options Analysis (ROA) as the analysis method rather than more common, existing methods. Having a full appreciation of the limitations of existing methods and of the advantages of new ways of implementing ROA, will provide useful context for detail in Chapter 3.

2.1 Biomass industry in Australia

Development of the modern mallee industry began in the early 1990s and was conceived as a pioneer woody crop industry for the wheat-belt areas of Australia, initially to be based in Western Australia (Bartle and Abadi, 2009). *Mallee* refers to a category of eucalyptus species that are characterised by multiple woody stems originating from an underground lignotuber (Wildy et al., 2003). Mallee species are common across large regions of Australia, in particular, dry Mediterranean and semi -arid areas of southern Australia. Mallee species are slow growing and can be extremely long lived, with some estimates of age possibly exceeding 6000 years (Rossetto et al., 1999) and are extremely well adapted to Australia's naturally low fertility soils, variable rainfall including periods of drought, high temperatures (Wildy et al., 2003) and a capacity to regenerate after fire . Mallee's have outstanding coppicing ability and many mallee species have a high concentration of oil in their leaves which has been sold into small traditional markets (Bartle and Abadi, 2009).

Unfilled markets for eucalyptus oil exist and there is potential for large-scale industrial use (Enecon, 2001). Traditional markets for eucalyptus oil were never considered likely to generate sufficient revenue to alone drive a modern industry (Bartle and Abadi, 2009). As a result, the motivation for investment to develop woody biomass crops for dryland agriculture in Australia over the past several decades has been primarily environmental (Bartle et al., 2007). The major historic use of trees within agriculture has been for shelter from wind for erosion control as well as stock and crop protection (Bartle and Abadi, 2009; Nuberg, 1998). In addition, the replacement of agricultural crops and pastures with deep-rooted perennial biomass species can reduce deep drainage and groundwater recharge (Bryan et al., 2010c), however salinity benefits can take 20-30 years to be realised as a new landscape hydrologic equilibrium is established (Bartle and Abadi, 2009). In addition, biomass production has been proposed as a mitigation for future climate change. This can be done through sequestering CO_2 from the atmosphere in biomass and soils (Strengers et al., 2008), or through replacing electricity generated from high CO_2 emitting fossil fuels with that produced from renewable and carbon neutral biomass (Ravindranath et al., 2006).

Several potential pathways for developing a sustainable biomass industry have been proposed. The most immediately achievable is co-firing existing power stations with biomass. Biomass co-firing can be implemented immediately in nearly all coal-fired power plants in a relatively short period of time and without the need for huge investments and therefore offers the lowest cost, among the several technologies/options available for greenhouse gas reduction (Basu et al., 2011). Currently a number of co-firing installations exist worldwide, with approximately 100 in Europe, 40 in the USA and the remainder in Australia and Asia (Basu et al., 2011; Koppejan and Van Loo, 2012). There are three primary avenues for the integration of biomass into existing power plant operations (Basu et al., 2011):

1. Direct co-firing

   Direct co-firing involves biomass being injected directly into the boiler furnace through the coal burners, or in a separate system. The level of integration into the existing plant depends principally on the biomass fuel characteristics.

2. Indirect co-firing

   Indirect co-firing involves the installation of a completely separate biomass boiler to produce low-grade steam for utilization in the coal-fired power plant prior to being upgraded, resulting in higher conversion efficiencies.

3. Gasification co-firing

   Co-firing through gasification involves the gasification of solid biomass and combustion of the product fuel gas in the furnace of the coal-fired boiler.

The intensification of co-firing coal with biomass is reliant on several factors including access to economically viable biomass, usually in the form of forest industry residues (Rodriguez et al., 2011), government policies surrounding renewable energy targets and climate change mitigation, and the cost of fossil fuels such as coal and natural gas. However under current policy settings (REC prices) and global fossil fuel prices, as little as 3% of current biomass feedstocks may be economically available for electricity production (Rodriguez et al., 2011).

In addition to co-firing existing power plants with biomass, stand-alone biomass fuelled electricity generation has been proposed as a potential renewable energy source. It is hoped that with increasingly ambitious climate change mitigation policies, with a focus on electricity generation from renewables, such an industry could become economically viable. However, under current policies, the prices able to be paid for biomass by an electricity generator would be low (AU$ 30-50/t (Rodriguez et al., 2011) making electricity generation from biomass alone commercially unviable (for landholders), even with a modest level of renewable energy credits (Bartle and Abadi, 2009).

Integrated tree processing (ITP) has been proposed as an economically viable way to promote a broad scale biomass industry in Australia. An ITP plant takes coppiced, chipped mallee biomass as feedstock and produces a range of products including activated carbon, renewable energy and eucalyptus oil (Enecon, 2001). Activated carbon is used in a range of industrial applications including gold recovery and water treatment with worldwide demand being approximately 700,000 tonnes per annum (Enecon, 2001). The existing world market for eucalyptus oil is mainly for pharmaceutical and domestic cleaning uses and is approximately 4000 tonne per annum (Enecon, 2001), however research continues into processing eucalyptus oil into liquid biofuels for use in transport industries, including aviation (Murphy et al., 2015). One ITP plant is currently operational at Narrogin in Western Australia, successfully producing activated carbon, eucalyptus oil and renewable electricity. A schematic of the process is presented in Figure 2.1:

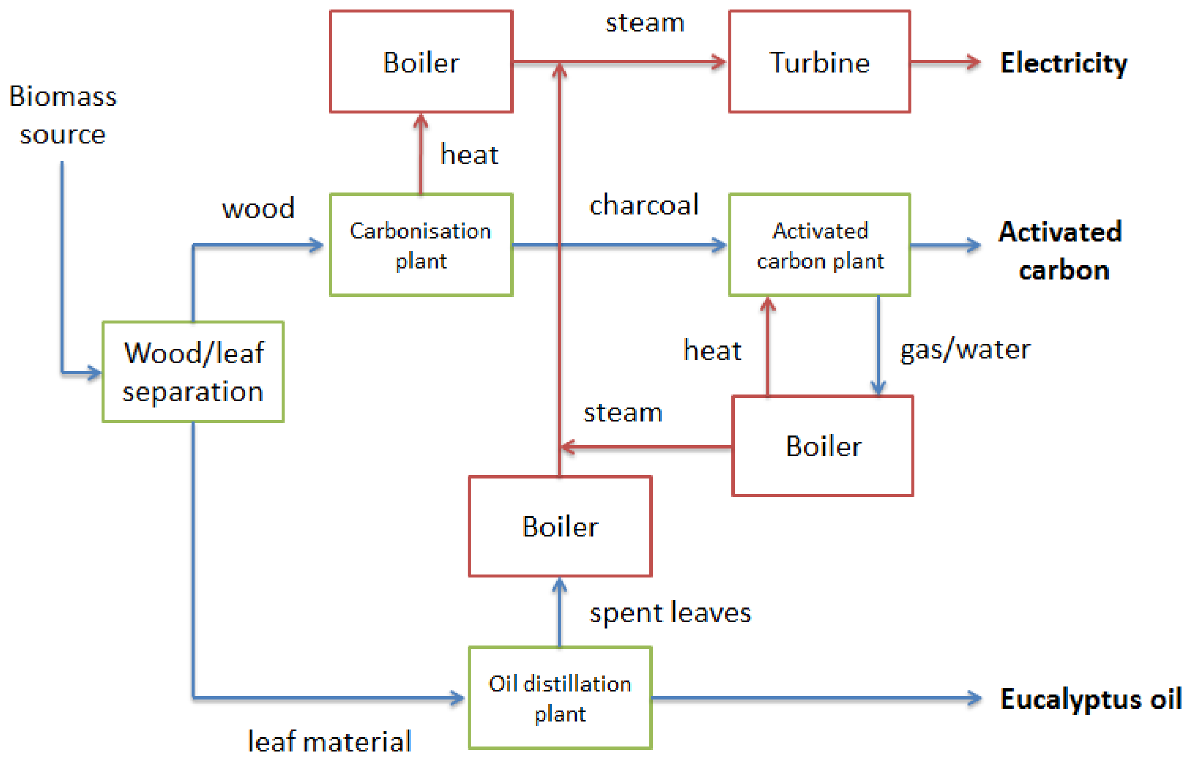

Figure 2.1– Schematic representation of the processes in an integrated tree biomass and oil processing plant (Adapted from Enecon, 2001).

Significant work has been conducted in identifying suitable species of eucalypts able to improve natural resource management outcomes, while providing profitable alternative enterprises to land holders (Bennell et al., 2009; Hobbs et al., 2009; Hobbs, 2009b). These primarily include Acacia and mallee Eucalyptus species. Despite impediments to the development of large scale integrated tree processing, there exists significant potential for such an industry if risks posed to both land holders and investors can be reduced and better assessed. This will involve the further expansion of markets for products such as eucalyptus oil and charcoal, clarity on government renewable energy policy, development of mature markets for ecosystem services and continued monitoring of the effects of climate change.

2.2 Choice of real options model

The topic of available ROA methods and their application is discussed in detail in chapter 3, however the selection of the ROA model used as the basis for this thesis warrants additional explanation. In broad terms, two methods for ROA application to land use change are available. The first involves the use of analytical methods such as those employed by Hertzler et al. (2013) and Sanderson et al. (2016). Applying analytical methods requires the solution of a partial differential equation. Analytical solutions only exist for rather simple situations considering limited sources of uncertainty (Odening et al., 2005). However most real world investments are not simple and involve multiple, simultaneous risks and therefore one must turn to numerical approximation methods, including Monte Carlo simulation based methods and binomial tree methods. The limitation of using binomial trees or other lattice methods is described at length in Chapter 3. In short, binomial trees are restricted by what is commonly termed *the curse of dimensionality*, meaning the tree can quickly grow burdensomely large as the number of time periods and sources of uncertainty increase. As a result they are more suited to more simple problems with few sources of uncertainty and where the investment time horizon is relatively short. Despite binomial trees being far simpler to implement, these limitations made the methods unfeasible for this research.

The main advantage of Monte Carlo simulation is its flexibility with respect to the stochastic processes used to model prices or returns and the number of risks that can potentially be included in the analysis. Its main disadvantage is that it is usually only applicable to European-type options (options that can only be exercised on the expiration date) and not to American-type options (options that can be exercised at any time within a predetermined time period). However many investment decisions in land use and management are analogous to American-type options. In order to allow Monte Carlo simulation methods to calculate American-type options, Ibanez and Zapatero (2004) proposed a method that combines Monte Carlo simulation with backward dynamic programming that aims to determine the optimal investment exercise frontier.

An important variable to consider in real options analysis is the time frame over which the investment can be made. The selection of an investment time horizon can be problematic. Odening et al. (2005) chose a 5 year time horizon over which to test the (dis)investment options in pig raising in Germany. The assumption of a 5 year time horizon was explained as more a tribute to the computational burden (Odening et al., 2005) rather than any reflection of a natural time limit, and in that respect was somewhat arbitrary. Indeed, situations will undoubtedly exist in which it is impossible to delay an investment indefinitely, for example legislative changes that will prohibit the investment at a future date, such as the introduction of environmental regulations or the termination of subsidies. The addition of an arbitrary or incorrect time horizon will affect/distort the exercise frontier and the optimal investment trigger (Figure 2.2). The addition of a definite investment horizon results in the exercise frontier of the ROA decreasing over time, reflecting the diminishing time value of the investment option, until it converges with the NPV investment trigger at the expiry date (Tubetov et al., 2013).

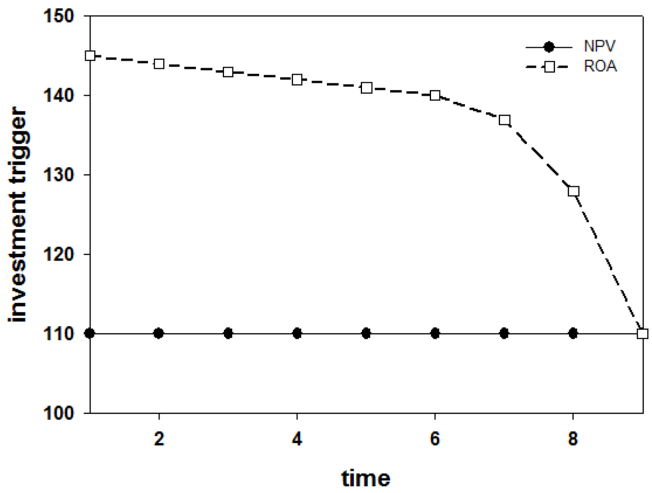

Figure 2.2 – Optimal exercise frontier for NPV and ROA showing diminishing time value of the investment option under the assumption of a finite investment horizon (Adapted from Tubetov et al., 2013)

Many investments in land use and management do not have any readily apparent natural time horizon. In essence, a landholder can make a decision on investment over an unrestricted time period. The decision to invest in biomass or carbon can be viewed as such an investment. In the absence of short run policies or incentives designed to drive land use change, a land holder can make the decision to invest at any time depending on the comparative financial performance of the land use alternatives. Furthermore they have the flexibility to move between enterprises multiple times. For example, after the useful lifetime of a biomass plantation a land holder can re-establish the land in biomass or return the land to conventional agriculture depending on the economic conditions encountered at the time. In situations where no natural or readily apparent timeframe is available Tubetov et al. (2012) and Musshoff (2012) applied an option pricing method based on stochastic simulation and the parameterisation of investment triggers. This ROA framework can be adapted to incorporate multiple sources of uncertainty and therefore provides the opportunity for a more comprehensive treatment of risk than simply price volatility. Additionally, the model is comparatively computationally efficient, allowing for the incorporation of spatial variables into the ROA, an area seldom addressed in the ROA literature in part due to the complexity and computational burden of analytical real options methods.

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CHAPTER THREE

Real options analysis for land use management: methods, application, and implications for policy

The work contained in this chapter has been published in *Journal of Environmental Management.*

STATEMENT OF AUTHORSHIP

Regan, C.M., Bryan, B.A., Connor, J.D., Meyer, W.S., Ostendorf, B., Zhu, Z., Bao, C., 2015. Real options analysis for land use management: Methods, application, and implications for policy. Journal of Environmental Management 161, 144-152.

Author contributions: By signing the statement of authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

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Signed

3 CHAPTER THREE

The purpose of this chapter is to provide a critical review of the use of discounted cash flow methods in land use and management investment analysis. The chapter discusses at length previous applications and discusses in detail the limitations of these methods, especially under conditions of uncertainty and sunk cost. This chapter introduces the real options analysis as an alternative method for the valuation of investments in land use and management. In the previous chapter (Ch. 2), I discuss the reasoning behind the choice of the real options model used in this thesis. In this chapter, I provide a detailed summary and critique of the major real options methods presented in the literature, with a focus on the potential for Monte Carlo based simulation methods to incorporate multiple sources of uncertainty in economic analysis of land use change. In order to demonstrate this potential, I provide a stylised example of a Monte Carlo based simulation method applied to a land use change problem. The results of this modelling are analysed and the implications of the results obtained from real options analysis for natural resource managers and policy makers are discussed.

Abstract

Discounted cash flow analysis, including net present value is an established way to value land use and management investments which accounts for the time value of money. However, it provides a static view and assumes passive commitment to an investment strategy when real world land use and management investment decisions are characterised by uncertainty, irreversibility, change, and adaptation. Real options analysis has been proposed as a better valuation method under uncertainty and where the opportunity exists to delay investment decisions, pending more information. We review the use of discounted cash flow methods in land use and management and discuss their benefits and limitations. We then provide an overview of real options analysis, describe the main analytical methods, and summarize its application to land use investment decisions. The review concludes that uncertainty, irreversibility, and the presence of sunk costs can significantly affect the timing and magnitude of land use investment decisions in response to policy and economic drivers, and influence the cost of land use policies such as payment schemes. Real options analysis is largely underutilized in evaluating land use decisions, but new simulation methods offer the potential for overcoming current technical challenges to implementation. We provide an example of a real options simulation model used to evaluate an agricultural land use decision in South Australia. We conclude that considering option values in future policy design will provide a more realistic assessment of landholder investment decision making and provide insights for improved policy performance.

Keywords: land use, real options, agriculture, planning, economic

3.1 Introduction

New markets and policies are emerging which are exerting transformational pressure on land use (Bryan et al., 2013). Diversification of land use—moving away from production agriculture to multifunctional land uses—has been recognised globally as being important for remediating environmental problems and enhancing the sustainability of food and fibre production (Crossman and Bryan, 2009; Lovell and Johnston, 2008; O'Farrell and Anderson, 2010). Many studies worldwide have examined the financial profitability of alternative land uses and the attractiveness of economic incentives through mechanisms such as payments for ecosystem services and agri-environment schemes (Connor et al., 2008; Hein et al., 2013; Wunder et al., 2008). Carbon forestry (Paterson and Bryan, 2012), biodiversity plantings (Polglase et al., 2013), the production of biofuels (Bryan et al., 2010b; Fischer et al., 2010) and bioenergy (Bryan et al., 2010c; Schneider and McCarl, 2003) feedstock may all potentially provide economically viable alternatives to conventional agriculture under the right policy settings. However, the widespread uptake of these alternatives faces many challenges. Psychological inertia, the sunk cost fallacy (Ross and Staw, 1993), the status quo bias (Burmeister and Schade, 2007), along with other factors have all been invoked to explain the reluctance to change. While the decision to adopt an alternative land use or management regimes involve more than purely economic considerations—financial competitiveness is a key component (Lambin et al., 2001; Lubowski et al., 2006).

Capital budgeting is an established process by which organisations evaluate long term investment decisions, typically in new plant and machinery, new products, and in research and development. Discounted Cash Flow (DCF) analysis is one way of evaluating investments using the concept of time value of money. The value of an investment depends on its propensity to generate cash flow. A measure of DCF—net present value (NPV)—has been used widely to assess investments (Bryan et al., 2008a; Harper et al., 2007; Paterson and Bryan, 2012; Walsh et al., 2003). However, NPV often has limited ability to account for the value landholders place on managerial flexibility, or the option to wait for further information in the face of uncertainty and risk (Arya et al., 1998)—important considerations in typical land use investment decisions.

A more recent capital budgeting method—real options analysis (ROA)—has been proposed as a better model for valuing investments and describing investment behaviour in the presence of uncertainty (Isik and Yang, 2004; Schatzki, 2003; Song et al., 2011). ROA is applicable when investment decisions are irreversible and where there is the opportunity to delay decisions until more information is gained (Fenichel et al., 2008). This review examines the use and limitations of DCF techniques in evaluating land use and management decisions. We review the application of ROA to land use management and consider the potential for ROA to provide insights into the timing of land use investments. A simulation based real options model is applied to a land use change problem and the implications for policy makers and land holders are discussed.

3.2 Discounted cash flow

3.2.1 Concepts

DCF analysis and the calculation of NPV is a practical and widely used method for evaluating agricultural and other investments (Cocks, 1965; Marra et al., 2003). It is based on a fundamental principle of finance— due to inflation, economic growth and risk, a dollar today is worth more than a dollar tomorrow (Homer and Leibowitz, 2013). In DCF analysis, future income streams are discounted and expressed in present value terms (Johnson and Hope, 2012). NPV is the sum of the discounted annual cash flows (inflows and outflows) and is a widely used indicator of an investment's profitability. Numerous metrics have been used in capital budgeting problems to evaluate investments based on DCF analyses and NPV including: Internal Rate of Return (IRR), Benefit-Cost (B/C) ratios, and payback periods (Arya et al., 1998; Baker and English, 2011). However, in its simplest application, a project is regarded as economically feasible if the NPV is positive as this indicates positive cash flow compared to a targeted rate of return over the life of the project.

In calculating NPV, each year's cash flow is discounted back to its present value (PV). The PV is calculated as:

$$PV = \frac{R_t}{(1+i)^t} \tag{1}$$

Where t is the time period of the cash flow; i is the discount rate and R_t is the net cash flow in time period t. The NPV is the sum of all present values incoming and outgoing over the total number of periods N.

$$NPV\ (i, N) = \sum_{t=0}^{N} \frac{R_t}{(1+i)^t} \tag{2}$$

In calculating NPV, some key variables need to be specified including inflation, taxes, and importantly, discount rate (Dixit and Pindyck, 1995). NPV evaluations have advantages in that they: are relatively simple to explain and understand; have clear and consistent decision criteria; rely on quantitative data, and; account for time and risk (Mun, 2006b). Another great benefit of NPV is that it enables the comparison of investments that involve uneven costs and returns over time.

3.2.2 Application in land use and management

For decades cost-benefit analyses and NPV have been used to compare streams of net benefits in agricultural and resource economics over time (Cocks, 1965; Nelson et al., 1996). DCF analysis has been used to evaluate agricultural and conservation technology and investment scenarios both in Australia and internationally including investment in conservation tillage (Stonehouse, 1997), precision agriculture (Robertson et al., 2007; Swinton and Ahmad, 1996), technology adoption (Marra et al., 2003), new crop varieties and rotations (Bell et al., 2008; Doole and Pannell, 2008), extension programs (Robertson et al., 2009) and the value of ecosystem services and environmental restoration (Birch et al., 2010; Bryan and Crossman, 2013; Kaiser and Roumasset, 2002; Sathirathai and Barbier, 2001). Land use studies using DCF methods have often incorporated a spatially explicit framework to estimate the profitability of land uses such as reforestation (Bateman, 2009; Burns et al., 2011; Crossman et al., 2011; Lawson et al., 2008; Paterson and Bryan, 2012; Polglase et al., 2011; Polglase et al., 2013) and bioenergy feedstock (Bryan et al., 2010c; Bryan et al., 2008a) at a landscape level. Despite the widespread use of DCF methods, there are important limitations to the use of these methods in the analysis of land use and land use change.

3.2.3 A critique

A commonly cited weakness of NPV is that it only considers the opportunity to invest as a *now or never* decision (Dixit and Pindyck, 1995). NPV analyses make implicit assumptions concerning future cash flow scenarios and assume management's passive commitment to an investment strategy where a firm starts and completes a project without any contingencies (Trigeorgis, 1996). In reality an investment may become less risky into the future, interest rates may change, or the projected cash flows may differ from those initially forecast. These factors may have significant impacts on investment decisions (Trigeorgis, 1993). For the majority of capital budgeting decisions that rarely go beyond twenty five years, this may not pose such a significant problem (Pindyck, 2007). However, many land use investments, particularly involving forestry, have significant time horizons over which decisions may be undertaken and benefits accrued (Ross, 1995; Van Der Werf and Peterson, 2009). A long time horizon exacerbates the uncertainty over an investment's costs and benefits (Pindyck, 2007). While firms sometimes find it wise to invest early, for example to pre-empt investment by competitors, generally, the cost of immediate investment must be weighed against the benefits of waiting for new information that will resolve or lessen uncertainties (Pindyck, 1991). The inability of NPV to consider an investors' ability to wait for new information poses challenges for DCF use in environmental decisions with long time horizons.

A further critique of NPV is that it doesn't account well for risk when investments are not easily reversible and expenditures cannot be fully recovered should market conditions deteriorate (Ross, 1995). Yet, many investments in land management are not easily, cheaply or quickly reversible. Related plant and equipment are subject to considerable depreciation and resale values are often well below purchase costs (Pindyck, 1991). To compensate for risk and uncertainty, a risk premium can be added to the discount rate for all future cash flows thereby creating a hurdle rate that the investment return must exceed in order to be considered. However, risk-adjusted hurdle rates can be a blunt instrument which do not always adequately account for risk. In highly uncertain environments, hurdle rates have been seen to be three or four times the cost of capital (Dixit, 1992), resulting in investment inertia (the reluctance to invest) becoming the optimal investment strategy (Ross, 1995). To overcome inertia, excessively large project cash flows are required (Ross, 1995) which can lead to underinvestment and compromise a firms competitiveness (Baker and English, 2011).

As a result of these limitations, DCF and NPV calculations have often failed to explain actual landholder investment responses, often despite favourable NPV valuations (Musshoff, 2012). While NPV is a good starting point to analyse the feasibility of investments in land use, where there is uncertainty over future cash flows, long investment horizons and investment is irreversible, the NPV rule systematically undervalues the benefits of waiting (Kemna, 1993). New methods such as real options analysis can better capture the value of flexibility and the opportunity to update decisions with new information and consequently may provide better models of investment behaviour.

3.3 Real Options Analysis

3.3.1 Concepts

The concept of ROA derives from markets for financial options (Borison, 2005; Mun, 2006b). Financial options in commodity markets are derivative securities that take their value from other financial securities known as the *underlying asset*. In brief, an option provides the right, but not the obligation, to buy (*call* option) or sell (*put* option) an underlying asset at a fixed price by a certain specified time in the future (Chance and Brooks, 2009). There are two primary option exercise styles, European and American. European style options can be exercised on the expiration day only, while American style options can be exercised at any time before or on the expiration day (Chance and Brooks, 2009). Myers (1977) first proposed an analogy between financial options and a firm's real world capital budgeting decisions. He viewed an investment decision as a *real option* where the gross projected value of expected cash flows can be considered the underlying asset, the investment needed to obtain the underlying asset is the exercise (*trigger* or *strike*) price and the period over which the decision maker can defer investment can be considered the time to maturity.

Increasingly, real world capital budgeting decisions are evaluated as a set of options that unfold over time. Managers alter their operating strategy as new information becomes available and uncertainty about market conditions and future cash flows is gradually resolved. When a firm invests it gives up the option to make an alternative investment and incurs the opportunity cost associated with losing the option for investment elsewhere. Unlike traditional, static DCF approaches, the real options approach considers a series of decision points over an investment horizon (Miller and Waller, 2003). At each decision point the investor considers whether to invest, or to defer and maintain the option to invest later. Investments must not only have a positive NPV, but the expected returns from investing now must also exceed returns expected by deferring investment (Dixit and Pindyck, 1995). Multiple industries have used ROA to value potential investments. These investments are often expensive, long term, affected by multiple risks (market, political, regulatory, societal), and involve irreversible costs (Chvalkovská and Hrubý, 2010). Figure 3.1 shows the simplified boundaries of applicability for NPV and ROA.

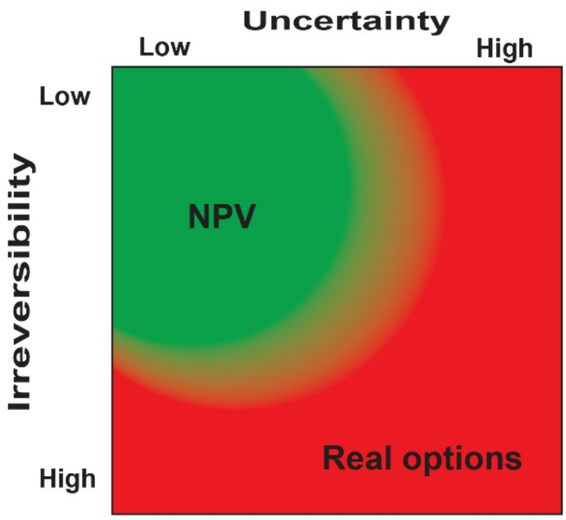

Figure 3.1– Boundaries of applicability for NPV and ROA adapted from Adner and Levinthal (2004) .

The essence of ROA, when compared to DCF, is that the investment triggers—which define the critical levels of revenue at which an investor finds it optimal to enter or abandon an investment—will be shifted upwards (downwards) if the investment involves inter-temporal opportunity costs (Musshoff, 2012; Seyoum and Chan, 2012).

Many investment decisions can potentially be regarded as real options, these are outlined in Table 3.1.

Table 3.1 – Summary of common options analysed in ROA (Antikarov and Copeland, 2001; Duku-Kaakyire and Nanang, 2004; Trigeorgis, 1996; Trigeorgis and Mason, 1987):

Waiting options	Where waiting to invest allows for uncertainty to be better resolved.
Growth options	Where a project can be phased in two or more steps and the initial investment provides a growth option that can be fully realised by subsequent investments.
Switching options	Where initial project design incorporates the ability to dynamically switch among different markets, technologies and products depending on market conditions.
Initiation options	Where there is flexibility as to when to start a project (call option).
Abandonment options	Where there is an option to cease a project during its life, and potentially realise its salvage value (Put option).

A major benefit to users of ROA lies in refocusing risk management away from simply avoiding negative outcomes towards actively pursuing and exploiting positive aspects of uncertainty (Nelson et al., 2013; Neufville, 2003). Rather than treating risk as something to be avoided, real options thinking encourages managers to focus less on the most-likely scenario and more on the distribution of possible outcomes (Triantis, 2005). Volatility can become a source of value and incorporating the flexibility to respond to volatility into project design allows upside potential of investments to be capitalized upon, more so than an investment strategy based on the most likely scenario (Triantis, 2005).

3.3.2 Methods

There are three main methods used for calculating option values: partial differential equations, simulation, and lattice methods (Mun, 2006b), and these are introduced below.

Partial differential equations

Partial differential equations are a continuous time, analytical, mathematical approach to valuing real options—the most well-known being the Black-Scholes-Merton model (Dixit and Pindyck, 1994). Models of this type calculate options values by equating the change in option value with the change in the underlying asset's value and are based on a strict set of assumptions. First, that there are perfect markets. Second, that the future development of an asset's value be regarded as a random walk, allowing for the use of stochastic processes such as geometric Brownian motion (GBM) (Collan, 2011). Last, that the opportunity to invest is time continuous (Wolbert-Haverkamp and Musshoff, 2014a).

The Black-Scholes-Merton formula has several limitations. Originally designed for valuing financial derivatives, it was never intended to value complicated derivatives such as compound options (Copeland and Tufano, 2004). When applied to complex real option problems with multiple sources of uncertainty, simplifying assumptions are often needed. For example, the Black-Scholes-Merton model assumes volatility to be constant over the life of the option, the returns to the project are normally distributed and that the projects underlying value is log-normally distributed (Gilbert, 2004). While such simplifying assumptions may not significantly affect some valuations, they can lead to significantly distorted valuations and suboptimal investment decisions in many cases (Triantis, 2003).

The Black-Scholes-Merton model also assumes that options can be exercised only at their maturity date. Therefore, it is most useful for the valuation of European style options as the model requires a fixed decision date (Triantis, 2003; Trigeorgis, 1996). However, investment decisions related to land use change can often be regarded as an option which could be exercised at any time, akin to an American style option. In addition, many land use investment decisions are not time continuous as decisions relating to changing land use are often made once a year in conjunction with seasonal factors.

Further, and perhaps most significantly, the mathematics behind the Black-Scholes-Merton model and other partial differential equations are advanced. The models often lack transparency and it is therefore difficult to develop sound intuition of the methods (Triantis, 2003). This has often led to ROA appearing to be an uncertain *black-box* to managers (Luehrman, 1998).

Lattice-based methods

Lattice-based option valuation models are numerical, time discrete models that use simpler mathematics to ascertain the price variation of an asset and are regarded as the most intuitive, generic, and flexible way to value real options (Copeland and Tufano, 2004; Cox et al., 1979; Gilbert, 2004). Lattice models can value both European and American options, allow for changing levels in volatility and deal with more than one state variable (Gilbert, 2004). Typically lattice methods are binomial (two states) or trinomial (three states). However, quadrinomial lattices may be used for jump diffusion processes and pentanomial lattices for options with two combined and correlated underlying assets (Mun, 2006b).

The simplest presentation of a lattice model is a binomial model (Figure 3.2). The binomial process allows two possible evolutions for the underlying asset's value in each time step, up or down, with associated probabilities p and 1- p. The binomial process used for modelling the future value distribution results in a discontinuous, quasi log-normal distribution, that given enough time steps approaches the continuous distribution achieved through the Black-Scholes-Merton model using geometric Brownian motion (GBM) (Collan, 2011).

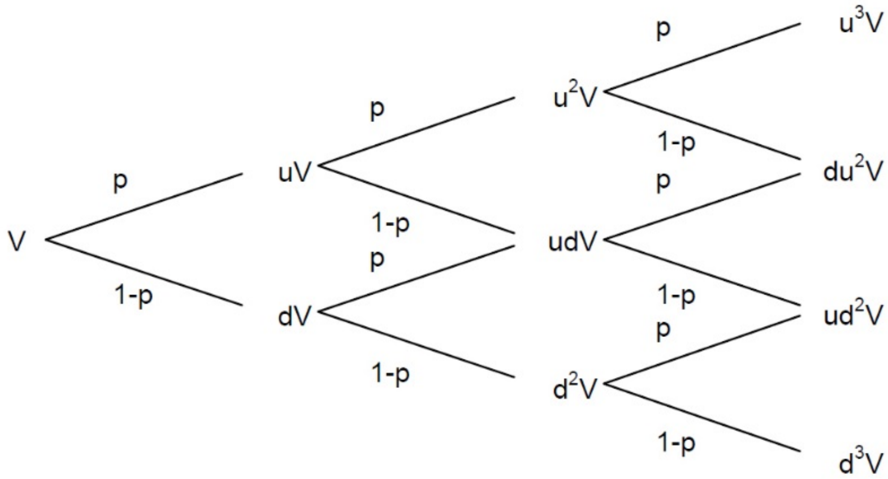

Figure 3.2 – The evolution of underlying asset value in a binomial lattice (Nelson et al., 2013).

Despite being more intuitive than continuous time models, lattice models suffer from the *curse of dimensionality* and can quickly grow burdensomely large as the number of time periods and sources of uncertainty increase (Gamba, 2003; Lander and Pinches, 1998). Many real world valuations require the modelling of three or more state variables making the use of lattices cumbersome (Broadie and Glasserman, 1997; Longstaff and Schwartz, 2001). This presents a challenge to real option problems in land use management which are typically characterised by multiple uncertainties and long time frames.

Simulation

Simulation methods for asset pricing were introduced to finance by Boyle (1977). The simulation approach calculates the option value by randomly simulating the thousands of possible future scenarios for uncertain variables, with the most common method used being Monte Carlo simulation (Mun, 2006a). Monte Carlo simulation draws upon similar valuation principles as other real option models. A number of values for underlying uncertainties are generated based on probability distributions adjusted for systematic risk (Triantis, 2003). Simulation methods have been applied to solve real options problems commonly by creating a distribution for the future value of an asset (Boyle, 1977). However, there are multiple possible roles for simulation in real options models including obtaining inputs for other models such as price volatility, discount rates, or gaining a range of possible discounted cash flow outcomes (Mun, 2006b).

The principal advantage that Monte Carlo simulation provides over the other valuation techniques is its ability to deal with multiple uncertainties, particularly if they have non-standard distributions, changing distributions, or are correlated (Triantis, 2003). Monte-Carlo simulation is particularly useful for problems that exhibit path dependency, where future decisions or outcomes depend on decisions made at earlier points in time (Longstaff and Schwartz, 2001; Triantis, 2003).

Until recently, the valuation of American style options with simulation was not possible (Triantis, 2003). However recent methods that incorporate a least squares method with simulation, allow for the valuation of real options which are both multidimensional and American styled (Broadie and Glasserman, 1997; Cortazar et al., 2008; Longstaff and Schwartz, 2001).

3.4 Application in land use and management

ROA has been widely used in forestry applications including optimal harvest and rotation (Gjolberg and Guttormsen, 2002; Insley, 2002; Plantinga, 1998; Saphores, 2001; Thorsen, 1999), processing capacity (Duku-Kaakyire and Nanang, 2004), and valuing forestry concessions (Rocha et al., 2006; Yap, 2004). In an agricultural context, ROA has been applied to organic farming (Irene and Konstadinos, 2009; Kuminoff and Wossink, 2010; Tanner Ehmke et al., 2004), adoption of precision agriculture (Tanner Ehmke et al., 2004; Tozer, 2009), expansion of agricultural enterprises (Hinrichs et al., 2008; Odening et al., 2005; Tozer and Stokes, 2009), the adoption of genetically modified crops (Nadolnyak et al., 2011) and adaptation to climate change (Hertzler, 2007). Fewer examples of environmental ROA applications exist, but have included investigating the option to develop wilderness areas (Arrow and Fisher, 1974; Chambers et al., 1994; Conrad, 2000; Conrad and Kotani, 2005) and preserve biodiversity (Kassar and Lasserre, 2004).

Real options theory asserts that the investment cash flows not only have to compensate for the investment costs but also the opportunity costs generated if the investment was postponed (Maart and Musshoff, 2011). The effect of the option value is to raise the threshold for a project to be undertaken due to greater uncertainty, thereby delaying investment relative to the NPV rule (Mason and Weeds, 2010). The impact of options values on investment thresholds can be substantial (Schatzki, 2003; Song et al., 2011). For example, Tozer (2009) found the rates of returns need to trigger investment in precision agriculture equipment in Western Australia were 96–156% higher than the NPV breakeven point.

In addition to investment decisions, real options analysis has been used to explain disinvestment decisions—particularly why firms continue in the face of persistent losses. Real options demonstrates that psychological inertia, resulting from sunk costs and uncertainty about future payoffs, creates a zone of inaction where the wisest response is to wait until more information is gathered (O'Brien and Folta, 2009). Owners may be willing to accept low levels of performance with the hope that conditions will improve (Gimeno et al., 1997). Traditional economic theory states that sunk costs are irrelevant to today's decisions and those that violate this rule are acting irrationally. However, ROA suggests that in the presence of significant sunk costs, it is rational to persist and endure some amount of losses if there is some possibility that profitability may improve (Dixit, 1989). This has been demonstrated to apply to farming enterprises and land use decisions. Where previous costs are at least partially sunk, the price at which a farmer will exit an industry can be far below the breakeven price (Song et al., 2011; Tauer, 2006). To illustrate, Seyoum and Chan (2012) used ROA to provide an explanation for the sluggish response of wine grape farmers to declining farm revenue. They found that when large sunk capital expenditures and revenue uncertainty were accounted for, the trigger price for exiting the industry moved downwards by as much as 32% when compared to NPV break even revenues.

Despite its potential insight, the complexity of ROA methods has meant that adoption has been sporadic, even in corporate settings (Woolley and Cannizzo, 2005). Much of the academic work using real options has focused on complex analytical techniques (Nelson et al., 2013; Neufville, 2003). However, for many users, the benefit of ROA lies not in the precise value of options, but in refocussing investment decisions away from purely negating losses to exploiting the opportunities uncertainty can provide (Triantis, 2005). For environmental policy makers, the wider use of ROA could be a basis to better understand adaptive landholder decision making under uncertainty.

3.4.1 Challenges in real options modelling of land use change

While ROA can provide useful analyses of land use change decision making processes, the modelling of real options problems becomes increasingly complex as additional sources of uncertainty are considered, particularly with partial differential equations and lattice-based methods. As the models become more complex there is a risk that ROA will move beyond the comprehension of policy makers and investors and will be considered a *black box*. This factor has been seen to hamper the uptake of ROA in corporate capital budgeting problems (Rocha et al., 2001; Saphores, 2001) and confined it to extractive natural resource industries and companies with sophisticated analytical tools (Nelson et al., 2013). Several authors have questioned the need for complex analytical methods to precisely estimate the value of options, instead advocating for more accessible heuristics that rank alternatives (Eapen, 2002; Nelson et al., 2013; Neufville, 2003). These authors argue simpler, more intuitive methods, such as decision trees, are needed so that uncertainty and flexibility can be more readily incorporated in to economic evaluations of alternative land uses.

Indeed, simpler methods such as decision trees provide a flexible and powerful approach for dealing with risk. They provide a way to measure risk exposure and allow managers to assess how they will react to both adverse and positive outcomes. However, decision trees are most effective assessing sequential and discrete risks compounding over time. Risk is addressed in phases and the risk in each phase is captured in the possible outcomes and the probabilities those outcomes will occur (Schuyler, 2001). As a result, decision trees are well suited to assess strategic investment problems from the perspective of an individual firm or landholder over the medium term. However, many risks that are faced in the real world are not discrete or sequential but are continuously present and act concurrently. In addition, and as discussed above, simpler methods also suffer from the curse of dimensionality, making the modelling of decisions with long investment horizons cumbersome, resulting in decision trees that are unwieldy and complex, thereby losing the intuitive appeal of the method. For Investment decisions that involve continuous, simultaneous risks and/or have long investment time horizons, simulation methods may be more appropriate (Gamba, 2003; Longstaff and Schwartz, 2001).

Monte Carlo simulation methods for numerical valuation of real options, despite being more complex, have many inherent advantages including ease of accounting for more than one source of uncertainty, non-standard payoff structures, different probability distributions and excel where multiple risks occur simultaneously, (Longstaff and Schwartz, 2001; Schuyler, 2001). Although other methods are able to generate solutions to investment problems with one or two sources of uncertainty and could be used to generate a numerical solution to a simplified land use change problem, realistic models of real world investments often require three or more state variables be modelled (Broadie and Glasserman, 1997). The advantages of simulation-based ROA models become evident as complexity is added to a decision problem. For instance, in the example below, wheat prices are treated as deterministic, however it is unrealistic to assume the associated returns, yields and cost of wheat production are deterministic. The inclusion of these factors as stochastic variables can be easily and quickly accommodated in a simulation model. Lattice and decision tree methods could conceivably be used to assess a more complex land use change problem with the use of methods such as multidimensional interpolation (Kargin, 2005). However, model complexity and computational costs grow exponentially with the number of state variables considered (Broadie and Glasserman, 1997).

3.4.2 Unrealised opportunity: ROA simulation for policy

Our contention is that the decision tree approach can be particularly useful for individual firms for understanding staged decision making, for developing strategic contingency planning on how to proceed and alter decisions as time and initially uncertain conditions evolve. However, to inform policy where more aggregate and longer term outcomes of individual decisions are of interest, simulation approaches are likely to be more computationally feasible and informative, primarily because they offer the opportunity to understand the implications of multiple uncertainties and long decision time frames. ROA simulation approaches are now feasible to evaluate some core environmental land use policy questions such as realistic estimation of carbon sequestration supply from the reforestation of agricultural land or assessment of the cost of supplying feedstock to bio-energy plants and implications for plant viability. Such issues are now commonly evaluated with NPV analysis and this approach provides distorted estimates of land conversion thresholds and consequently policy advice about supply and economic viability. Below we illustrate with a small, stylised example, how accounting for multiple sources of uncertainty can lead to differing conclusions about the cost of supplying bio-energy feed stocks. In the conclusion, we discuss how it would be possible to expand this analysis to understand how varying biophysical production risk profiles of current agricultural and tree feedstock options change threshold prices for conversion.

3.5 A case study

In order to demonstrate the insight that simulation based real options models can provide, we used a ROA simulation method to analyse how accounting for multiple sources of risk influenced the threshold prices necessary to induce land use change from agriculture to bio-energy feedstock in southern Australia. We conclude with discussion of how ROA simulation could be expanded to understand comparative advantage in bioenergy feedstock production across multiple regions given differing biophysical production profiles and how realistic ROA based bio-energy production feasibility accounting, for a range of price or climate variability futures, could be implemented.

3.5.1 Decision Scenario

In this example, we consider a farmer's decision to either grow wheat or a coppicing tree crop harvested for biomass for electricity generation (BEC) according to discounted cash flow investment rules (NPV) and real options analysis. We assume the farmer is located in the Mallee district of South Australia. This area is characterised by low rainfall (<300mm per year) and calcareous earth soils (Griffin et al., 1986), with winter cereal production and extensive livestock grazing being the dominant agricultural land uses (Bryan et al., 2009). If the farmer switches land use he is obliged to continue growing BEC for the useful lifetime of the plantation. After this time the farmer can either re-invest and continue growing BEC or return the land to wheat production. Following Wolbert-Haverkamp and Musshoff (2014a), we assume an infinite time horizon under consideration as the farmer has the option to cultivate BEC multiple times.

3.5.2 Data and model assumptions

In order to compare the two land uses, gross margins (GM) for both enterprises (revenue – costs) were calculated. The costs associated with the cultivation of annual wheat production in South Australia were obtained from State Department of Agriculture gross margin guides (Rural Solutions SA, 2013) and average yields for the Mallee district were calculated from State Department of Agriculture crop and pasture reports 2002-2013 (PIRSA, 2014). Inflation adjusted historical wheat prices from 1970 to 2014 (The World Bank, 2014) were used to forecast the annual wheat GM in the stochastic wheat price model.

3.5.3 Biomass energy price

There currently exists no time series data for long term biomass prices for electricity generation in Australia. The prices for biomass in our example are derived from historical coal prices, as coal is the major source of fuel for electricity generation in Australia (Rodriguez et al., 2011). This process is explained in greater detail in appendix A. The model parameters can be seen in Table 2.

For the purposes of this model, the yields and variable costs associated with wheat and BEC were assumed to be deterministic. In the initial model, the gross margins received for wheat were also assumed to be deterministic. We evaluated scenarios with a fixed wheat GM, a scenario with both wheat GM and BEC GM treated stochastically to demonstrate the effects of deterministic versus single and multiple uncertainty source modelling.

According to the NPV model, the decision to change land use from wheat to BEC is a *now or never* decision. The NPV of future returns was calculated using the expected GM of wheat (AU$ 278 ha^{-1}) and the average GM of BEC (Wolbert-Haverkamp and Musshoff, 2014b). We then calculated the trigger GM of BEC that a farmer would need to earn in order to switch from wheat production. This threshold value is usually considered to be the price at which NPV equals zero for a discount rate that represents the cost of borrowing (Luehrman, 1998).

In contrast, the real options model uses stochastic processes to model the future development of the gross margin of BEC. The model parameters can be seen in Table 3.2.

Table 3.2 – Model Parameters[1] (Applicable to both the NPV model and real options model)

Model Parameters	
Investment cost BEC	1334 AU$ ha^{-1}
useful lifetime BEC rotation	20 years
Annual yield BEC	7.5 green tonnes ha^{-1}
Variable costs BEC	159.75 AU$ ha^{-1}
Recultivation costs BEC	1200 AU$ ha^{-1}
Mean BEC GM	244 AU$ ha^{-1}
Annual yield wheat	1.2 tonnes ha^{-1}
Variable costs wheat	200 AU$ ha^{-1}
Expected wheat GM	278 AU$ ha^{-1}
Time period considered for conversion	∞ (with annual conversion opportunity)
Stochastic process (wheat and BEC)	arithmetic Brownian motion (ABM)
Discount rate	5.41%
Simulation iterations	50,000

***1** In variant calculations, several deterministic expected wheat GM were tested ranging from AU$178ha^{-1} to AU$478ha^{-1} These results can be found in the technical appendix. Where expected wheat GM was treated as stochastic, their evolution was modelled using an ABM process, as is BEC GM. The yields of wheat and BEC are assumed deterministic.*

3.5.4 Results and Discussion

The results show that temporal flexibility and price uncertainty has an impact on the price at which a landholder should consider switching land use from wheat to BEC. A farmer investing as per the NPV rule would convert production from wheat to BEC when the GM of BEC was equal to or higher than approximately AU$420 ha^{-1} (Table 3.3). At this price the investment costs and the opportunity cost for the lost revenue of wheat is met, making BEC at least as profitable an enterprise as wheat. In contrast, a farmer investing according to the ROA assuming a stochastic BEC GM and an expected wheat GM of AU$278ha^{-1}, should not invest in a biomass crop for electricity generation until the GM of BEC is equal to or above approximately AU$600 ha^{-1}(Table 3.3).

Under stochastic wheat and BEC gross margins the prices needed to induce land use change is approximately AU$500 ha^{-1} (Table 3.3). This is significantly higher than the trigger value returned under the deterministic wheat GM of AU$ 278 ha^{-1} but not as high as the trigger price when only BEC price variability is considered. Considering uncertainty in wheat prices by adding stochastic wheat returns, introduces risk to the returns of both enterprises. This investment formulation is more realistic as the possibility of zero or negative returns associated with the production of wheat is introduced. The increased uncertainty lowers the investment trigger needed to induce land use change. The ability to capture the variability in multiple uncertainties in land use can significantly affect results and can add rigor to the results generated by ROA. While not addressed in this example, there is considerable scope to use simulation methods to model costs, yields and climate uncertainty as stochastic variables in order to increase the validity and applicability of simulation based models. However, caution needs to be taken as results depend significantly on the type of process underlying the valuation (Musshoff, 2012).The results indicate that forecasts solely based upon NPV valuations could lead to unrealistic estimates of land use change and potentially significantly underestimate the associated costs especially if levels of uncertainty are high.

While our example is theoretical, ROA has been shown empirically (Hinrichs et al., 2008; Isik and Yang, 2004; Schatzki, 2003; Seyoum and Chan, 2012) to have explanatory value, distinct from other behavioural factors (risk aversion, personal preference), for the often observed reluctance of landholders to invest/disinvest in alternative agricultural enterprises and land uses (Musshoff, 2012). The approach should be considered alongside other behavioural factors when considering initiatives, policies or programs that will rely upon or promote land use change. The implications of ROA for land use policy are discussed below.

Table 3.3 – Trigger GMs for conversion of land from wheat production using NPV and ROA

	Expected GM wheat (AU$ ha^{-1})	
	Fixed GM_W (278 AU$ ha^{-1})	Stochastic GM_W
NPV(AU$ ha^{-1})	420	420
ROA(AU$ ha^{-1})	600	500
Difference between NPV and ROA (AU$ ha^{-1})	180	80

3.6 Implications for land use policy

Globally, governments are using public policies to improve environmental outcomes such as greenhouse gas emissions abatement or habitat preservation (Bryan and Crossman, 2013). In an Australian context, several studies that have determined the economic viability of forestry under varying carbon price scenarios (Burns et al., 2011; Crossman et al., 2011; Lawson et al.; Polglase et al., 2008b; Polglase et al., 2011; Polglase et al., 2013). DCF analysis used in these studies indicates significant potential for carbon markets to spur profitable carbon bio-sequestration and drive biodiversity outcomes from the reforestation of agricultural lands. However, carbon forestry offset projects will invariably involve significant upfront costs, incrementally generate revenue over decades, are particularly susceptible to regulatory changes and due to these risks, may not be an attractive investment, despite a positive NPV (Polglase et al., 2011; Polglase et al., 2013).

Evidence provided by land use change studies using ROA show that landholders (dis)invest later than traditional capital budgeting models would predict (Ihli et al., 2013; Wolbert-Haverkamp and Musshoff, 2014a). This has important implications for agri-environment schemes that rely on price or quantity based mechanisms to drive change. These studies imply that under conditions of uncertainty and irreversibility, the rates of subsidy which are required to encourage land use change are likely to be significantly higher than those indicated by NPV analysis and land holders may participate later and at higher prices than anticipated. Furthermore, ROA indicates that not only is payment level important but payment time frame has implications for the effectiveness of subsidies. Tubetov et al. (2012) demonstrated the effect of subsidies can be improved if the payment scheme is time limited. The opportunity cost is reduced over time as the scheme's termination date nears and the decision is moved closer to a now or never proposition (as per the NPV rule), thereby lowering the investment trigger. ROA can guide policy makers on the level of incentive required and with incentive policy structure.

For land managers, the consideration of variability in biophysical land attributes appears intuitive. While studies using NPV methods have addressed spatial heterogeneity to understand the distribution of *cost-effective* land use change (Bateman, 2009; Bryan et al., 2008a; Crossman et al., 2011; Polglase et al., 2008a), the underlying landscape heterogeneity has been largely overlooked in ROA applied to land use change to date though they are likely to result in different uncertainties and thus conversion trigger prices across space. The diverse pattern of land resources and heterogeneity in many of the factors underpinning land use decisions requires that spatial complexity be incorporated into economic valuations (Bateman, 2009). While this may present computational challenges, there is scope for the incorporation of spatial data in to real options models through the application of high-performance computing (Bryan, 2013a). The consideration of spatial variability can reveal spatial patterns important for individual land holders, investors and policy makers alike. ROA applied at the appropriate spatial scale (at regional level for example) can provide more robust guidance for investment and supporting policy development. For instance, better understanding how comparative advantage in bioenergy feedstock production across multiple regions will affect the location and viability of bioenergy processing. Improved understanding of what potential trade-offs with agriculture are likely could influence community support for alternative industries. While incorporating potential climate futures can aid the understanding of the impact climate change may have on the biophysical processes that drive industry viability. Simulation based models provide the opportunity to incorporate spatial variables, at different scales, into ROA, an objective difficult to achieve with simpler, heuristic real options models.

3.7 Conclusion

DCF methods have been widely used to value alternative land uses. DCF methods provide a static analysis that assumes investments are *now or never* propositions, are reversible, and management remains passive throughout the investment's life. In reality, many investments can be seen as a series of strategic options that unfold over time. Managers often have flexibility in when and how investments are made, and under uncertainty this flexibility can have substantial value. Decisions in land use and management are characterised by multiple uncertainties and irreversibility, and involve sunk costs. Real options analysis can incorporate these factors into the evaluation of land use and management decisions. ROA has revealed that in the presence of uncertainty, landholders intuitively value flexibility and often (dis)invest later than suggested by DCF methods. When considering option values, rates of return for investing in a new land use need to be substantially higher than suggested by NPV calculations. This effect is magnified with greater levels of sunk costs, irreversibility, and uncertainty and has consequences for policy evaluation. Payment schemes or structural adjustment policies can be significantly under-priced when option values are not considered. Recognising the role of option values in landholder decisions is important for designing policies to meet environmental objectives and in understanding the true cost associated with motivating change in land use and management practice. Despite its insight, the complexity of ROA has meant that adoption has been sporadic, even in corporate settings. Although simpler heuristic methods do exist, and provide insight, their application is limited to problems with fewer sources of uncertainty and where risk is addressed sequentially in phases. For addressing more complex investment problems, new simulation approaches have emerged that are flexible, can consider multiple uncertainties, and are much simpler than earlier methods. Spatial applications of ROA can now be explored given that computational barriers can be overcome through the use of high-performance computing techniques. Improved understanding of the interactions between landscape heterogeneity and option values will better inform policy makers' understanding of the location, timing and extent of future land use investments. ROA offers significant, largely untapped potential for assessing land use and management decisions.

Acknowledgements

This work was made possible by the Charles John Everard Scholarship awarded through the University of Adelaide and the support of CSIROs Sustainable Agriculture Flagship. The authors would like to thank Dr. Tim Capon and Dr. Andrew Reeson for their suggestions on improving this manuscript.

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CHAPTER FOUR

Spatial real options analysis: informing better incentive policy for motivating biomass agroforestry in agricultural land

The work contained in this chapter has been submitted as a research article to *Land Use Policy*

STATEMENT OF AUTHORSHIP

Regan, C.M., Connor, J.D., Bryan, B.A., Meyer, W.S., Ostendorf, B., 2016. Spatial real options analysis: informing better incentive policy for motivating biomass agroforestry in agricultural land. Land Use Policy. Submitted, manuscript ID LUP_2016_139.

Author contributions: By signing the statement of authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

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4 CHAPTER FOUR

In Chapter Three the potential for Monte Carlo based simulation methods to be applied to land use change decisions was demonstrated. Like other real options analyses of land use change, the stylised example in Chapter Three used deterministic (static) yield parameters. However, in reality a significant source of uncertainty in agricultural land use investment decisions is commodity yields. A significant contributing factor to yield uncertainty is the underlying biophysical factors affecting production. Significant spatial variability exists in biophysical determinants of production at a regional level, however if and how yield and price uncertainties interact has not been widely examined in the real options literature. Given price uncertainty effects all locations in a region equally, do underlying geographical differences in biophysical determinants of production effect the returns required to invest in a new land use over and above those calculated by discounted cash flow homogeneously? Or will the effect of interacting uncertainties in some locations be more pronounced than others? This chapter incorporates multiple uncertainties across several locations in an agricultural region of south eastern Australia in order to understand the effect of interacting uncertainties. Uncertainty has been seen to create a risk premium and often increases the returns required to induce investment. This chapter also examines the role supplementary payments (subsidies or payments for environmental services) can play in reducing the risk hurdles created by price uncertainty and examines if these subsidies act homogenously across the study region.

Abstract

Biomass production for use in electricity generation has been promoted as having broad environmental benefits as well as providing a valuable diversification option for landholders. However, landholders often display considerable reluctance to convert land use away from conventional agriculture, despite indications of profitability according to discounted cash flow analysis (DCF). One reason may be DCF models largely neglect the effects of major uncertainties of price, yield and policy on landholder decision making. To examine the effects of such interacting uncertainties we use a simulation-based real options model. Our focus is on the effects of spatially varying risk across climatically diverse regions of southern Australia, and on payment policies that include alternative treatments of risk. Our results indicate that real options analysis provides valuable insight into how the premium required to motivate land use change differs with spatially-varying risks. Furthermore, we demonstrate how incentive policies that reduce risk can reduce the returns required to trigger land use change, and where the magnitude of these effects may be most and least pronounced. The results from real options suggest potential to design lower cost spatially-targeted policies and incentive structures through more realistic accounting of landholder risks.

4.1 Introduction

Biomass production for use in electricity generation (hereafter simply biomass) is proposed as a way to mitigate the effects of climate change through both direct CO_2 sequestration and carbon emissions abatement through the replacement of higher CO_2 emitting fuels such as coal and oil (Bryan et al., 2008b; Evans et al., 2010; Styles and Jones, 2007). In combination with new technologies such as carbon-capture-and-storage in power plants, the use of biomass has been suggested as a viable way of achieving negative emissions (Azar et al., 2013; Obersteiner et al., 2001; Obersteiner et al., 2002). Economically, biomass production has been found to be potentially competitive with conventional agriculture (Bryan et al., 2010c; Heaton et al., 1999; Styles et al., 2008) as the yields associated with production of woody perennials are often less sensitive to climatic variables, require fewer inputs, and may provide an important diversification option for farmers (Coleman and Stanturf, 2006; Musshoff, 2012). Despite this, landholders have been slow in switching land use, particularly between agriculture and forested use, despite potential profitability (Plantinga, 1996; Schatzki, 2003; Stavins and Jaffe, 1990). Governments have historically offered landholders incentives to motivate land use change (Bryan, 2013b; Yang et al., 2010), and subsidies to landholders have been critical in accelerating investment in biomass(Di Corato et al., 2013). The structure and timing of incentive payment schemes have affected both the land use change decisions of landholders, and the cost to industry or governments instituting the incentive policy (Wolbert-Haverkamp and Musshoff, 2014a).

The long term nature of an investment in perennial biomass crops necessitates capital budgeting techniques such as discounted cash flow analysis (DCF) to be used to evaluate such investments (Bryan et al., 2010d; Bryan et al., 2008b). From a DCF perspective, a profit-maximising landholder should invest in the land use that returns the highest net present value (NPV) (Musshoff, 2012). NPV assumes that the investment is reversible and expenditures can be recovered should market conditions deteriorate. It also assumes that investment is a *now or never* proposition and the investment opportunity instantly disappears if not immediately taken (Dixit and Pindyck, 1995). There are three characteristics that can reduce the suitability of NPV for evaluating such long term land use change decisions. First, an investment in biomass will involve substantial upfront costs that are at least partially, if not completely, sunk, and cannot be recouped if the investment proves unprofitable. Second, investments are rarely now or never propositions. Landholders often have significant flexibility in the timing of any land use investment, and this flexibility has value. Third, there is significant uncertainty over future returns (Trigeorgis, 1996). Variation and volatility in commodity prices can differ significantly between crops and this affects the risk profiles of alternative crops, invalidating the assumption that evaluation of investments made on average prices can provide an accurate basis for analysis (Reeson et al., 2015). For these reasons DCF is limited for evaluating future landholder investment behaviour (Wolbert-Haverkamp and Musshoff, 2014a).

Real options analysis (ROA) has been proposed as a better model under uncertainty and flexibility exists to delay investment (Dixit and Pindyck, 1994). When compared with NPV, the returns required to induce an investment (or *trigger*) have been found to be higher under ROA (Schatzki, 2003). This is because ROA can consider opportunity costs over time in terms of the value of waiting to invest (Wolbert-Haverkamp and Musshoff, 2014a). Conventional dry land agricultural systems, comprising annual crops and livestock, provide landholders with some flexibility to respond to the uncertainties associated with farming enterprises. These uncertainties include future commodity prices, climatic conditions, input prices and other agronomic factors such as pest and disease effects. Long term land uses such as biomass can notionally represent a significant loss of flexibility for landholders. In combination with uncertainty over alternative crop performance and future revenue (often only accrued many years into the future), this has been seen to cause investment inertia (Musshoff, 2012). As such, prices required to induce land use change to biomass not only need to compensate the landholder for the costs of establishing a plantation and the foregone returns from agriculture, but also for lost management flexibility and the uncertainty of returns from the new enterprise (Reeson et al., 2015).

Key uncertainties influencing ROA outcome exhibit significant geographic variation (Dumortier, 2013; Yemshanov et al., 2015). Crop productivity varies spatially due to a combination of factors including variability in rainfall, temperature and soil types (Bryan et al., 2014). Research using conventional economic analysis has incorporated spatial heterogeneity to understand the distribution of *cost-effective* land use change (Bateman, 2009; Bryan et al., 2008a; Crossman et al., 2011; Polglase et al., 2008a) and have found that underlying landscape heterogeneity can influence the timing and location of land use change. While these factors have been largely overlooked in ROA applied to land use change to date, the limited inclusion of spatial factors in ROA has resulted in differing conversion threshold prices and conversion probabilities across space (Dumortier, 2013; Sanderson et al., 2016; Yemshanov et al., 2015). While geographical differences in primary productivity are beginning to receive attention in ROA, temporal variability in primary productivity has received less attention. Climate variability is the principal source of risk affecting long term economic viability of rain-fed agricultural systems (Kandulu et al., 2012) and primary production is not only sensitive to annual changes but also to seasonal distribution of rainfall (Iglesias and Quiroga, 2007). ROA studies to date, even those addressing spatial variability, have used invariant yield data (Musshoff, 2012; Reeson et al., 2015; Wolbert-Haverkamp and Musshoff, 2014a), or have accounted for production variability in stochastic processes modelling returns to agriculture (Isik and Yang, 2004; Sanderson et al., 2016).

We address this firstly by considering yield as a random, variable source of risk and secondly, accounting for yield risk using geographically specific distributions.

Governments have historically offered landholders incentives to motivate land use change, with varying success (Moon and Cocklin, 2011). The implementation of incentive programs can themselves introduce further uncertainty and landholders cite uncertainty over government policies as a barrier to involvement in agri-environmental programs (Baumber et al., 2011; Bennett and Cattle, 2014; Herbohn et al., 2005; Isik and Yang, 2004; Lockie and Rockloff, 2004). Additionally, the structure of incentive payment schemes can influence land use change decisions (Wolbert-Haverkamp and Musshoff, 2014a). Ridier (2012) reported landholders prefer annual incentive payments, however if annual payments are perceived as uncertain, landholders are more likely to change land use (from agriculture to short rotation woody crops) if an up-front investment cost subsidy is offered. Previous work has shown the impact of financial incentives on ecosystem service provision, through their effect on land use profitability—a key driver of land use change – is spatially heterogeneous (Bryan, 2013b). It is therefore conceivable that the effect of incentive payment uncertainty on land use change also varies spatially. Few ROA studies included the interaction between incentive payment uncertainty, geographically varying primary production risk and price risk on threshold prices required to encourage land use change.

The aim of this study is to go beyond the consideration of commodity price uncertainty to include the simultaneously interacting effects of commodity price uncertainty, production yield variability, and landholder investment flexibility on the returns to biomass required to induce land use conversion in five climatically distinct locations in southern Australia. We evaluated the potential for alternate incentive policy (payments for below-ground carbon sequestration) to reduce uncertainty and lower the returns to biomass required to induce land use conversion. We analysed several scenarios that use incentive payments to reduce risk to landholders and reduce returns needed to see land use change to biomass and examined the spatially varying effects of incentive payments. Finally, we discuss the implications of our results for policy makers wanting to encourage biomass or other industries that rely on land use change away from conventional agriculture under uncertainty.

4.2 Methods

4.2.1 Study Area

Figure 4.1 – Location of lower Murray-Darling Basin study area.

This study focuses on the Lower Murray region in southern Australia. We compared five climatically distinct locations in the study area that are representative of the climatic variation found throughout the region (Figure 4.1). The region is climatically diverse, ranging from semi-arid in the north west to temperate in the south east (Bryan et al., 2010c). Annual rainfall across the region varies greatly (Table 4.1). Rain-fed mixed farming, consisting of the dryland winter cropping of cereals (wheat, barley, oats), pulses (beans, lupins, peas), oilseeds (canola) and extensive grazing of sheep (Bryan et al., 2011). The average farm size in the region is approximately 1000 ha (Kandulu et al., 2012).

Table 4.1 – Historical growing season and annual rainfall for the study location.

	Historical mean growing season rainfall (mm/year)	Standard deviation (mm)	Historical mean annual rainfall (mm/year)	Standard deviation (mm)
Florieton	103	61	239	88
SA Murray Mallee	125	68	278	91
Manangatang	144	68	314	102
Natimuk	249	83	436	97
Wimmera	358	101	566	118

4.2.2 Biomass production in Australia

The growth of deep rooted perennial vegetation for electricity production or integrated tree processing is still novel in Australian agricultural landscapes. In Western Australia considerable work has been done to include perennial vegetation, commonly in the form of mallee Eucalypts, to farming systems primarily to address dry land salinity due to deep drainage issues (Bartle et al., 2007; Wu et al., 2007). Significant work has been conducted in identifying suitable plant species able to improve natural resource management outcomes, while providing profitable alternative enterprises to land holders (Bennell et al., 2009; Hobbs et al., 2009; Hobbs, 2009b) and primarily include Acacia and mallee Eucalyptus species.

In a coppice system, once harvested, the cut stumps re-sprout to provide a subsequent crop. Estimates surrounding the productive lifetime of a eucalyptus stand used for short rotation coppice vary, but include estimates of approximately 20 – 21 years (Gabrielle et al., 2013; Hobbs, 2009a) . We use a useful stand lifetime of 21 years consistent with the literature and expert consultation.

The development of a large scale biomass industry in Australia has been suggested as a resilient diversification option for agricultural landscapes. Integrated tree processing is seen as a promising development for mallee based industries in Australia as it offers a number of commercial opportunities including renewable energy generation, and co-products of oil and activated carbon (Enecon, 2001). Australia’s biomass industry is underdeveloped and large scale land use change is unlikely given missing markets for biomass. However, in this study we assume a more developed biomass industry for the purpose of examining the effect of yield, price and climate risks have on the returns required to trigger land use change over and above those calculated using traditional valuations methods (NPV).

4.2.3 Modelling of biomass and wheat yields

Biomass productivity for all sites was modelled using the *Carbon Sequestration from Revegetation Estimator* (Hobbs et al., 2013). The model was derived from local climate and soils data and empirical measurements of biomass accumulation and hence carbon sequestration from reforestation in the agricultural regions of southern Australia. The model uses multiple linear regression and forward-stepwise regression techniques to identify the best predictors of productivity rates (Hobbs et al., 2013). Historical annual rainfall data from 1891 to 2005 for all locations was acquired from the SILO data base (Jeffrey et al., 2001), and used as inputs into the biomass model in order to calculate biomass yield (Table 4.2). Soil data was obtained from the Australian Soil Resource Information System (ASRIS).

Wheat is the most commonly cultivated crop in the study area (ABARES, 2013; Bryan et al., 2014) and was used to represent agricultural production. While the study area is characterised by mixed farming enterprises including livestock and a variety of crops (barley, oats, legumes, and oilseeds) diversification is primarily done for cultural reasons including disease and weed control in aid of increased wheat productivity (Kirkegaard et al., 1994; Kirkegaard et al., 2011). The inclusion of one crop to analogously represent agricultural production in a location has been previously used by Wolbert-Haverkamp and Musshoff (2014a) who used rye to represent agricultural production in Germany and Sanderson et al. (2016) who used wheat to represent dryland cropping regimes in South Australia.

Annual wheat yields from 1891 to 2005 for the study areas were modelled by Kandulu et al. (2012) using the Agricultural Production Systems Simulator (APSIM, Keating et al., 2003) based upon historical meteorological data (Table 4.2) obtained from the SILO database (Jeffrey et al., 2001). APSIM is a process based yield model and has been widely used and validated for Australia (Luo et al., 2005a; Luo et al., 2007; Luo et al., 2005b; Wang et al., 2009a; Wang et al., 2009b).

Uncertainty associated with future biomass and wheat yields was accounted for by representing historical modelled yields with Project Evaluation and Review Techniques (PERT) distributions. The PERT distribution is characterised by its smoothness and continuity, and its greater weighting to the most likely values rather than to the tails (Benke and Pelizaro, 2010). PERT models have been used to analyse uncertainty in complex systems such as hydrology (Benke et al., 2008), land suitability analysis (Benke and Pelizaro, 2010), forecasting emissions from dairy farms (Benke et al., 2008), and to model uncertain grain yields (Dillen et al., 2010).

Yield data derived from the *Carbon Sequestration from Revegetation Estimator* (biomass) and APSIM (wheat) was used to specify the distributions (Table 4.2). PERT distributions are a special case of a scaled Beta distribution (Benke and Pelizaro, 2010) and are specified by assigning minimum, maximum, and most likely values ($x_{min}, x_{max}, x_{mode}$) to the probability function (Benke et al., 2008). The mean value can then be calculated as follows (as described by Benke et al. (2008));

$$x_{mean} = \frac{x_{min} + \lambda x_{mode} + x_{max}}{\lambda + 2} \tag{1}$$

Where λ is the scale parameter for the height of the distribution and has a default value λ = 4.

The mean value can then be used to calculate the shape parameters, v and w, which are used with the maximum and minimum scale parameters to sample the Beta distribution.

$$v = \frac{(x_{mean} - x_{min})(2x_{mode} - x_{min} - x_{max})}{(x_{mode} - x_{mean})(x_{max} - x_{min})} \tag{2}$$

$$w = \frac{v(x_{max} - x_{mean})}{(x_{mean} - x_{min})} \tag{3}$$

The beta distribution is characterised by the density function;

$$f(x) = \begin{cases} \dfrac{x^{v-1}(1-x)^{w-1}}{B_{(v,w)}}, & 0 \le x \le 1 \\ 0 & otherwise \end{cases} \tag{4}$$

And the distribution function:

$$f(x) = \begin{cases} \dfrac{B_{x(v,w)}}{B_{(v,w)}}, & 0 \le x \le 1 \\ 0 & otherwise \end{cases} \tag{5}$$

Most auditable accounting for carbon is done on above ground biomass, however there is an important below ground component that should be included. Over half of the assimilated carbon in agroforestry systems is eventually transported below ground via root growth and turnover, root exudates, and litter deposition, and therefore soils contain the major stock of carbon in the ecosystem (Montagnini and Nair, 2004). As such we examined policy scenarios where land holders received a payment for below ground carbon sequestration (the policy scenarios are outlined in section 4.2.8).

The modelling of below-ground carbon accumulation was done analogously to above-ground biomass productivity using the Carbon Sequestration from Revegetation Estimator (Hobbs et al., 2013). The below-ground carbon accumulation was not treated as a stochastic variable for reasons of computational tractability and parsimony. The mean modelled below-ground carbon accumulation (tCO_2-e/ha/year) from 1891 to 2005 was calculated for all locations and treated as a deterministic input (Table 4.2) into the ROA model in Scenarios 2 and 3.

Table 4.2 – Modelled biomass yields, below-ground carbon sequestration and wheat yields for each location 1891 to 2005.

	Florieton	SA Murray Mallee	Manangatang	Natimuk	Wimmera
Mean modelled biomass yield (DM t/ha/year)	1.51	2.41	2.85	5.10	10.00
Standard deviation (DM t/ha/year)	0.80	1.40	1.66	2.30	4.11
Standard deviation (%)	52.98	58.09	58.25	45.10	41.10
Mean modelled below-ground carbon sequestration (tCO_2-e /ha/year)	1.25	1.7	2.0	4.18	7.36
Mean APSIM modelled wheat yield (t/ha/year)	0.50	0.72	1.03	1.76	3.20
Standard deviation (t/ha/year)	0.55	0.66	0.66	0.79	0.88
Coefficient of Variation	110.29	91.02	63.54	45.00	27.36

4.2.4 Commodity price time-series

No long-term time-series data on the price of biomass in Australia exists. Coal is the most commonly used fuel source for electricity generation in Australia (Rodriguez et al., 2011). We used historical inflation-adjusted monthly coal price (Figure 4.3), 1970 – 2013 (The World Bank, 2014), as an analogue for biomass price in order to provide a time-series of the prices paid per gigajoule of energy used for electricity production. This process was adopted by Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014a) who used long term heating oil prices to provide equivalent biomass prices in Germany. The monthly coal price was divided by average gross calorific value of brown coal (23.8 GJ/dry weight tonne(CSIRO, 2006), and multiplied by the average gross calorific value of *Eucalyptus spp*. (19.4 GJ/dry weight tonne(CSIRO, 2006).

It is reasonable to expect that in the event of poor returns to biomass for electricity generation, landholders would consider alternative uses for the timber such as pulp wood or sawlogs. However, alternative uses for mallee species are not readily available. The current export chip wood industry is dominated by high-quality pulp species and mallee would not be suitable as very few of these species have proven, good-quality pulping characteristics (Bartle, 2009; Marcar, 2009) and do not grow to a size appropriate for sawlog production. Plantations are therefore assumed to be planted for the sole purpose of electricity generation.

The modelling of the development of future biomass and wheat prices was done using the Box and Jenkins (1976) linear time series model. Of these models, Auto-Regressive Integrated Moving Average (ARIMA), is the most general class of models for forecasting a time series (Iqbal et al., 2005). ARIMA models have been widely used in forecasting agricultural and other commodity prices (Bessler and Brandt, 1981; Brandt and Bessler, 1983; Contreras et al., 2003; Dooley and Lenihan, 2005; Pope et al., 1979; Shahwan and Odening, 2007). The order of an ARIMA model is denoted by ARIMA(*p,d,q*), where *p* is the order of the autoregressive component, *d* is the order of differencing which is conducted prior to calculation using the formula (Appendix B) and *q* is the order of the moving average process. The general form of an ARIMA(*p,d,q*) can be written as (following Enders, 1995):

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_p y_{t-p} + \epsilon_t + \beta_1 \epsilon_{t-1} + \cdots + \beta_q \epsilon_{t-q} \tag{6}$$

Where a are the autoregressive parameters to be estimated, β are moving average parameters to be estimated, y are past observations of the original time series, and ϵ_t are unknown random errors that are assumed to follow a standard normal distribution.

A major challenge when using ARIMA models for forecasting is estimating appropriate values for *p, d* and *q.* A detailed explanation of this process can be found in the Supporting Information. We modelled future price evolution with an ARIMA(0,1,1) model (zero auto regressive terms, one non-seasonal difference to obtain time-series stationarity, one lagged forecast error in the prediction equation). These forecasts were based on several assumptions including the absence of significant shocks in the global economy, and that the structure of agricultural and energy prices and policies, and consumer preferences, remain unchanged (Iqbal et al., 2005).

4.2.5 Calculation of economic returns

The comparison of the two land use alternatives was done based on gross margin (GM) per hectare. GM is a widely used measure of profitability in agricultural industries. The GM represents the annual gross revenue per hectare for an enterprise minus the variable costs per hectare directly associated with that enterprise as represented for wheat with equation 8. Annual gross revenue per hectare in year t was calculated for both wheat and biomass as:

$$Revenue_t^m = Yield_t^m \times Price_t^m \qquad m = \begin{cases} biomass \\ wheat \end{cases} \tag{7}$$

The costs associated with wheat production were taken from Rural Solutions SA Farm Enterprise Planning Guide, 2014 (PIRSA, 2014). These include variable costs (VC_t^{Wheat}) routinely encountered in a broad-acre cropping enterprise including the costs of seed, fertiliser, chemicals, freight, and contract work. The costs associated with the production of wheat varied according to rainfall zone but were treated as invariant over time (Table 4.3). The gross margin of wheat at time t, GM_t^{Wheat}, was calculated as:

$$GM_t^{Wheat} = Revenue_t^{Wheat} - VC_t^{Wheat} \tag{8}$$

Variable costs associated with the cultivation of biomass included fertiliser (FC), maintenance costs *(MC)*, transport (TC) and harvest (HC) and were taken from Bryan et al. (2010c). The costs associated with the cultivation of biomass were treated as deterministic and did not vary over time. These costs were summed each year (t) so that:

$$VC_t^{BEG} = MC_t + FC_t + TC_t + HC_t \tag{9}$$

The GM for biomass (GM_t^{BEG}) in year t was therefore calculated as:

$$GM_t^{BEG} = Revenue_t^{BEG} - VC_t^{BEG} \tag{10}$$

For the purposes of DCF analysis the average yield expected from biomass was calculated with the Carbon Sequestration from Revegetation Estimator using the average annual rainfall of each location. The inflation-adjusted, mean biomass price 1970 – 2013 was used as the expected price in the NPV calculation. The costs associated with biomass harvest and transport were averaged over the useful lifetime of the plantation and included in annual variable costs. Similarly, the expected wheat yield was taken as the average modelled APSIM yield for each location. The expected wheat price received was the inflation adjusted mean wheat price taken from the historical wheat price time series 1970 – 2013. As such GM_t^{BEG} and GM_t^{Wheat} used in the calculation of NPV indicate the annual average GM received at each study location.

GM includes revenues and variable costs, however, for long-run (infinite horizon) investment evaluation, the occasional, periodic fixed cost of biomass planting and re-establishment must also be taken into account. Estimates of biomass establishment costs (EC) associated with the plantation of agricultural land vary greatly. Commodity prices, management decisions, planting methodologies, and biophysical parameters (e.g. soil type, terrain) all influence establishment costs for revegetation of agricultural land (Summers et al., 2015). Published estimates of reforestation costs for a plantation of Mallee eucalypts ranged from A$700–800/ha (Bartle and Abadi, 2009; Bryan et al., 2010c), to A$400-1200/ha (Bryan et al., 2008a), A$1500/ha (Abadi et al., 2003), and up to A$9097/ha (Summers et al., 2015). We assumed *EC to* be A$1000/ha. Estimates of costs associated with the recultivation (RC) of biomass plantations either back to agricultural production or in preparation for reinvestment in biomass, obtained through expert consultation, were set at A$1000/ha.

Table 4.3 – Model parameters (applicable for both the NPV and ROA calculations)[1].

		Model Parameters				
		Florieton	SA Mallee	Manangatang	Natimuk	Wimmera
Expected wheat yields (t/ha/year)	$Yield_t^{wheat}$	1.0	1.5	1.5	2.5	3.5
Expected total variable costs wheat (AU$/ha/year)	VC_t^{Wheat}	$157.00	$157.00	$157.00	$324.00	$421.00
Expected price wheat (AU$ /t)	$Price_t^{wheat}$	$430.00	$430.00	$430.00	$430.00	$430.00
Expected biomass yields (DM tonnes/ha/year)	$Yield_t^{BEG}$	1.51	2.4	2.85	5.05	10
Expected total variable costs biomass (AU$/ha/year)	VC_t^{BEG}	$32.08	$32.08	$32.08	$57.00	$111.73
Expected price biomass (AU$/t)	$Price_t^{BEG}$	$88.00	$88.00	$88.00	$88.00	$88.00
Biomass Establishment costs (AU$/ha)	EC_t	$1,000				
Biomass Recultivation costs (AU$/ha)	RC_t	$1,000				
Transport cost *(TC)* (AU$/tonne/km)	TC_t	$0.05				
Mean distance to processing plant		55km				
Fertilizer costs (AU$/ha/year)	FC_t	$40				
Harvest Costs (AU$/t)	HC_t	$12				
Useful lifetime of biomass plantation	N	21 years				
Risk free rate	r	4.51%				
Stochastic process		ARIMA(0,1,1)				

4.2.6 Investment decision using discounted cash flow

In DCF analysis, future income streams are discounted at an appropriate discount rate, r, and expressed in present value terms. The value of an investment at time = 0 is given as the difference between the present value of returns and the present value of expenditures, or NPV (Luehrman, 1998).

We calculated NPV following Wolbert-Haverkamp and Musshoff (2014a). If a landholder changed land use and converted their land to biomass, they will incur EC at the beginning of each useful lifetime. In each year of the biomass rotation the landholder will earn the expected GM of biomass (GM_t^{BEG}) and forgo the expected GM of wheat (GM_t^{wheat}). At the end of a biomass rotation RC will be incurred. DCF analysis cannot consider a reconversion option that switches the land use back from biomass to wheat. Therefore the DCF analysis evaluated an investment possibility where the land

[1] For the purposes of the DCF analysis, average expected yields for each location, were also taken from state Department of Agriculture farm enterprise planning guides PIRSA, 2014. Crop and Pasture Reports South Australia Archive. Department of Primary Industries and Regions South Australia, Adelaide.. The inflation adjusted, mean wheat price 1970–2013 was used as the expected wheat price in the NPV calculation.

holder cultivated biomass for an infinite amount of useful lifetimes and earned the average GM of biomass (GM_t^{BEG}). To calculate the NPV of returns to an investment in biomass, the present value of returns, for an infinite time series, from biomass (PV^{BEG}) must be calculated as:

$$PV^{BEG} = GM_t^{BEG} \cdot \frac{1}{r} \tag{11}$$

The establishment costs (EC) are incurred in year zero as well as in each of the following N=21 years. Given the finance analytical formulas for infinite series, present value of EC can be calculated as:

$$PV^{EC} = EC + EC \cdot \frac{1}{r(p = N)} \tag{12}$$

Where:

$r(p = N) = (1 + r)^p - 1$
p = the number of time periods.

In addition, the recultivation costs (RC) must be accounted for and are incurred every N years in addition to EC. The present value of RC was calculated as:

$$PV^{RC} = RC \cdot \frac{1}{r(p = N)} \tag{13}$$

If a landholder switches land use to biomass they can no longer receive the GM associated with wheat. As such the present value of forgone wheat GM (GM_t^{Wheat}) must be accounted for.

$$PV^{Wheat} = GM_t^{wheat} \cdot \frac{1}{r} \tag{14}$$

The NPV of investing in biomass (NPV^{BEG}) can then be calculated as:

$$NPV^{BEG} = PV^{BEG} - PV^{EC} - PV^{RC} - PV^{Wheat} \tag{15}$$

Under the DCF investment rules, the critical value (trigger value) of GM^{BEG}, at which a farmer should change land use from wheat, is when NPV equals zero. If the NPV is zero, the trigger GM of biomass, GM^{BEG*}, at which a landholder should convert land use from wheat to biomass (GM_0^{BEG*}) can be calculated as:

$$GM_0^{BEG*} = NPV_0 - EC_0 - RC_0 - PV^{Wheat} \quad (16)$$

In this model, we assumed a risk-neutral investor and future revenues were discounted using a risk-free interest rate. Risk-neutral valuation was first advocated by Cox et al. (1979) and has become central in options pricing theory. Their key insight, observed from other options models was that option values were independent of investors' risk preferences and that the same valuations will be obtained even when all investors are assumed to be risk-neutral. This important assumption simplifies the calculations by eliminating the need to estimate the risk premium in the discount rate (Kellogg and Charnes, 2000). The risk-free interest rate was 4.51%, calculated from the average nominal returns of Australian 10 year Government Bonds 1985 to 2013 adjusted for inflation over the same period (The Reserve Bank of Australia, 2014).

4.2.7 Investment decision using ROA

Two ROA methodologies are widely used in examining questions of land use and land use change. The first involves analytical methods such as those employed by Hertzler et al. (2013), Sanderson et al. (2016) which are well suited to providing advice to individual firms regarding strategic investment decisions, specifically the probability of investment thresholds being met in the future and the optimal timing of land use investment. However, these models are limited by their inability to easily incorporate multiple sources of uncertainty as separate stochastic processes or spatially varying risks (Sanderson et al., 2016). The second approach involves numerical, simulation methods such as those demonstrated by Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014a). These methods can be adapted to incorporate multiple sources of uncertainty, separate stochastic processes or distributions. However, these methods are limited in their ability to calculate the probability and optimal timing of land use change especially where there is a long investment horizon (Longstaff and Schwartz, 2001). Consequently these methods are better suited to examining problems where there are multiple, interacting uncertainties on the returns required to trigger land use change and can be readily applied to policy questions that require nuanced accounting of spatial variability.

To value the option to convert land from wheat to biomass, we adapted a numerical, stochastic simulation-based real options model (Tubetov et al., 2012; Wolbert-Haverkamp and Musshoff, 2014a, b). The parameterisation procedure for determining the test trigger gross margin is described in detail in Tubetov et al. (2012), Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014b). In short, the optimal GM of biomass at which a farmer should convert land use was found by testing a number of triggers (GM^{BEG*}) and identifying the trigger returning the highest real option value. As the investment decision can be indefinitely postponed, the optimal conversion trigger GM conforms to a constant conversion trigger that remains unchanged over the entire lifetime ($t = 0, 1, \ldots, \infty$) (Dixit and Pindyck, 1994; Wolbert-Haverkamp and Musshoff, 2014b). This can be explained by the unchanged opportunity costs over time (Wolbert-Haverkamp and Musshoff, 2014b).

To determine the trigger GM at which a farmer should convert land use under ROA, the present value of future returns from converting to biomass ($R_t GM^{BEG*}$) were valued as an iterative series of ROA trigger values and random draws for values specified as uncertain (price of wheat, price of biomass, biomass yield, wheat yield) for each year in the 500 year time series used as a finite approximation to the infinite horizon conceptual model following Tubetov et al. (2012). The resulting approximation error is trivial (Musshoff, 2012) :

$$R_t GM^{BEG*} = 0, \qquad if\ LU_t = 0 \wedge \mathrm{GM}_t^{\mathrm{BEG}} < \mathrm{GM}^{\mathrm{BEG*}} \tag{17a}$$

In any year t, the returns to biomass ($R_t GM^{BEG*}$) are 0 if the stochastic GM of biomass (GM_t^{BEG}) are lower than the trigger GM (GM^{BEC*}) being tested. The land will be used for wheat production ($LU_t = 0$) and the land will remain in wheat production in the next time period ($LU_{t+1} = 0$).

$$R_t GM^{BEG*} = \text{-EC} \times (1+r)^{-t}, \quad if\ \mathrm{LU_t} = 0 \wedge \mathrm{GM}_t^{\mathrm{BEG}} \geq \mathrm{GM}^{\mathrm{BEG*}} \tag{17b}$$

The returns to biomass ($R_t GM^{BEG*}$) equal the present value of the establishment costs *(EC)* if the land is currently being used for wheat production ($LU_t = 0$) and GM of biomass in time *t (GM_t^{BEG}*) is higher than the biomass trigger GM(GM^{BEC*}) being tested. In the next time period the land will be converted to biomass ($LU_{t+1} = 1$).

$$R_t GM^{BEG*} = \mathrm{GM}_t^{\mathrm{BEG}} \times (1+r)^{-t} - \mathrm{GM}_t^{\mathrm{wheat}} \times (1+r)^{-t}, \quad if\ \mathrm{LU_t} = 1 \wedge \mathrm{H_t} < \mathrm{LH} \tag{17c}$$

When land use is in biomass ($LU_t = 1$) the returns to biomass ($R_t GM^{BEG*}$) correspond to the present value of the stochastic GM of biomass in time *t (GM_t^{BEG}*) minus the present value of the GM of wheat in time *t* (GM_t^{wheat}). This applies when biomass harvest (H_t) has not reached the last harvest (LH) within the plantation's useful lifetime (i.e. *t* < 21).

$$R_t GM^{BEG*} = (\mathrm{GM}_t^{\mathrm{BEG}}\text{-RC}) \times (1+r)^{-t} - \mathrm{GM}_t^{\mathrm{wheat}} \times (1+r)^{-t}, \quad if\ \mathrm{LU}_t = 1 \wedge \mathrm{H}_t = \mathrm{LH} \wedge \mathrm{GM}_t^{\mathrm{BEG}} < \mathrm{GM}^{\mathrm{BEG*}} \qquad (17d)$$

The returns to biomass ($R_t GM^{BEG*}$) correspond to the present value the GM of biomass in time *t (* GM_t^{BEG}) minus the present value of the recultivation costs (*RC*), minus the present value of the GM of wheat in time *t* (GM_t^{wheat}). This applies when biomass has reached the last year of its useful lifetime and the stochastic GM_t^{BEG} received in the year of the last harvest (*t*=21) is less than the (GM^{BEG*}) being tested. As the biomass trigger GM (GM^{BEG*}) being tested is not met, the land is returned to wheat production in the next period ($LU_{t+1} = 0$).

$$R_t GM^{BEG*} = (\mathrm{GM}_t^{\mathrm{BEG}}\text{-RC-EC}) \times (1+r)^{-t} - \mathrm{GM}_t^{\mathrm{wheat}} \times (1+r)^{-t}, \quad if\ \mathrm{LU}_t = 1 \wedge \mathrm{H}_t = \mathrm{LH} \wedge \mathrm{GM}_t^{\mathrm{BEG}} \geq \mathrm{GM}^{\mathrm{BEG*}} \qquad (17e)$$

The returns to biomass ($R_t GM^{BEG*}$) correspond to the difference between the present value of GM biomass in time *t (*GM_t^{BEG}) and the sum of the present value of recultivation costs (*RC*) and the establishment costs (*EC*), minus the present value of the GM of wheat in time *t* (GM_t^{wheat}). This applies when biomass has reached the last year of its useful lifetime (*t*=21) and GM_t^{BEG} received in the year of the last harvest (LH) is greater than the GM^{BEG*} being tested. As GM^{BEG*} is met, the land is used for biomass in the next time period ($LU_{t+1} = 1$) and remains in biomass for another rotation.

The option value associated with each test trigger was calculated by summing the present value of future investment returns R_t during the planting period ($t = 0, 1, \dots, \infty$). The option value for each test trigger equals the average present value of farm returns for all simulated paths. In order to determine the optimal GM of biomass (GM^{BEG*}) that triggers investment, the function F_0 that corresponds to the maximum option value can be found:

$$F_0 = \sum_{t=0}^{\infty} R_t GM^{BEG*} \rightarrow max!\ GM^{BEG*} \qquad (18)$$

In the model, a time period of $t = 500$ years was observed. MS Excel and @Risk (Palisade Corporation, 2014) were used to run the ROA simulation model. We followed Tubetov et al. (2012), Wolbert-Haverkamp and Musshoff (2014a) and (2014b) and performed 50,000 simulations for each test trigger GM (GM^{BEG*}). The initial test triggers were chosen from results from the NPV analysis. The NPV trigger (GM^{BEG*}) acts as the lower limit, while the maximum test trigger was initially estimated (i.e. three times the NPV trigger price). The range between the initial maximum and minimum values was divided into equal intervals and the intervening triggers tested. The range was narrowed according to the simulation results and the new range was divided into equal intervals and tested. This process was repeated until a small range of test triggers emerged leading to the optimal trigger price.

4.2.8 Policy analysis

In order to examine the effects of incentive policy intervention and uncertainty on the trigger prices required to induce land use change, we tested several policy scenarios involving incentive payments (Table 4.4). In the base case scenario (Scenario 1), no incentive or subsidy payment was offered. In Scenarios 2 and 3 we introduced a payment for below-ground carbon sequestration accumulated by the biomass plantation. In Scenario 2 a fixed price ("certain incentive") for carbon of AU$25 tCO_2-e/ha/year was paid for below-ground carbon accumulation. In Scenario 3, incentive uncertainty was included through a random below-ground carbon payment. In this scenario, the landholder received a random carbon payment in any one year that could range between AU$0/$tCO_2$-e/ha/year to AU$50/tCO_2-e/ha/year, with the most likely price being AU$25/$tCO_2$-e/ha/year. The carbon price is independently random and not linked to either commodity price.

Table 4.4 – Summary of ROA scenario treatments.

ROA scenario treatments	Price uncertainty	Yield uncertainty	Certain incentive payment	Uncertain incentive payment
Scenario 1	✓	✓	✗	✗
Scenario 2	✓	✓	✓	✗
Scenario 3	✓	✓	✗	✓

4.3 Results

The simulated time-series data and a sample of future commodity price paths can be seen in Figure 4.2 and Figure 4.3.

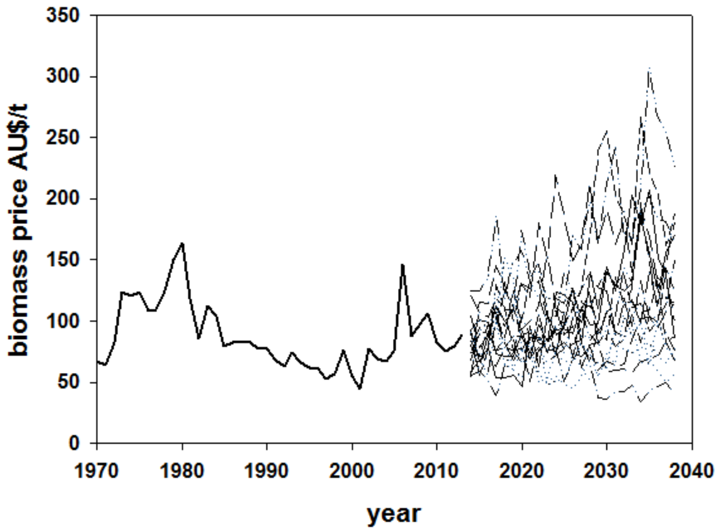

Figure 4.2 – Derived biomass prices 1970–2013 and a sample of development of future biomass prices using an ARIMA(0,1,1) model in A$/t.

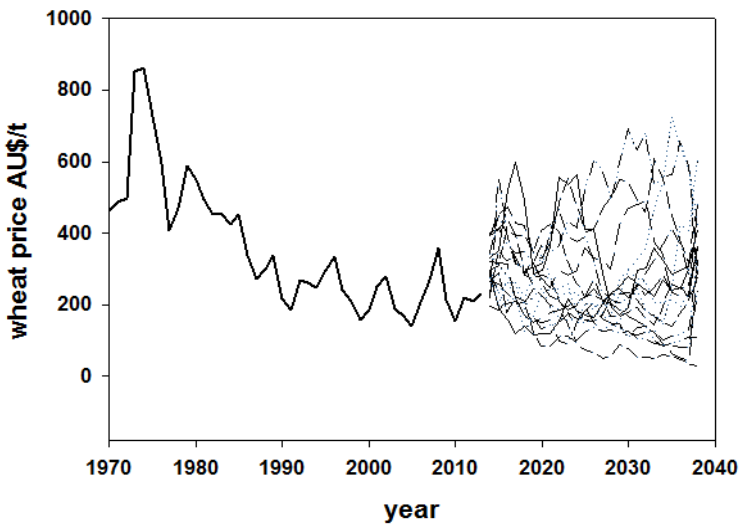

Figure 4.3 – Wheat prices 1970–2013 and sample of development of future wheat prices using an ARIMA(0,1,1) in A$/t.

Table 4.5 shows the trigger prices required to induce land use change from wheat to biomass under DCF and ROA in Scenario 1, the no incentive scenario. In the base case there is a significant difference in the GM/ha required to trigger land use change to biomass between the DCF methods and ROA. For example, a risk neutral landholder in the SA Murray Mallee region, who valued their opportunity to change land use to biomass using DCF, would convert land use at a gross margin of approximately A$595/ha. At this level of net returns (revenue - costs), expenditures associated with the cultivation of biomass, plus the opportunity cost of foregone wheat production was met. In contrast, the ROA, which considers the temporal flexibility in the land use change decision, the GM required to induce land use change was approximately A$890/ha. The present value of returns at a gross margin of A$890/ha was approximately A$16,451/ha. The investment multiple (the ratio of the present value of returns to the present value of expenditures) required to trigger land use change in the SA Murray Mallee was 1.50 (Table 4.5). In other words, a landholder should only invest in biomass if the present value of net returns is at least 1.50 times higher than the present value of expenditures.

Table 4.5 – Trigger GM/ha, critical present values of returns and investment multiples needed for land use conversion using DCF and ROA for Scenario 1.

		Discounted cash flow		Real options analysis	
		Trigger GM/ha	PV of returns/ha	Trigger GM/ha	PV of returns/ha
Scenario 1	Florieton	$381	$7,035	$810	$14,972
	SA Murray Mallee	$595	$10,998	$890	$16,451
	Manangatang	$595	$10,998	$860	$15,896
	Natimuk	$858	$15,860	$1,660	$30,684
	Wimmera	$1,192	$22,025	$2,760	$51,017

Results from the SA Murray Mallee—a low rainfall environment—differed from the higher rainfall Wimmera area. Under the DCF model, the conversion trigger GM/ha in the Wimmera was AU$1192/ ha. Under ROA this rises to AU$2760/ha, which equates to present value of returns for biomass of AU$51,017/ha. The investment multiple required was 2.32 reflecting the higher opportunity cost involved with cultivating biomass at this location. This is higher than the investment multiple in the drier areas of the region such as Manangatang (1.45), Natimuk (1.93) and Florieton (2.13).

In Scenario 2, the effect of the fixed carbon payment of AU$25/t$C0_2$-e/ha/year for below-ground carbon accumulation was to reduce the trigger GM/ha in comparison to Scenario 1 (Figure 4.4).

However, the effect of the payment was not uniform across the region. The fixed carbon price had the largest effect in Florieton and Natimuk, where the trigger GM/ha reduced by 35.8 percent and 24.1 percent when compared with Scenario 1. The carbon payment had smaller effects in the Wimmera, where the trigger GM/ha was reduced by 12 percent when compared to Scenario 1.

In Figure 4.4, comparing Scenario 2 and 3 outcomes illustrates the impact of certain (Scenario 2) versus uncertain (Scenario 3) but equal expected-value carbon payments for below-ground carbon accumulation. The effect of uncertain carbon payments (Scenario 3) had the largest effect in the SA Murray Mallee and Manangatang, increasing the trigger GM/ha by 5.8 percent and 6.1 percent when compared to the fixed carbon payment Scenario 2. The effect of the uncertain carbon payment has least effect in the Florieton and the Wimmera, where the trigger GM/ha was raised by 3.85 percent and 3.29 percent, respectively.

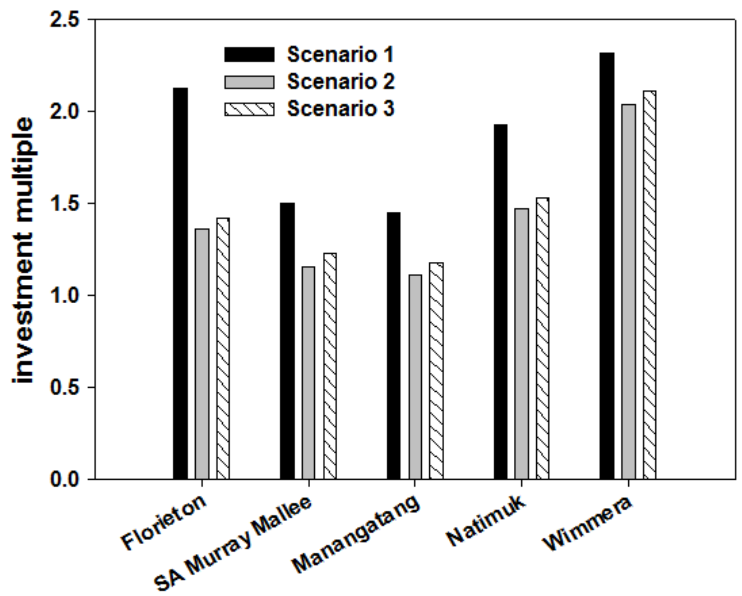

Figure 4.4 – Trigger gross margins and investment multiples calculated using ROA required for land use change from wheat to biomass in the 5 study locations in Scenario 1, 2 and 3.

4.4 Discussion

4.4.1 Effect of policy on land use change

Biomass grown from woody perennials for electricity generation may provide an economically feasible and environmentally-beneficial alternative to conventional agriculture both in Australia, and globally (Bryan et al., 2010a; Bryan et al., 2010c; Heaton et al., 1999; Ward and Trengove, 2004). In this study, we have shown that real option values add significantly to the GM required to trigger land use change from conventional agriculture to biomass, across a climatically diverse region of southern

Australia. We tested the effect of incentives and payment policies and geographically-varying production uncertainty on land use change decisions across the study area. Our results indicate that the structure of incentive policy and spatially-differing yield variability affects the prices needed to encourage land use change to biomass across the study area.

The results for the base case scenario (no incentive payment) show that the consideration of price and yield uncertainty adds substantially to the GM required to trigger land use change from wheat to biomass when compared to results from the DCF analysis (Table 4.5) as has been found in previous ROA studies (Musshoff, 2012; Schatzki, 2003; Wolbert-Haverkamp and Musshoff, 2014a). These results reflect the present situation internationally (Lubowski et al., 2006; Smith et al., 2005) and in Australia (Herbohn et al., 2005) where landholder preference is to remain in agriculture, despite the potential profitability of alternative land uses such as forestry. While landholders cite a range of factors for their reluctance to convert land to agroforestry including satisfaction with current land uses (Herbohn et al., 2005) and conflicting land use objectives (Byron and Boutland, 1987), our results indicate that uncertainty over returns to agroforestry, high upfront (largely sunk) costs, and loss of flexibility associated with agroforestry provide the landholder with a valuable option to delay reforestation and wait for uncertainties to resolve. Our results showed that for the lower Murray study area, the value of this option can be substantial, ranging from 1.45 to 2.32 times the present value of expenditures (DCF break-even point).

In addition to revenue uncertainty, landholders commonly cite poor returns relative to current land uses, uncertainty over government policies, and the limited longevity of incentive schemes as barriers to investment in reforestation (Baumber et al., 2011; Bennett and Cattle, 2014; Herbohn et al., 2005; Isik and Yang, 2004; Lockie and Rockloff, 2004). Scenario 2 illustrates the effect including a fixed price for below-ground carbon accumulation to reduce conversion triggers. We found that a \$25/t CO_2-e carbon payment reduced the trigger price substantially but this effect varied across the study area locations (12– 36 percent compared to Scenario 1). Comparing scenarios with differing incentive payment variability, but the same expected value, allowed us to test payment uncertainty on biomass conversion triggers. While the effect of an uncertain carbon payment policy was to increase the conversion trigger GM when compared to a fixed carbon payment, the effect of added uncertainty was found to be small (3.29 – 6.06 percent compared to Scenario 1) across the study area. The small effect of payment uncertainty in Scenario 3 reflects that the additional payment acted more as an additional top up payment, not a main source of revenue from conversion of wheat to biomass. This highlights a need to understand the role of incentive payments in the overall revenue stream created from any land use change. An explanation of this small effect is that when a large proportion of revenue from land use change is reliant on government policy, not market demand, policy risk effects are higher. Academic discussion of payments for environmental services, such as carbon sequestration, are often framed in terms of 'either-or'(government payment versus markets), the more policy-relevant question, given our results, may therefore concern how different instruments can be combined to achieve policy objectives (Engel et al., 2008) and in doing so reduce the effects of policy/market uncertainty for landholders.

Our findings are consistent with survey-based studies—that risky policy environments can adversely affect landholder willingness to change land use (Baumber et al., 2011; Herbohn et al., 2005; Lockie and Rockloff, 2004). A caveat is that while our results focus on incentive price variability, there are many additional factors that affect landholder willingness to change land use including household dependency on agricultural incomes, age and education levels, the presence of a successor and the ability to make progressive rather than step changes to agricultural activities (Lastra-Bravo et al., 2015). These may be hard to fully quantify from economic models alone and the magnitude of the effect may well be larger and more ambiguous than the impacts of incentive payment level risk that we assessed here (Lagerkvist, 2005).

The results of the ROA highlight that there are regional differences in the way uncertainty regarding incentive payments affected land use change decisions. The magnitude of the effect of price and yield uncertainty varied substantially across the region. The effects were largest in the highest rainfall and lowest rainfall areas—Wimmera and Florieton, respectively (Figure 4.4). The increases in trigger GM were smallest in the SA Murray Mallee and Manangatang. An explanation for this is the comparative differences in the variability of expected biomass and wheat yields across the study area. For example, the Wimmera is not only a higher-yielding wheat production area, but the variability in wheat yields is far lower than in either the SA Murray Mallee or Manangatang. As such, the effect of options values on opportunity cost reflected the nature of the risk and returns (Sanderson et al., 2016) and the opportunity cost was associated with foregoing higher wheat production value than in other locations. In contrast, in a less agriculturally-productive location like Florieton, the interaction between the burden of high establishment costs, low yields, and high production risk was particularly influential on potential land use economic decision-making.

4.4.2 Implications for policy

This study highlights some important considerations for policy makers. Firstly, it supports previous ROA of biomass which have shown that the addition of uncertainty, sunk cost and temporal flexibility can add significantly to the return needed to induce land use change away from traditional agriculture (Musshoff, 2012; Regan et al., 2015; Schatzki, 2003; Wolbert-Haverkamp and Musshoff, 2014a, b). However, it also shows that there can be significant geographical differences in the magnitude of the effect of uncertainty, even within the same region (Table 4.5). Given the substantial heterogeneity of agricultural productivity across the landscape, these results indicate that there are likely areas with production profiles that are better suited, economically, to the production of biomass. Opportunities therefore exist in targeting specific areas like the more variable SA Murray Mallee or Manangatang where the increased economic returns required to induce land use change are significantly lower (as a proportion of current agricultural returns) than more reliable areas such as the Wimmera. It is clear from our results, differing trigger levels across locations result from combined price and yield uncertainty effects and future research is required to analyse the relative contributions of different types of uncertainty.

Secondly, experience from countries with more developed biomass industries have found that subsidies are often required to encourage the adoption of biomass (Johansson et al., 2002). However, previous research has indicated landholder distrust for the longevity of price based supports due to their susceptibility to political change (Baumber et al., 2011; Herbohn et al., 2005). Our results indicate that incentive payments can have a considerable effect on lowering the returns required to trigger investment in biomass. Developing efficient methods with which to fund long term annual payments may be needed. One option worth considering is to compensate landholders for the environmental benefits derived from the cultivation of biomass. For example, Bryan et al. (2010c) estimated that a conservative estimation of the ecological benefits derived from the adoption of biomass in the study area could likely address 22 335 – 59 757 ha at high risk of dryland salinization, 0 – 276 078 ha at high risk of wind erosion, and reduce carbon emissions by 1.3 – 3.5 million tonnes annually. Valuing these services in the form of an annual payment or allowing landholders to forward contract carbon sequestration to fund establishment costs could reduce the returns required from biomass to trigger conversion.

Thirdly, it is clear that offering broad raging incentive payments over the entire study area may produce perverse outcomes. For example, the Wimmera has an absolute yield advantage in producing biomass when compared to Florieton. However, the incentive provided had the largest effect in Florieton. This has the potential to encourage biomass production in Florieton over the Wimmera, which may be counter to the interest of the policy maker.

4.4.3 Innovation and limitations

Previous real options papers (Isik and Yang, 2004; Musshoff, 2012; Reeson et al., 2015; Schatzki, 2003; Song et al., 2011; Wolbert-Haverkamp and Musshoff, 2014a) addressing observed friction in land use change have concluded that the presence of price uncertainty, sunk costs, and loss of flexibility delay land use change away from conventional agriculture. However few studies have examined if these effects are consistent across the landscape or differ according to primary production risk profiles. We show that the magnitude of the effects of uncertainty differs across the landscape, and that substantial geographical differences may exist in how these factors influence land use change decisions. We demonstrate that incentive payment policies can have substantial effects on lowering conversion triggers needed to encourage land use change; however the effect of support policies can also vary considerably across the landscape due to the unique geographical interactions between payment policy, return uncertainty and production risks.

Real options models are especially valuable in data-poor environments where the ability to study landholder behaviour through econometric approaches is limited (Yemshanov et al., 2015). Our results build on previous real options studies in that they go some way in accounting for not only price uncertainty, but also regional variability in productive capacity and production risk. These results are given credence through economic experiments conducted internationally that have shown that real options models approximate the behaviour of landholders (Ihli et al., 2013) as landholders demonstrably consider the value of waiting over time in experimental settings (Maart-Noelck and Musshoff, 2013). However, socio-demographic and farm-specific factors also affect the investment behaviour of landholders (Ihli et al., 2013). Yet, few economic experiments have been conducted in Australia in order to understand the proportional influence of socio-demographic and farm-specific factors in relation to the effects of price uncertainty, sunk costs and loss of flexibility. This is especially true in the case of emerging land uses such as biomass and carbon agroforestry. In the absence of data describing actual land use conversion rates, experimental data derived from Australian landholders would add rigour to the results presented by real options studies and this is an area prime for future research.

Finally, it is important to note that the results presented here should be interpreted in the context of the assumptions made. Firstly, the stochastic process used for the future development of biomass and wheat prices, while chosen based on empirical testing, is only one of a number that could be used. Musshoff (2012) and Reeson et al. (2015) showed that the selection of stochastic process can have significant effects on the outcome of ROA. Secondly, modelled biomass yield and yield variation were calculated using the *Carbon Sequestration from Revegetation Estimator* (Hobbs et al., 2013). While this model is based on empirical observations from across the study area, it is not specifically calibrated to each location. Additionally, in many drier areas, extensive grazing of livestock is preferred to annual crop production due to more stable returns and suitability to climatic conditions (Kandulu et al., 2012). In marginal cropping areas, including livestock enterprises in the analysis may be a fairer comparison, and provide a better analysis of GM needed to encourage conversion on land currently under permanent pasture to biomass. Furthermore, below-ground carbon accumulation was treated as invariant over time. In reality this would be subject to some temporal variability and this would have some effect on income derived from below-ground carbon payments and therefore the trigger GM. Additionally, while biomass may provide a valuable diversification option for landholders, the long term nature of such enterprises may dissuade participation and may contribute to income variability in the short term. This is primarily due to an enterprise such as biomass reducing the land available with which landholders could practice conventional diversification strategies to manage short term climate and market risk. This is an area that warrants further investigation.

Finally, this study was done at a regional scale based upon average soil conditions expected in each location. However there is often significant within-field variability in yield in both high and low yielding locations (Robertson et al., 2008). Finer scale variability in agricultural production may offer substantial opportunity for the adoption of biomass at lower costs than indicated by an analysis conducted at regional scale (Lyle et al., 2009).

Conclusion

Landholders have often displayed considerable reluctance to convert land use from agricultural commodity production to biomass crops. Studies using ROA have found that price uncertainty, the effect of sunk costs, and flexibility in investment timing can somewhat account for observed investment inertia. We used a numerical, simulation-based real options model to investigate the effect these factors have in an Australian context. Consistent with previous studies, our results indicate that the consideration of uncertainty, irreversible establishment costs, and temporal flexibility significantly increased the returns required in order to trigger land use change when compared to DCF analysis. The present value of returns required to trigger land use change varied from 1.45 to 2.32 times the present value of expenditures. Our results show that it is not only the most agriculturally productive locations that require the highest returns to induce land use change, but the least agriculturally-productive locations also require high returns in order to trigger land use change. Although initially somewhat counterintuitive, the extremely low returns exacerbate the burden of high investment costs in highly-variable locations. Our model shows that complementary incentive policies such as payments for below-ground carbon sequestration can decrease the returns required to trigger land use change considerably. These results are important for policy makers as they emphasise the effect uncertainty has on landholder decision-making. In order to understand the economics of land use change, policy makers and investors in industries reliant on land use change such as biomass must consider option values. Projections of land use change or incentive policies that fail to account for options values are likely to underperform. Additionally, the effect of incentives is likely to vary geographically. While this holds challenges for policy-makers in that it complicates the implementation of broadly applied policies, it holds promise as there are likely to be geographic areas appreciably more responsive to policy initiatives, where land use change is more readily achievable and at substantially lower cost.

Acknowledgments

This work was made possible by the Charles John Everard Scholarship awarded through the University of Adelaide and the support of CSIRO Sustainable Agriculture Flagship. The authors would like to thank Mr. Darran King and Dr. Raymundo Marcos Martinez for their assistance with this research.

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CHAPTER FIVE

Climate change and the economics of biomass energy feedstocks in semi-arid agricultural landscapes: A spatially explicit real options analysis.

The work contained in this chapter has been submitted as a research article to *Journal of Environmental Management*

STATEMENT OF AUTHORSHIP

Regan, C.M., Connor, J.D., Raja Segaran, R., Meyer, W.S., Bryan, B.A., Ostendorf, B., 2016. Climate change and the economics of biomass energy feedstocks in semi-arid agricultural landscapes: A spatially explicit real options analysis. Journal of Environmental Management. Submitted, manuscript ID JEMA-S-16-01136.

Author contributions: By signing the statement of authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

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5 CHAPTER FIVE

Abstract

The economics of establishing perennial species as renewable energy feedstocks has been widely investigated as a climate change adapted diversification option for landholders, primarily using net present value (NPV) analysis. NPV does not account for key uncertainties likely to influence relevant landholder decision making. While real options analysis (ROA) is an alternative method that accounts for the uncertainty over future conditions and the large upfront irreversible investment involved in establishing perennials, there have been limited applications of ROA to evaluating land use change decision economics and even fewer applications considering climate change risks. Further, while the influence of spatially varying climate risk on biomass conversion economic has been widely evaluated using NPV methods, effects of spatial variability and climate on land use change have been scarcely assessed with ROA. In this study we applied a simulation-based ROA model to evaluate a landholder's decision to convert land from agriculture to biomass. This spatially explicit model considers price and yield risks under baseline climate and two climate change scenarios over a geographically diverse farming region. We found that underlying variability in primary productivity across the study area had a substantial effect on conversion thresholds required to trigger land use change when compared to results from NPV analysis. Areas traditionally thought of as being quite similar in average productive capacity can display large differences in response to the inclusion of production and price risks. The effects of climate change, broadly reduced returns required for land use change to biomass in low and medium rainfall zones and increased them in higher rainfall areas. Additionally, the risks posed by climate change can further exacerbate the tendency for NPV methods to underestimate true conversion thresholds. Our results show that even under severe drying and warming where crop yield variability is more affected than perennial biomass plantings, comparatively little of the study area is economically viable for conversion to biomass under $200/DM t, and it is not until prices exceed $200/DM t that significant areas become profitable for biomass plantings. We conclude that for biomass to become a valuable diversification option the synchronisation of products and services derived from biomass and the development of markets is vital.

Keywords: Real options analysis, Climate Change, Spatial, Biomass, Economic, Australia

5.1 Introduction

De-carbonising global electricity generation is seen as key to stabilise atmospheric greenhouse gas levels (Edenhofer et al., 2014). Biomass production for use in electricity generation (hereafter biomass) is proposed as a renewable energy source that can contribute to the mitigation of climate change through direct CO_2 sequestration and through the replacement of higher CO_2 emitting fuels such as coal and oil (Bryan et al., 2008b; Evans et al., 2010; Styles and Jones, 2007). The use of biomass (often in the form of agricultural residues, bagasse, forestry residues) is widespread globally, producing 280 TWh of electricity, equivalent to 1.5% of global electricity generation per annum (Eisentraut and Brown, 2012). But for biomass to play a significant role in future global energy supply, dedicated energy crops often grown on current agricultural land will be essential (Coleman and Stanturf, 2006; Evans et al., 2010).

Economically, biomass production has been found to be potentially competitive with conventional agricultural enterprises as the yields associated with production of woody perennials are often less sensitive to climatic variables and require fewer inputs (Bryan et al., 2010c; Heaton et al., 1999; Styles et al., 2008). In agricultural areas with variable climate and soil, the introduction of short rotation woody perennial production systems that use adapted woody species could provide a valuable diversification option. Moreover, it may offer the opportunity to buffer seasonal and annual variations in rainfall that cannot be reliably used by annual crops (Hobbs, 2009a). Internationally, where biomass supply chains are more developed, landholders have been slow in switching land use, particularly between agriculture and forested use despite potential profitability (Plantinga, 1996; Schatzki, 2003; Stavins and Jaffe, 1990). An explanation of this perceived investment inertia is that financial analysis of land use change has traditionally assumed the decision to switch land use can be modelled based on the Net Present Value (NPV) which compares current agricultural land uses with biomass alternatives (Yemshanov et al., 2015). However, several factors are commonly omitted from NPV analysis. Among them are sunk investment cost, investment irreversibility, significant uncertainty over future returns and flexibility in the timing of investment (Dixit and Pindyck, 1994; Trigeorgis, 1996). These omitted factors influence land holder decisions (Ihli et al., 2013) and lead to the erroneous NPV analysis conclusion that the land currently in agriculture would be more profitable in other forest based land uses (Frey et al., 2013; Parks, 1995; Stavins and Jaffe, 1990).

Real options analysis (ROA) has been proposed as a better model of investments decisions under conditions of uncertainty that are costly to reverse and where significant flexibility exists to delay investments (Dixit and Pindyck, 1994). ROA investment triggers, defined as the levels of revenue required to invest in a new land use, are often higher than NPV required returns if the investment involves inter-temporal opportunity costs (Musshoff, 2012). The effect of including ‘option values’ in investment decision analysis can be substantial (Regan et al., 2015; Schatzki, 2003). Unlike NPV analysis, the revenues required to trigger land use change must not only compensate the landholder for establishment cost and foregone returns from agriculture, but also for lost management flexibility and the revenue uncertainty from the new enterprise (Reeson et al., 2015).

Many of the key uncertainties influencing agricultural production such as rainfall, temperature and soil types vary spatially (Bryan et al., 2014). Heterogeneity of these factors has been widely included in NPV analysis in order to understand the spatial distribution of *cost-effective* land use change (Bateman, 2009; Bryan et al., 2010a; Crossman et al., 2011) which have found that landscape heterogeneity is likely to affect the location and timing of land use change. While qualitatively acknowledged, spatial variability has been largely overlooked in quantitative ROA of land use change. Limited exceptions demonstrating differing conversion threshold prices and conversion probabilities across space include Dumortier (2013), Yemshanov et al. (2015) and Sanderson et al. (2016).

Another gap in the ROA of land use change is the effect of climate variability through time on yield. It has been shown to be the principal source of risk affecting long term economic viability of rain-fed agricultural systems in NPV assessments for semi-arid regions such as south east Australia (Kandulu et al., 2012). Despite NPV assessment showing that climate change is likely to provide landholders with additional production risks, surprisingly few studies have addressed the effect of climate change on agricultural land use change in a ROA framework. Hertzler (2007); Hertzler et al. (2013) and Sanderson et al. (2016) are exceptions. They address these factors across an agricultural region with ROA employing spatial transects as an analogue for temporal changes due to climate change. There are limitations to this approach as temporal climate change effects are only roughly approximated by spatial transects. They exclude, for example, accounting for changing CO_2 concentrations and their interactions with higher temperatures (Sanderson et al., 2016).

In this study we address both the gap in broad spatial coverage and the gap in accounting for climate change in ROA of land use changes. This study specifically modelled land use change from agriculture to biomass production in a spatially explicit framework across a broad region accounting for effects of climate change on yield variability. The analyses allow for the assessment of regional biomass industry viability with calculations and spatial mappings of areas where biomass land use is economically viable at several price points under alternative assumptions about climate change.

This article is organised as follows: The next section discusses the stochastic simulation-based real options model applied. This is followed by mapping the land use conversion to biomass with varying price and climate change assumptions. The final discussion focusses on how conclusions about regional biomass industry viability differ with ROA and traditional NPV analysis in the context of climate change futures.

5.2 Methods

5.2.1 Study area

Our study focused on the lower Murray region of southern Australia (Figure 5.1). The dominant land use covering 50% of the region is rain-fed mixed farming, consisting of the dryland winter cropping of cereals (wheat, barley, oats), pulses (beans, lupins, peas), oilseeds (canola) and grazing of sheep (Bryan et al., 2011). The average farm size in the region is approximately 1000 ha (Kandulu et al., 2012). The region is typical of semi-arid rain dependant farming regions found globally. These regions, similar to our study area, cover approximately 15% of the global land area (UNEMG, 2011), including large areas of southern Africa, western North America and the Middle East. Such semi-arid areas are characterised by high rainfall variability within the growing season, between years and in longer-term cycles. Combined with generally low average rainfall (250 mm – 600 mm/year), rainfall variability is a primary risk to agricultural enterprises in these areas (Hansen et al., 2012; UNEMG, 2011).

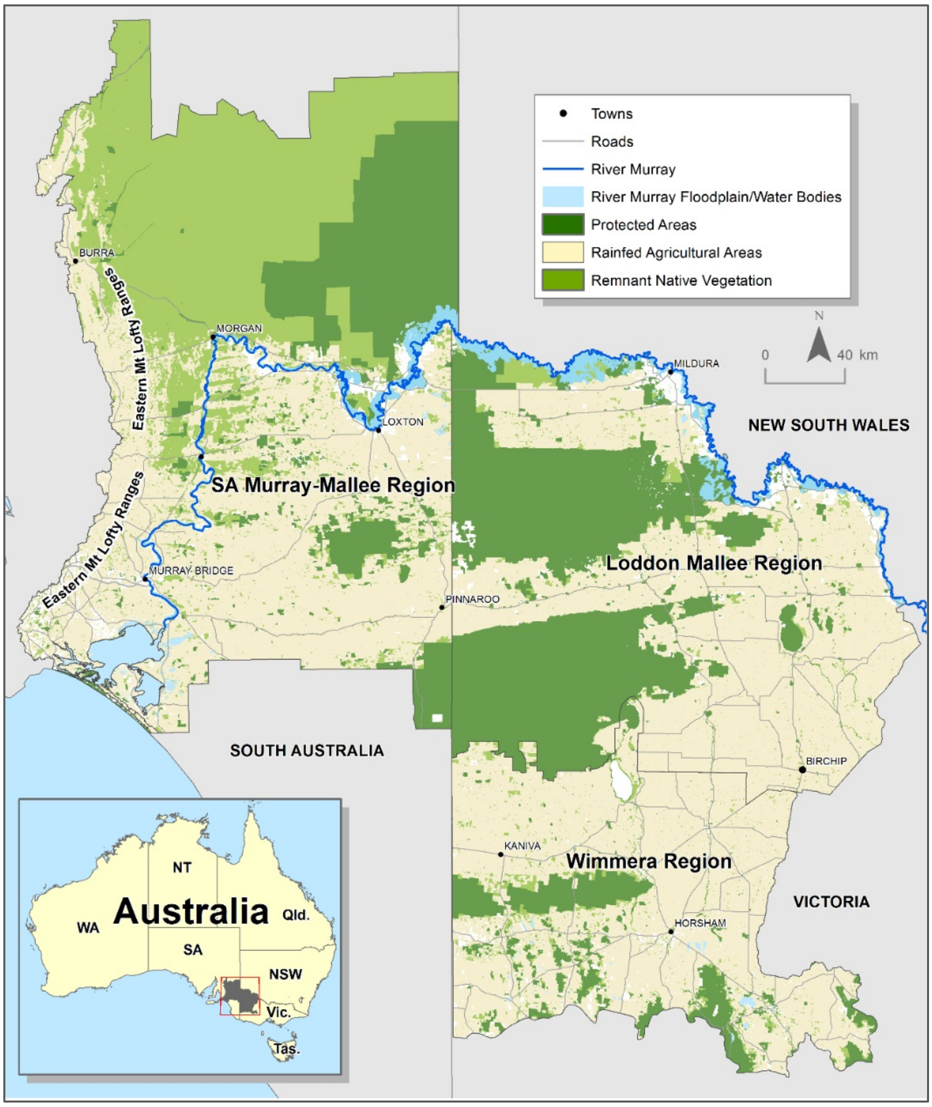

Figure 5.1 – Location map of the Lower Murray study area (adapted from Kandulu et al. (2012)).

5.2.2 Climate scenarios

IPCC climate change models predict average temperature increases in the study area between now and 2100, ranging between 1.0 and 6.0 degrees Celsius, depending on Representative Concentration Pathways (RCPs) (Pachauri et al., 2014). Bryan et al. (2010c) developed feasible climate change scenarios for the study area based on climate change modelling for southern Australia (Suppiah et al., 2006). We used three of the four climate scenarios developed by Bryan et al. (2010c) (
Table 5.1); baseline (S0), moderate drying and warming (S2) and severe drying and warming (S3).

Table 5.1 – Climate scenario description

Scenario	Description	Temperature	Rainfall
S0	Baseline	Historical mean	Historical mean
S2	Moderate warming/drying	2 °C warmer	15% dryer
S3	Severe warming/drying	4 °C warmer	25% dryer

5.2.3 Representing spatial diversity

Despite the general categorisation as semi-arid, climatic diversity is found across southern agricultural areas in Australia. These regions are often broadly categorised into "low", "medium" and "high" rainfall zones according to mean annual rainfall for both agronomic and economic analysis. While the precise definition of zones is often elastic, this categorisation is a good way to broadly delineate areas of similar production systems, productivity and, important for this study, variable costs associated with crop production. In this study we use the rainfall zones as described by Rural Solutions (2015) in their gross margin and enterprise planning guide for the study area. They classify low rainfall zone as <350 mm/year, medium rainfall zone as 350 mm – 400 mm/year and high rainfall as >400 mm/year (Figure 5.2) in order to assign variable production costs. Inescapable production costs vary between regions for agronomic reasons. This is primarily due to the intensity of the production systems, for example the application of nitrogen is likely to be higher in higher rainfall areas, sowing rates will differ and chemical use for the control of weeds and pests is typically higher in higher rainfall areas.

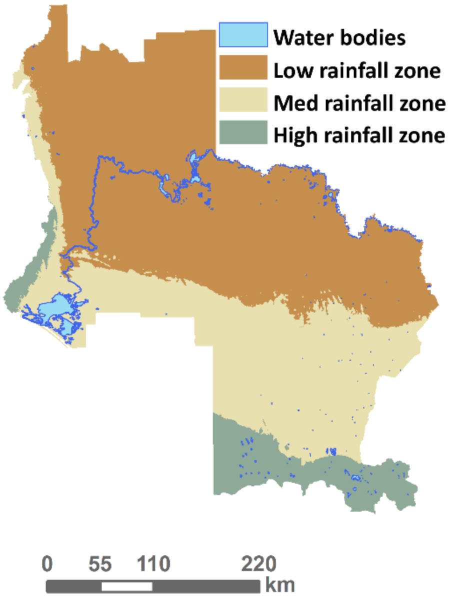

Figure 5.2 – Classification of the study area into low, medium and high rainfall zones according to long-term annual rainfall data (Jeffrey et al., 2001) and Rural Solutions (2015) rainfall zone delineations.

In order to capture finer scale spatial variation in climate and soil, and therefore productivity, the study area was further categorised into 138 geographic zones of homogenous agricultural production potential following Bryan et al. (2010c). Each of the 138 zones represents a unique combination of soil type and climate characteristics drawn from 115 years of historical climate data taken from the SILO database (Jeffrey et al., 2001) and soil data assembled from state government field data (Bryan et al., 2007).

5.2.4 Methodology overview

The analysis involves the following steps:

1. Calculate biomass production potential across 138 spatial units in the study area across climate scenarios involving time series for each spatial unit and climate scenario.
2. Calculate wheat yield for each climate scenario for every spatial unit and a time series of years for each spatial unit and climate scenario.
3. Characterise the variability in prices of wheat and biomass that together with variable yields create risks in returns to the two land use options.
4. Compute and map the spatial distribution of land conversion to biomass at several price points and for all three climate scenarios with both NPV and ROA analysis.

5.2.5 Biomass production scenario

The growth of deep rooted perennial vegetation for electricity production or integrated tree processing is still novel in Australian agricultural landscapes. There has been considerable analysis on perennial vegetation, commonly in the form of mallee eucalypts, to farming systems. The analyses have primarily addressed dry land salinity issues (Bartle et al., 2007; Wu et al., 2007) or other natural resource management outcomes while also providing profitable alternative enterprises to land holders (Bennell et al., 2009; Hobbs et al., 2009; Hobbs, 2009b).

This analysis modelled a coppice system to produce biomass, where once harvested, the cut stumps re-sprout to generate a subsequent crop. The capability of eucalypts to coppice declines with age (Sims et al., 1999). The productive lifetime of a Eucalyptus stand used for short rotation coppice vary, but have been estimated to approximately 20 – 21 years (Gabrielle et al., 2013; Hobbs, 2009a) . We use a useful stand lifetime of 21 years consistent with the literature and expert consultation.

In the event of poor returns to biomass for electricity generation, landholders would consider alternative uses for the timber such as pulp wood or sawlogs. However, alternative uses for mallee species are not readily available. The current export chip wood industry is dominated by high-quality pulp species and mallee species are not suitable as very few of these species have proven good-quality pulping characteristics (Bartle, 2009; Marcar, 2009) and do not grow to a size appropriate for sawlog production. Plantations are therefore assumed to be planted for the sole purpose of biomass production for electricity generation.

Australia's biomass industry is underdeveloped, and the viability of a biomass energy plant requires large enough scale land use change within close proximity to ensure supply at a scale sufficient for economic plant operation. In this study we assume a viable biomass production facility for the purpose of examining the effects yield, price and climate risks have on the returns required to trigger land use change over and above those calculated using traditional valuations methods (NPV).

5.2.6 Biomass productivity

The spatial variation of biomass productivity across the study area and how it varies with climate was modelled using the *Carbon Sequestration from Revegetation Estimator* (Hobbs et al., 2013). The model was derived from local climate empirical measurements of biomass accumulation from the reforestation of Kyoto compliant (>2 m in height) native *Eucalyptus* species in the agricultural regions of southern Australia. The model uses multiple linear regression and forward-stepwise regression techniques to identify the best predictors of productivity rates (Hobbs et al., 2013). Historical annual rainfall data from 1891 to 2005 for all locations was acquired from the SILO data base (Jeffrey et al., 2001), and used as inputs into the biomass model for scenario S0. Rainfall data for scenarios S2 and S3 were taken from Bryan et al. (2010c), which consisted of adjusted SILO data.

Uncertainty associated with future biomass and wheat yields was accounted for by representing each with standard normal distributions. While literature exists suggesting yield distributions are not normally distributed (Day, 1965; Gallagher, 1987; Ramirez et al., 2003) there is no consensus on how crop yield risk should be modelled. In fact the level of skewness is likely to depend on the availability of reliable data and the level of aggregation at which yields are measured (Antón, 2009). It is reasonable to expect yield distributions to be more symmetric at higher levels of aggregation (Antón, 2009). Reliable time series of yield data across the study area is scarce; therefore no reliable conclusions as to the shape of the distribution can be made. To aid model tractability, standard normal distributions were chosen.

5.2.7 Wheat productivity

Wheat is the most commonly cultivated crop in the study area (ABARES, 2013; Bryan et al., 2014) and was used as an analogue to represent agricultural production (following Wolbert-Haverkamp and Musshoff (2014a)) who used rye as an analogue for agricultural production). While this approach ignores some of the nuance of diversification strategies available to farmers to manage short term climate risks, diversification is primarily done for cultural reasons including disease and weed control in aid of increased wheat productivity (Kirkegaard et al., 1994; Kirkegaard et al., 2011). We contend that the approach does not introduce major distortions in analysis. Given that changes in cropping mix and intensity don't involve major capital expenditures, and are easily changed from year to year, they don't require evaluation with real options.

Annual wheat yields from 1891 to 2005 for the study areas were modelled by Bryan et al. (2010c) for the three climate scenarios using the Agricultural Production Systems Simulator (APSIM, Keating et al., 2003). APSIM is a process based yield model and has been widely used and validated for Australia (Luo et al., 2005a; Luo et al., 2007; Luo et al., 2005b; Wang et al., 2009a; Wang et al., 2009b). Following Bryan et al. (2010a) spatial variation was captured by classifying the study area into 138 geographic zones of homogenous agricultural productivity, or APSIM zones. Each APSIM zone is a unique combination of 14 soil types and 16 climate zones defined by overlaying climate and soil layers in a GIS.

5.2.8 Commodity price time-series

Biomass is a largely undeveloped industry in Australia and as such no long-term time-series data on the price of biomass in Australia exists. Coal has historically been the most commonly used fuel source for electricity generation in Australia (Rodriguez et al., 2011). We used historical coal prices as an analogue for biomass price in order to provide a time-series of the prices paid per gigajoule of energy used for electricity production. This process was used by Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014a) who use long run heating oil prices as an analogue for biomass prices in Germany. Inflation-adjusted monthly coal price 1970 – 2013 (The World Bank, 2014) was divided by average gross calorific value of brown coal (23.8 GJ/dry weight tonne (CSIRO, 2006), and multiplied by the average gross calorific value of Eucalyptus spp. (19.4 GJ/dry weight tonne (CSIRO, 2006)). Monthly wheat prices 1970 – 2013 were taken from The World Bank (2014) and adjusted for inflation.

Future biomass and wheat prices were modelled using a geometric Brownian motion (GBM), the parameters of which can be seen in Table 5.2. GBM is extensively used in real options modelling due to its use in the well-known Black-Scholes-Merton analytical solution for options prices (Reeson et al., 2015; Sanderson et al., 2016). In addition to being widely used, the GBM is a plausible non-stationary process for commodity price modelling as the stochastic variable (prices) cannot change sign, meaning that in case of a positive initial value no negative values can occur (Musshoff, 2012). GBM contains the Markov property, meaning that the price varies each year dependent on the last value observed and by a random increment based on a normal distribution which represents the annual price volatility (Musshoff, 2012; Reeson et al., 2015). The functional representation and implementation of the GBM is described further in online supplementary material.

5.2.9 Investment decision using discounted cash flow

In order to form a point of comparison with the ROA, the returns to biomass needed to trigger land use change from agriculture were calculated with NPV for each spatial unit under each of the climate change scenarios based on *returns* per hectare. The returns presented represents the annual gross revenue per hectare for an enterprise minus the variable costs per hectare directly associated that enterprise.

The costs associated with wheat production were taken from Rural Solutions SA Farm Enterprise Planning Guide, 2015 (Rural Solutions, 2015). These include variable costs routinely encountered in a broad-acre cropping enterprise including the costs of seed, fertiliser, chemicals, freight, and contract work. The costs associated with the production of wheat varied according to rainfall zone but were treated as invariant over time (Table 5.2). Variable costs associated with the cultivation of biomass included fertiliser (FC), maintenance costs *(MC)*, transport (TC) and harvest (HC) and were taken from Bryan et al. (2010c).

In addition to revenues and variable costs, fixed cost of biomass planting and re-establishment were taken into account. We assumed the establishment cost (EC) to be AU$1000/ha. Estimates of the costs associated with recultivating (RC) biomass plantations either back to agricultural production or in preparation for reinvestment in biomass, obtained through expert consultation, were set at AU$1000/ha.

For the purposes of calculating the NPV, the expected yield of biomass for each APSIM zone and for each climate change scenario was taken to be the average yield calculated from the Carbon Sequestration from Revegetation Estimator. Similarly, the expected wheat yield was taken as the average modelled with the wheat yield simulation model APSIM yield for each APSIM zone under each climate change scenario. The expected wheat and biomass price received in the NPV calculations was the mean price taken from the respective historical commodity price time series 1970 – 2013 (Table 5.2).

We assumed a risk-neutral investor and future revenues were discounted using a risk-free interest rate of 5.41%, calculated from the average nominal returns of Australian 10 year Government Bonds 1985 to 2013 adjusted for inflation over the same period (The Reserve Bank of Australia, 2014).

Table 5.2 – Overview of assumed parameters applicable to both NPV and ROA calculations

		Low Rainfall Zone	Medium Rainfall Zone	High Rainfall Zone
Expected total variable costs wheat (AU$/ha/year)	VC_h^{Wheat}	$164	$338	$449
Expected price wheat (AU$/t)	$Price_t^{wheat}$	$420	$420	$420
Expected total variable costs biomass (AU$/ha/year)	VC_h^{BEG}	$32	$57	$112
Expected price biomass (AU$/t)	$Price_t^{BEG}$	$88	$88	$88
Biomass establishment costs (AU$/ha)	EC_h	$1000		
Biomass recultivation costs (AU$/ha)	RC_h	$1000		
Transport cost *(TC)* (AU$/tonne/km)	TC_t	$0.05		
Mean distance to processing plant (km)		55		
Fertilizer costs (AU$/ha/year)	FC_h	$40		
Harvest costs (AU$/t)	HC_t	$12		
Useful lifetime of biomass plantation (years)	N	21		
Risk free rate	r	5.41%		
Stochastic process		GBM		

5.2.10 Investment decision using ROA

We adapted a numerical, simulation-based real options model (Tubetov et al., 2012; Wolbert-Haverkamp and Musshoff, 2014a, b) to value the option of converting land from wheat to biomass. The model is based on stochastic simulation of random variables and the parameterisation of the investment trigger. The parameterisation procedure for determining the test trigger is described in detail in supplementary material and by Wolbert-Haverkamp and Musshoff (2014b). The advantages of simulation-based ROA methods is that they are flexible and can consider multiple uncertainties over long times (Longstaff and Schwartz, 2001; Triantis, 2003). However, they are limited in their capacity to indicate optimal land use change timing and other tactical business decisions. Analytical approaches such as those used by Sanderson et al. (2016) and Hertzler et al. (2013) can provide information on optimal timing and some tactical decisions provided the complexities of varying prices, climate uncertainties and spatial variability are greatly simplified or ignored. The consideration of the influence of these real complexities is the advantage of ROA and is the subject of this article.

Unlike other commercial investments, a land holder has the ability to delay land use change indefinitely. Therefore, there is no natural time horizon to place on the valuation of the option to change land use. As such the model assumed an infinite investment horizon and the possibility for multiple re-establishments of biomass crops and possibilities to convert back to cropping at the end of each biomass production cycle. As a result the optimal conversion trigger return is asymptotic, conforming to a constant conversion trigger that remains unchanged over the entire lifetime ((t=0,1, $\cdots,\infty$) Dixit and Pindyck, 1994; Wolbert-Haverkamp and Musshoff, 2014b). For computational feasibility a long horizon is used to approximate an infinite one with this methodology. In our model, a time period of $t = 250$ years was used. The approximation error as a result is trivial as $100,000 discounted at 5.41% over 250 years is $0.19. To determine the trigger returns at which a farmer should convert land use under ROA, the present value of future returns after converting from wheat to biomass were valued as an iterative series of ROA trigger values and random draws for values (price of wheat, price of biomass, biomass yield, wheat yield) specified as uncertain for each year in the 250 year time series.

5.3 Results

5.3.1 Regional primary productivity

Significant spatial heterogeneity of primary productivity was evident across the study area, determined primarily by rainfall and soil characteristics with greatest agricultural productivity in the high and medium rainfall areas. Modelling of both agricultural and biomass productivity suggest declines in both wheat and biomass production in response to warmer and drier climate futures in the low and medium rainfall zones (Figure 5.3). But in the high rainfall zone, where winter crop production can be restricted by conditions such as waterlogging of soils and low temperatures, wheat yields are expected to increase slightly due to more favourable growing conditions. Biomass production conversely relies on year round rainfall (as opposed to growing season rainfall) and was expected to decline due to the overall reduction in annual rainfall in such areas.

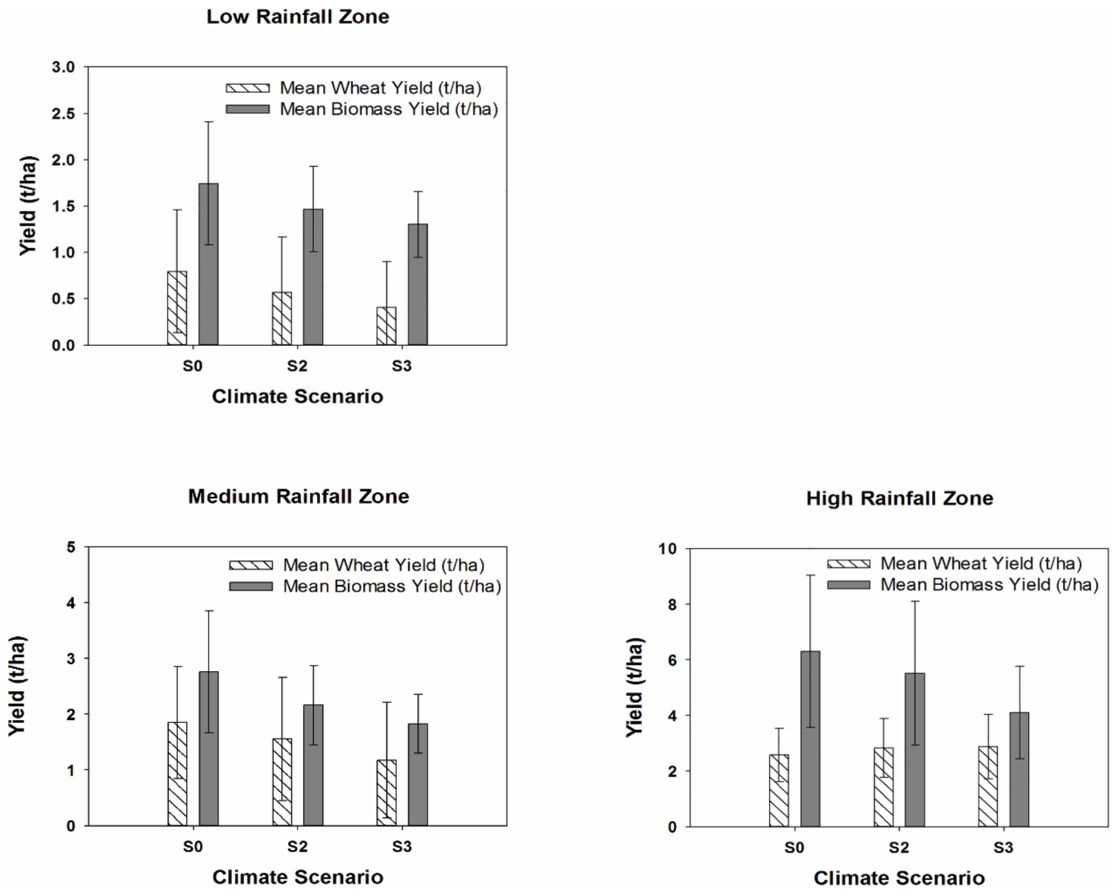

Figure 5.3 — Mean wheat and biomass productivity in the low, medium and high rainfall zones of the study area under baseline (S0) climate and two climate change scenarios (S2 and S3) where the error bars depict the standard deviation.

5.3.2 Economic returns to production for NPV analysis

On average, across the study area, the effects of climate change were projected to reduce returns to both wheat and biomass, but more so for wheat as shown in Table 5.3. However, mean returns to agriculture in the high rainfall zone were seen to increase as a result of the more favourable growing conditions. In the high rainfall zone, average returns for wheat increased from $634/ha under baseline climate to $761/ha under climate scenario S3.

Table 5.3 — Summary of mean economic profitability of wheat and biomass production across the study area under baseline and two climate change futures.

	S0 —Baseline	S2 —Moderate warming/drying		S3 —Severe warming/drying	
	Mean return ($/ha/year)	Mean return ($/ha/year)	ΔMean	Mean return ($/ha/year)	ΔMean
Wheat	373.57	315.19	-15.62%	233.28	-37.55%
Biomass	187.41	173.50	-7.42%	128.52	-31.42%

5.3.3 Returns required to trigger land use change using NPV

The trigger returns required to induce land use change were found initially using NPV analysis for baseline climate and two climate change scenarios (Figure 5.4).

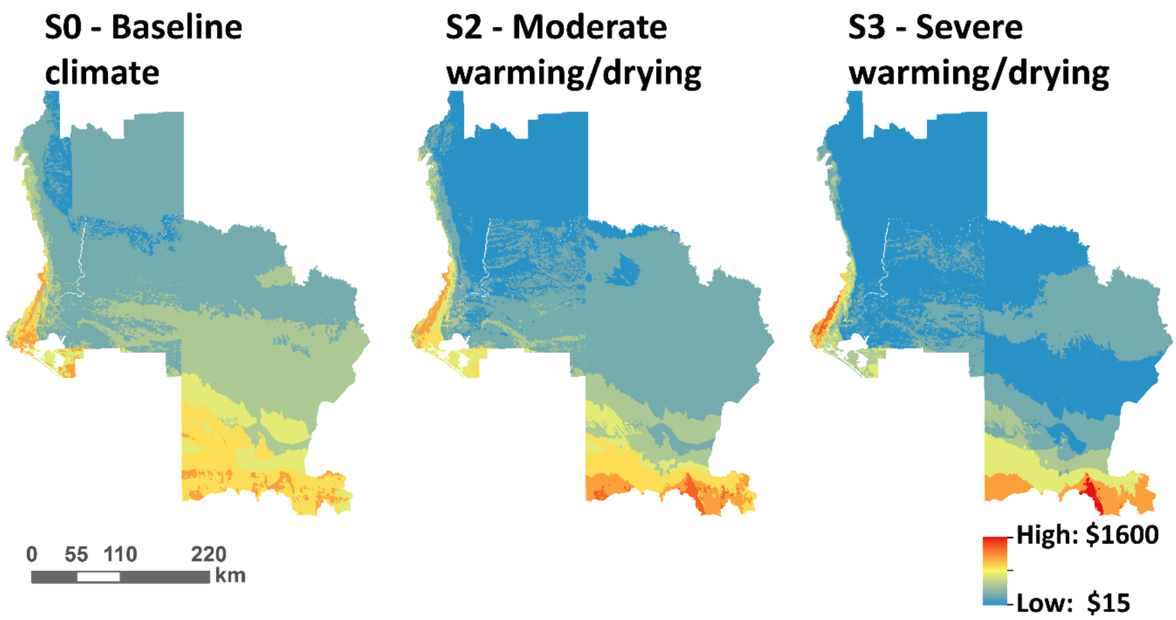

Figure 5.4 – Returns ($/ha) from biomass required to trigger land use change from conventional agriculture (wheat) to biomass under NPV investment rationale for baseline climate conditions and two climate change scenarios.

Clear spatial heterogeneity of trigger returns was found across the study area. Under a baseline climate scenario trigger returns ranged from $123/ha to $1190/ha. Broadly, the climate change scenarios reduced the trigger returns across the study area. For example, the mean trigger returns across the study area were reduced from $500/ha under S0 to $360/ha under S3. This result held nearly universally in drier areas. For example, in scenario S3, the minimum returns required to induce land use change were reduced by $108/ha, compared to the baseline scenario S0 to $23/ha in the low rainfall zone. An exception to the broad trend was found in high rainfall zones where the effect of the climate change scenario was to increase the trigger returns required to induce land use change away from conventional agriculture. For example, the maximum trigger return under climate S3 increased by $331/ha to approximately $1521/ha.

5.3.4 Returns required to trigger land use change using real options

The returns required to trigger land use change from wheat to biomass using ROA are illustrated in Figure 5.5. Under S0 the trigger returns ranged from $230/ha to $1650/ha with an average of $688 across the study area with the mean trigger return in the low rainfall zone of $410/ha being substantially lower than the medium rainfall zone, $750/ha, and the high rainfall zone at $1077/ha. In addition there was considerable variation in trigger returns within rainfall zones (Table 5.4), particularly in the medium rainfall zone of the study area where trigger returns ranged between $360/ha to $1640/ha.

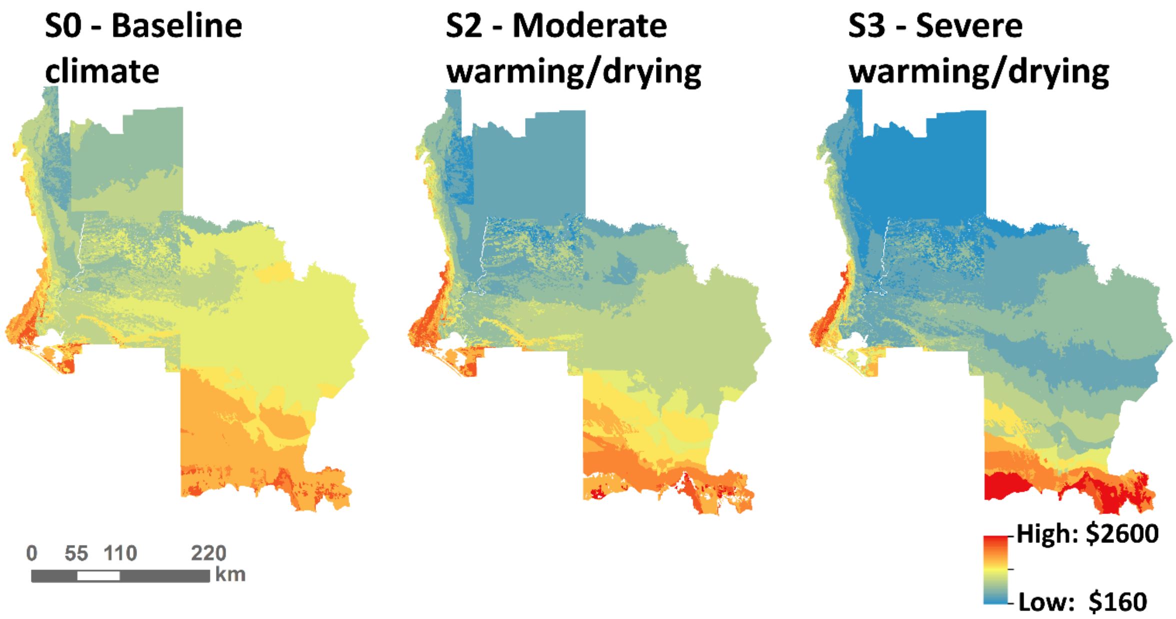

Figure 5.5 — Returns ($/ha) from biomass required to trigger land use change from conventional agriculture (wheat) to biomass using ROA under baseline climate conditions and two climate change scenarios.

5.3.5 Climate change impacts on land use conversion economics

Figure 5.5.5 illustrates the effects of potential future climate change on the trigger returns required to switch land use to biomass. For the moderate drying/warming scenario (S2) in the low rainfall zones of the study area the mean trigger return was reduced by 26.6% (Table 5.4), where the trigger return in the low rainfall zone declined from $410/ha in scenario S0 to $301/ha in S2. In the medium rainfall zone the mean trigger returns declined by 14.3% (Table 5.4), but the range in trigger returns across the medium rainfall areas increased from $1280/ha to $1400/ha (9.4%). By contrast, in the high rainfall areas of the region, the mean trigger return increased by 23.1% (Table 5.4) from S0 to S2, while the range in returns increased from $1160/ha to $1760/ha (52%).

Table 5.4 — Summary of ROA trigger returns required across the study area under baseline climate and two climate change futures.

	S0 –Baseline				S2 –Moderate warming/drying					S3 –Severe warming/drying				
Rainfall Zone	Min ($/ha)	Mean ($/ha)	Max ($/ha)	Median ($/ha)	Min ($/ha)	Mean ($/ha)	Max ($/ha)	Median ($/ha)	ΔMean	Min ($/ha)	Mean ($/ha)	Max ($/ha)	Median ($/ha)	ΔMean
Low	230	410	710	390	190	301	500	280	-26.60%	160	233	410	230	-43.17%
Medium	360	750	1640	655	310	643	1710	540	-14.26%	220	434	1160	320	-42.13%
High	490	1077	1650	1135	690	1326	2450	1425	23.12%	790	1439	2370	1385	33.61%

The severe drying and warming climate change scenario (S3) had more pronounced effects on the trigger returns required to induce land use change to biomass than that in S2 (Figure 5.5). Interestingly, the relative effect on the trigger returns in the low and medium rainfall zones of the study area was comparable in S3, after being substantially different in S2. In the low rainfall zone the mean return was reduced to $233/ha, a reduction of 43.2% when compared to that of S0 (Table 5.4), while the within rainfall zone range reduced from $310/ha (S2) to $250/ha (-19.4%). In the medium rainfall zone the mean trigger return declined to $433/ha, a reduction of 42% compared to the trigger return in S0 (Table 5.4), while the intra-rainfall zone range declined from $1400/ha (S2) to $940 (-32.9%). The trend of increasing trigger returns in the high rainfall areas continued under severe warming and drying with the mean trigger return increasing 33.6% over S0 to $1439/ha (Table 5.4). While the range in trigger returns between S2 and S3 in the high rainfall zone decreased by 10.2%.

5.3.6 Comparison of real options and net present value results

The effect of option values of the trigger returns needed for land use change was measured through the Investment Multiple (IM). The IM was determined by dividing the trigger return calculated using ROA by the trigger return calculated using NPV methods. The mean effect of climate change across the study area was to increase IM from 1.41 in S0, 1.54 in S2 and to 1.84 in S3. When the mean IM is examined by rainfall zone, differences emerge (Figure 5.6). The mean IM increased the most in the low rainfall zones, from S0 (1.41) to S3 (2.03). In contrast, the medium rainfall zones and high rainfall zones change comparatively little between S0 and S2. Mean IM in medium rainfall zone increased from 1.31 (S0) to 1.47 (S2) and decreased from 1.57 (S0) to 1.53 (S2) in the high rainfall zones. The results for the medium and high rainfall zones diverge under a severe drying and warming climate scenario. The IM in the high rainfall areas increases slightly from S2 (1.53) to S3

(1.62). In comparison the mean IM in the medium rainfall zones increase substantially more from S2 (1.47) to S3 (1.77).

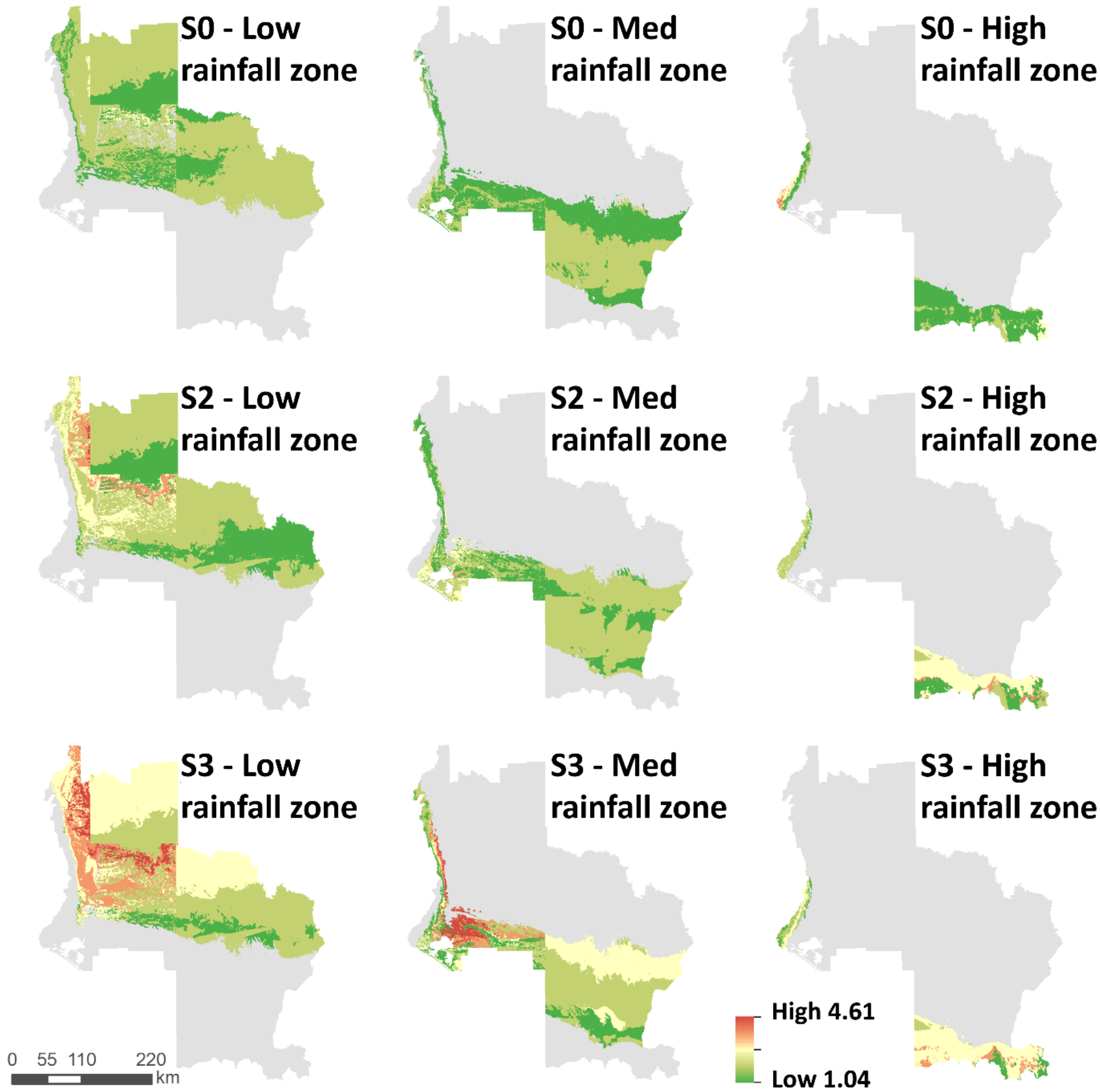

Figure 5.6 – The effect of uncertainty as measured by IM on the returns required to trigger land use change to biomass using ROA. An IM of 1 = no change from the trigger returns calculated under the NPV model.

While spatial variability of IM could be seen across the study area as a whole, it is most apparent within rainfall zones and were quite pronounced between climate change scenarios (Figure 5.6). In the low rainfall zone the difference between the lowest IM and the highest IM increased significantly from S0 (1.04 – 1.87) to S3 (1.28 – 4.61). A similar increase was evident in the medium rainfall zones between S0 (1.09 – 1.65) and S3 (1.13 – 3.85). Interestingly, in the high rainfall zone, the within rainfall zone IM range reduced between S0 (1.19 – 3.80) and S3 (1.21 – 2.21).

5.3.7 Viable areas for land use change to biomass

There has been considerable theoretical assessment of options for a mallee biomass supply chain for both electricity production and integrated tree processing by government, industry and academia (Bartle, 2009; Bartle et al., 2007; Bryan et al., 2008a; Farine et al., 2012; Hobbs, 2009a; Rodriguez et al., 2011; Schmidt et al., 2012; Ward and Trengove, 2004). There is broad consensus that ultimately prices achievable per dry matter tonne (DM t) of biomass will be a key to the success of any future industry. Possible future prices for biomass quoted in the literature range from AU$40/DM t (Bartle, 2009) up to approximately AU$300/DM t (Schmidt et al., 2012) [2]. The results in this paper present the conversion thresholds based on historical coal and wheat price variability, without any additional income from a carbon price, Renewable Energy Credits (REC), payments for potential environmental services or other incentive policies. As such, the results represent the returns if prices for energy ($/GJ) were to continue to be broadly representative of historical coal prices and biomass was to replace coal on a per GJ basis without the effect of other distorting price mechanisms paid for biomass production.

Figure 5.7 maps the extent of land use conversion estimated with ROA over a range of biomass feed stock prices for baseline climate and two climate change scenarios. Given our assumptions, very little land use conversion could be expected across the study area at biomass prices below AU$100/DM t. At a price of AU$200/DM t 457,331 ha would become profitable under climate scenario S0 (Figure 5.7). Under the climate change scenarios, significantly more of the study area would meet the threshold returns at prices up to AU$200/DM t, with 693,386 ha being profitable under S2 and 930,986 ha profitable under S3. At a biomass price of AU$300/DM t significantly more areas would produce biomass returns high enough to meet the trigger returns calculated using ROA ranging from 2,166,398 ha under S0 to 2,738,463 ha under S3 (Figure 5.7).

Many factors complicate forecasts of future biomass prices, including future electricity demand, fossil fuel prices, future food crop prices, the price of and eligibility of biomass feedstocks to receive REC's or carbon credits for below ground biomass. However, our results show that on an energy equivalence basis, to be competitive with an oil price of AU$41/barrel (current at the time of writing) biomass would have to be priced at less than AU$130/DM t. Similarly, to be competitive with coal at AU$68/t, the energy equivalent price of biomass would have to be less than AU$52/DMt (see online support material for energy equivalent price calculation methods and data). For substantial biomass industry development to occur in the study area, the synchronisation of

[2] Schmidt et al (2012) reported a price of $185/green tonne. Assuming moisture content of 39% (CSIRO, 2006) we report an equivalent price of $303/DM t.

products and services derived from mallee and the development of receiving markets is paramount (Huxtable et al., 2007), but currently no clear pathway exists to achieve this.

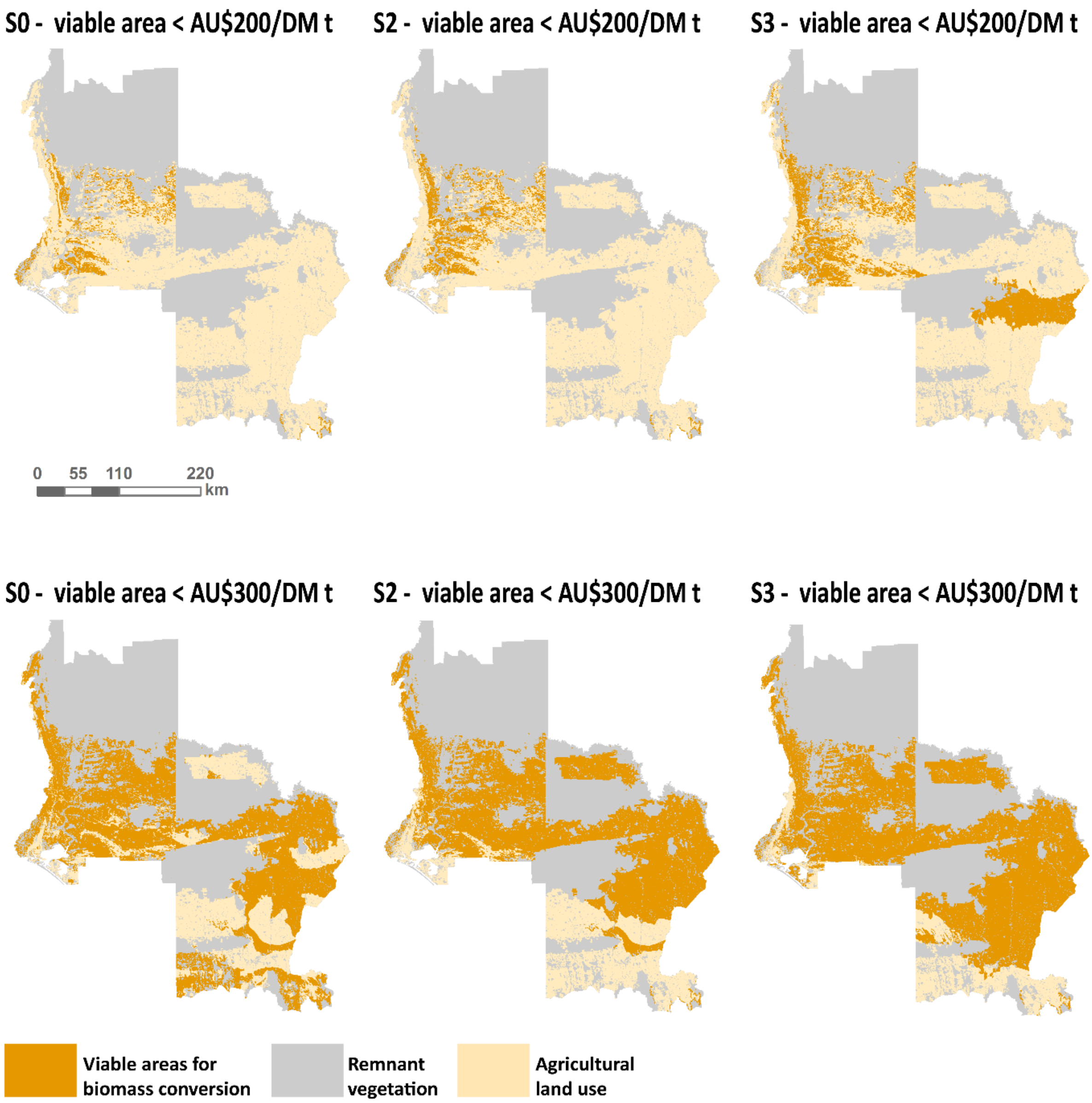

Figure 5.7 – Areas economically viable for land use change to biomass (shown in orange), calculated from the ROA trigger returns at biomass prices of up to $200/DM t and up to $300/DM t. Very little area is viable at prices up to $100/DM t, and therefore is not displayed here.

5.4 Discussion

The development of a large scale biomass industry in Australia has been suggested as a climate change resilient diversification option for agricultural landscapes. Currently, there are impediments to realising this potential. These include large reserves of accessible coal, the low cost of electricity generated in coal-fired power plants and uncertain greenhouse and renewable energy policy

(Raison, 2006). Integrated tree processing is seen as a promising way forward for mallee based industries in Australia as it offers a number of commercial opportunities including renewable energy generation, and co-products of eucalyptus oil and activated carbon (Enecon, 2001).

Our modelling highlights that in semi-arid regions such as our study area climate change is likely to affect the economics of land use conversion from agriculture to biomass production by changing the relative productivity and yield risks of the two land uses. In the low and medium rainfall zones the two climate change scenarios reduced mean wheat yields and increased year-to-year yield variability (Figure 5.4). In these areas the returns from biomass relative to wheat improved under the climate change scenarios and as a result the returns needed to trigger land use change declined over the scenarios across much of the study area (Figure 5.4).

In the high rainfall zone, however, the productivity of wheat increased slightly under hotter and drier climate scenarios in some areas where the productivity of wheat is inhibited under baseline climate conditions by biophysical factors such as water logging. This is exemplified in the southern Wimmera (south eastern regions of the study area as labelled in Figure 5.1). As a result, wheat is likely to become more competitive relative to biomass in high rainfall areas.

Comparison of ROA and NPV results showed that the inclusion of uncertain returns and temporal flexibility in investment analysis timing adds to the returns needed to trigger land use change, consistent with the findings of previous ROA studies (Musshoff, 2012; Reeson et al., 2015; Yemshanov et al., 2015). Under baseline climate conditions, the required returns from biomass yield and price uncertainty to trigger land use change away from agriculture were between 104% and 305% (mean 141%) of NPV calculated returns required to trigger change.

Results also appear to suggest that climate change will increase variability in trigger returns required to induce change in the high rainfall zone. The mean returns required to trigger land use change in the low and medium rainfall zones were estimated to decrease with climate change.

We found that not only is NPV likely to underestimate the returns required to trigger land use change as shown in previous studies (Musshoff, 2012; Reeson et al., 2015; Wolbert-Haverkamp and Musshoff, 2014a), but that changing risks associated with land use resulting from climate change can further exacerbate the tendency for NPV methods to underestimate true conversion thresholds. A further complicating factor for policymakers/investors is that this effect varies spatially (Figure 5.6) not only between high and low rainfall areas as one would intuitively expect, but within areas which would tend to be classified similarly on the basis of average yields (not accounting for yield variability).

5.4.1 Caveats and future directions

The results presented here should be interpreted in relation to the key assumptions made. Firstly, modelling of commodity yields assumed no adaptation to climate change. Several potential adaptations are currently available to landholders (e.g. changing input levels and or altered timing of activities), most of which are variations of existing climate risk management or are theoretical and require advancements beyond current technological capabilities (i.e. significant advancements in plant breeding). However, there is uncertainty over the actual efficacy of changes in nitrogen application levels, wheat cultivar or their synergistic effects on the negative effects of climate change (Luo et al., 2009). Such adaptive responses, to wheat production in particular, may have some marginal effects on the land use conversion thresholds, but most of the benefits of marginal adaptations within existing systems accrue with moderate climate change, and there are limits to their effectiveness under more severe climate changes (Howden et al., 2007). Moreover, yield benefits from adaptation are likely greater under scenarios of increased rainfall reflecting that there are many ways of more effectively using more abundant resources, whereas there are fewer and less-effective options for significantly ameliorating risks when conditions become more limiting (Howden et al., 2007).

Secondly, this study uses GBM to forecast future commodity price development. While precedent for this abound in the literature (Duku-Kaakyire and Nanang, 2004; Isik et al., 2001; Isik and Yang, 2004; Musshoff, 2012; Schatzki, 2003; Yemshanov et al., 2015), there are certain consequences that should be noted. Musshoff (2012) found that the models are sensitive to the stochastic process used to forecast future price development. He found that the conversion trigger and investment multiple differed when a mean reverting process (MRP) was used in place of a GBM or arithmetic Brownian motion. This difference was explained by the respective process characteristics. While prices fluctuate around their equilibrium level in an MRP, they can drift freely in analyses that use Brownian motion functions to generate price variability. The implication of this is that the free floating characteristics of the GBM have been found to increase the price risk posed to land holders in models cause delays in land use conversion under any given level of price volatility (Reeson et al., 2015).

Thirdly, we assume the cost of production for both biomass and wheat remain constant. Undoubtedly the costs of production are likely to change for both commodities. However, factors driving changes in costs of production of biomass and agriculture are similar and hence, likely to be highly correlated and as such likely to have limited influence on the results (Bryan et al., 2010c).

Finally the results presented here indicate the returns optimal for triggering land use change under conditions of uncertain prices and variable yields. Many other factors including status quo bias (Burmeister and Schade, 2007), differences in individual landholders' risk aversion (Wolbert-Haverkamp and Musshoff, 2014a) and an individual's objective in farming (Guillem et al., 2012) influences landholder decision making. Economic experiments (Ihli et al., 2013; Maart-Noelck and Musshoff, 2013) have found that farmers make irreversible investments later than NPV models predict, but sooner than optimal under real options values; although farmer decisions come to more closely approximate the real options framework with experience. Understanding the interactions between price and yield uncertainty and farmer typologies is an area worthy of further research.

Conclusions

The results presented here reaffirm that options values must be considered in land use change economics. However, the results demonstrate that the underlying variability in primary productivity has a substantial effect on the magnitude of uncertainty on the returns required to trigger land use change from wheat to biomass. Areas traditionally thought of as being quite similar on an average yield basis can display large differences in response to the inclusion of production and price risks due to local biophysical conditions that determine primary productivity variability. In addition, changing risks associated with land use, as a result of climate change, can further exacerbate the tendency for NPV methods to underestimate true conversion thresholds across the regions such as our study area. A further complicating factor for policymakers/investors is that this effect varies spatially, not only between high and low rainfall areas as one would intuitively expect, but within similarly classified areas. In broad terms climate change reduced returns required for land use change to biomass in low and medium rainfall zones typical of semi-arid rainfed grain farming regions and increased them in the higher rainfall areas. Severe climate change is likely to reduce variability in returns required from biomass across the study area, but moderate climate change futures may exacerbate variability in returns required in medium and high rainfall zones. Our results show that even under severe climate change comparatively small areas are economically viable for conversion to biomass under \$200/DM t, and it is not until prices exceed \$200/DM t that significant areas become profitable for conversion to biomass. Whether or not these prices are ultimately achievable is speculative, however, it is clear that for substantial biomass industry development to occur in the study area, the synchronisation of products and services derived from mallee and the development of markets is paramount.

Acknowledgements

This work was made possible by the Charles John Everard Scholarship awarded through the University of Adelaide and the support of CSIRO Sustainable Agriculture Flagship. The Authors wish to acknowledge Darran King and John Kandulu from CSIRO for proving spatial data sets and Matt Westlake and Waseem Kamleh from the University of Adelaide for assistance with high performance computing.

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CHAPTER SIX

CONCLUSIONS

6 CHAPTER SIX

Conclusions

6.1 Key finding and conclusions

Traditional capital budgeting techniques relying on the calculation of Net Present Value (NPV) have shown emerging land uses may provide landholders with profitable diversification options in the future (Bryan et al., 2010c; Bryan et al., 2008a; Paterson and Bryan, 2012; Polglase et al., 2011; Ward and Trengove, 2004). However NPV methodologies have been criticised for providing unrealistic valuations as these models inadequately account for return uncertainty, temporal flexibility and sunk costs (Dixit and Pindyck, 1994; Kemna, 1993; Tozer, 2009; Trigeorgis, 1996). Real options analysis is an alternative valuation method with the advantage of being able to incorporate uncertainty into the economic analysis. A feature of previous ROA studies has been a focus on price uncertainty alone (Musshoff, 2012; Schatzki, 2003; Wolbert-Haverkamp and Musshoff, 2014a). Price uncertainty notwithstanding, climate variability is the principal source of risk affecting long term economic viability of rain-fed agricultural systems (Kandulu et al., 2012). However the consideration of temporal and spatial yield risk has been largely lacking in ROA to date. Furthermore, the potential future effects of climate change are likely to pose addition challenges and risks to conventional farming systems and is anticipated to drive substantial transformational changes to agricultural systems (Sanderson et al., 2016). It is clear optimal land use will be different under future climate. However, spatial consideration of the risks posed by climate change and faced by landholders has received limited attention in the ROA literature to date.

Two methods for ROA application to land use change are apparent in the literature. One method involves the use of analytical methods such as those employed by Hertzler et al. (2013), Sanderson et al. (2016) and Schatzki (2003). These methods involve the solution of partial differential equations. The solution of these equations is not trivial and analytical solutions exist only for simple valuation problems with specific preconditions. These include, for example, that the evaluated investment option has a time continuous opportunity to invest, future revenue can only follow a GBM and there should not be interactions between the investment option and other options, such as reinvestment and disinvestment options (Musshoff, 2012; Wolbert-Haverkamp and Musshoff, 2013). However in the instance of an investment in biomass, the investment opportunity is not time continuous. Landholders generally have, at most, only several opportunities a year to make a decision on land use due to seasonal factors and to re-invest in biomass at the end of a plantation's useful lifetime. The nature of land use change decision making is such that numerical approximation methods are more applicable (see Chapter 3 for a detailed discussion of relative merits of different numerical approximation methods). Monte Carlo simulation methods are the most tractable way to currently address multiple sources of uncertainty regardless of the distributions' complexity concerning the stochastic variable (Wolbert-Haverkamp and Musshoff, 2014b), and to incorporate this in a spatially explicit environment.

This research highlights that there are pros and cons to the use of each ROA method (analytical, decision tree, Monte Carlo simulation methods) as outlined in Chapter 3, leading to the conclusion that there is no one ROA methodology suitable for investigating all problems. For example, there are distinct advantages to analytical methods in analysing strategic investment decision making. However, these models do not easily incorporate multiple sources of uncertainty as separate stochastic processes (Sanderson et al., 2016) or spatially varying risks. This appears to limit their applicability to larger (geographical) scale analysis or policy development. Conversely, while numerical approximation methods can be adapted to incorporate multiple sources of uncertainty, separate stochastic processes or distributions, they have limited capacity to calculate the probability of and optimal timing of land use change, unless arbitrary time frames are placed upon the analysis. Consequently these methods are better suited to examining problems such as the effect of multiple interacting uncertainties on the returns required to trigger land use change. Practitioners should be aware that some analytical approaches will sacrifice some attainable strategic information that may be of key interest. Particular issues such as optimal time to switch, require the consideration of multiple sources of uncertainty and nuanced accounting of spatial variability.

The results of this research broadly agree with other real options research into land use change from conventional agriculture to forested land uses such as biomass. The addition of uncertainty over returns, flexibility in investment timing and recognising sunk costs can add significantly to the returns at which a landholder should optimally change land use (Musshoff, 2012; Reeson et al., 2015; Schatzki, 2003; Wolbert-Haverkamp and Musshoff, 2014a, b).This research has added to previous ROA studies by extending the analysis to multiple locations and examining how strongly the results are influenced by the location conditions and if difference existed between locations (Chapter 4) . The limited analysis of the locational effect of option values across an area can be mainly attributed to the difficulty in incorporating multiple sources of uncertainty to the models. Incorporating yield variability into a simulation model as in this thesis has facilitated the analysis of the effect temporal and spatial yield variability has on the risk premium required to trigger investment. The results show that the interaction of simultaneous price and yield risk does not act homogenously across space. The present value of returns required to trigger land use change varied from 1.45 to 2.32 times the present value of expenditures (Chapter 4).

Incentive policies are often employed by policy makers to encourage participation in agro-environmental programs by offsetting establishment costs or attempting to negate variability in returns from alternative land uses. However the results of this research show that the effect of incentive payments is unlikely to be uniform geographically. This was demonstrated by the analysis of the effect of subsidy payments to reduce risks and therefore conversion thresholds. In areas of low primary productivity, such as Florieton (chapter 4), incentive payments have a large effect as they provide a large stabilising role to returns, relative to more productive and less variable yield locations. This provides a dilemma for policy makers offering widely available incentives. Broadly offered policies will likely have a positive response from landholders in low productivity areas, however this may result in perverse outcomes as the payment is likely to encourage land use change in areas which are neither economically viable nor ecologically desirable. For example, the Wimmera region has a distinct competitive advantage over Florieton in terms of biomass potential yield; however the subsidies have the greatest effect in Florieton. Notionally this would encourage land use change in Florieton where long term integrated tree processing may not be viable; given likely drying and warming as climate changes.

Technical issues in analysing the results of ROA analysis, such as the measure of central tendency, may be of significance to policy makers. In Chapter 5 the mean conversion trigger was reported and commented upon, however in analysis involving multiple spatial units, the median may better represent the distribution of conversion triggers over space as the mean can be sensitive to outlier values. For example, in table 5.4 (S3, medium rainfall zone) the median is significantly lower than the mean indicating a positively skewed distribution in that rainfall zone under that climate change scenario. In this scenario and rainfall zone there are several large outliers in ROA conversion triggers. This is due to several spatial units being classified as medium rainfall, but on the cusp of being able to be classified as in the high rainfall zone. Under the severe warming and drying scenario these spatial units have responded in a similar fashion to the high rainfall zone as discussed in Chapter 5. The implication of this seemingly trivial choice of measure of central tendency may be quite profound for policy makers. In this scenario, a policy maker offing an incentive informed by the mean would be losing efficiency. In this situation, relatively little additional area would become viable for conversion by offering the mean trigger price when compared to the area eligible for conversion under the median trigger price. However, the cost difference is substantial with the median conversion trigger being 26 percent lower than the mean conversion trigger.

The results presented in Chapters 4 and 5 demonstrate that there are substantial differences between rainfall zones in terms of the risk premium required, over and above the NPV trigger, for land use change to occur. This was demonstrated by the investment multiple (IM) being highest in very low rainfall and also in high rainfall locations. Agricultural regions in the study have historically been categorised by rainfall zone, as outlined in Chapters 4 and 5. The precise definition of zones is often elastic; however this categorisation is generally a good way to broadly delineate areas of similar production systems, productivity and costs associated with crop production. However the results of this research also indicate that using this broad delineation in economic analysis could lead to biased predictions of the returns needed to witness land use change due to significant biophysical variability within these zones (Chapter 5). The inclusion of spatially explicit data into the ROA demonstrated that significant variability in trigger returns were found not only across rainfall zones but also amongst areas traditionally classified in the same broad zone (Chapter 5). These results show that not only is NPV likely to underestimate the returns required to trigger land use change as shown in previous studies (Musshoff, 2012; Reeson et al., 2015; Wolbert-Haverkamp and Musshoff, 2014a), but that the effect of yield risk shows considerable spatial variation, not only between high and low rainfall areas as demonstrated in Chapter 4, but within similarly classified ("homogenous") areas. These results show that while useful, simple spatial analogues may be too much of a simplification for analysing spatial variability or spatial response to price and climate risks in future ROA studies. Seemingly similar areas respond very differently to current production risks in terms of conversion thresholds and changes in production risks caused by climate change are likely to be complex and variable. Making comparison based on spatial-temporal transects does not account for this complexity and may over or underestimate the effect of current and changing production risks on conversion thresholds.

Climate change may pose an additional source of uncertainty to land holders and exacerbate existing production risks (Asseng et al., 2011; Luo et al., 2005a; Luo et al., 2005b), thereby affecting land use change decisions and conversion thresholds. In broad terms, the climate change scenarios examined, reduced the trigger GM required for land use change to biomass in the medium and low rainfall zones. However, in the high rainfall areas the returns needed for land use change to occur increased due to the improving competitiveness of wheat as a result of improving growing conditions for wheat cultivation. The southern Wimmera (south eastern regions of the study area in chapter 5) differs from the other regions in the study area in that, although rainfall and yield potential is comparatively high, the soils are poorly structured and waterlogging often occurs during winter (Armstrong et al., 2001; McDonald and Gardner, 1987). As a result of drying, and therefore improved conditions for the cultivation of wheat, wheat is likely to become more competitive relative to biomass in the high rainfall area and the conversion triggers will likely increase as a response. These results again highlight the importance of accounting for the complex interactions of spatial variables.

Ultimately prices achievable per tonne of biomass will determine the success of any future industry and the extent of land use change away from conventional agriculture. Possible future prices for biomass in the literature range from $40/DM t (Bartle, 2009) up to $300/DM t (Schmidt et al., 2012). Potential future price pathways for biomass and biomass generated energy remain uncertain and will rely on multiple factors such as climate change mitigation policies, fossil fuel prices, demand for integrated tree processing products and technological developments within the energy sector. The results outlined in Chapter 5 show that even under conditions of severe warming and drying, comparatively small areas of the study area would be viable for land use change to biomass under $200/DM t. This is in stark contrast to results reported in studies using NPV methods. Bryan et al. (2010c) and Bryan et al. (2008a) reported significant areas (in the same study area) could be viable for biomass at prices of approximately $50/green t [3]. This result further highlights the effect of price and yield uncertainty on land holder decision making. Ward and Trengove (2005) report that a price of $47/green t ($77/DM t – $94/DM t)[1] as the upper threshold that an integrated tree processing plant could pay for feedstock in order to maintain an internal rate of return of 15%. Initially this does not appear to bode well for widespread adoption of biomass as an alternative crop in the study area. However, unlike traditional agricultural crops, the inclusion of biomass in the form of deep rooted perennial plants can confer additional environmental benefits. These benefits can include reduced deep drainage and groundwater recharge and hence mitigate dryland salinity (Bryan et al., 2010c; Wang et al., 2008), stabilise eroding soils through the soil binding action of roots and reduce surface erosion through reducing wind speeds (Nuberg, 1998). In addition, a significant biomass industry may aid mitigation of climate change through both carbon sequestration in the form of below ground biomass or direct replacement of fossil fuels in electricity generation (Rodriguez et al., 2011). New markets and policies are emerging that may compensate landholders for the ecosystem services their land provides society and these markets have the potential to be transformational (Bryan et al., 2013).

With the long term development of the biomass industry in mind, several issues pertaining to industry development policy have become apparent throughout the course of this research. Concerning the targeted location for the development of the industry, Chapter 5 indicates that very wet areas and more arid areas are likely to be viable for land use change at the lowest cost.

[3] The results in this research report prices as $/DM t. The conversion of $/green tonne to $/DM t is dependent on moisture content. Assuming moisture content of between 39% and 50% this price would be equivalent to between $82/DM t and $100/DM t.

However, the nature of the land holdings in wetter areas may make it unfeasible to target these areas. In areas such as the Mount Lofty Ranges, land holdings are typically small introducing potentially high transaction costs associated with cajoling numerous land holders in to participating in the industry, despite the higher yields associated with biophysical determinants. In contrast, land holdings in more arid areas are typically much larger, often in orders of magnitude, when compared to high rainfall areas. While these areas are less productive, transaction costs are likely to be far lower as fewer land holders will need to be involved.

An additional factor that may make targeting more arid areas wise is the opportunity for diversification. Kandulu et al. (2012) showed that diversification of agricultural enterprises can help dampen fluctuation in commodity prices and may help mitigate the potential effects of future climate change. However, the opportunity for 'traditional' diversification of agricultural enterprises is limited in drier parts of southern Australia as it introduces water intensive and rainfall-sensitive enterprises. Conversely, higher rainfall areas can use a variety of diversification options to hedge against extreme losses in years with unfavourable climate, reduce the likelihood and magnitude of extremely low net returns while benefiting from high-returns obtained from wheat. The introduction of long term land uses such as biomass in to the higher rainfall areas may have perverse out comes for landholders. Biomass' inclusion to the enterprise mix could reduce a land holder's ability to effectively diversify their production system as a means of dampening the effect of climate and price variability or farm returns. Notionally at least, this would not be an issue in drier areas and the addition of a profitable, climate adapted and low labour diversification option may be welcomed by land holders and therefore more readily accepted. This research shows however, that for substantial biomass industry development to occur in the study area, multiple income streams from both products and services derived from mallee and the development of receiving markets will be needed to reach the returns required to trigger land use change to biomass based land uses. Currently, no clear pathway exists to achieve this.

6.2 Future research

This study has focused on applying a numerical simulation based real options model to examine the effect of price and yield variability on the returns required for farmers to change land use from conventional agriculture to perennial mallee species for use in electricity generation or integrated tree processing. Specifically, this study has sought to quantify the effects of multiple uncertainties on a) conversion thresholds required to trigger land use change; b) the quantum multiple that interacting uncertainties adds to the NPV conversion trigger; c) if this effect varies geographically and if it does, how does it vary spatially; and d) how climate change uncertainties influence returns from biomass needed to trigger land use change and how this varies across the landscape. Future work extending the results presented in this research could proceed in several ways:

- Economic experiments conducted internationally have shown that real options models approximate the behaviour of landholders (Ihli et al., 2013) as landholders demonstrably consider the value of waiting in experimental settings (Maart-Noelck and Musshoff, 2013). However, socio-demographic and farm-specific factors also affect the investment behaviour of landholders (Ihli et al., 2013) and these effects differ between countries (Tubetov et al., 2013). Behavioural economic experiments could be conducted in Australia in order to understand the influence of socio-demographic and farm-specific factors in relation to the effects of price uncertainty, sunk costs and loss of flexibility. In the absence of data describing actual land use conversion rates, experimental data derived from Australian landholders would add rigour to the results presented by real options studies and this is an area prime for future research. Failure to account for heterogeneous attitudes, motivations and variable willingness to participate, may result in further reduced investment with an attendant social cost (Ward et al., 2007).
- The analysis examining climate change did not account for potential effects of climate change on global commodity prices or input prices. For example, in a climate changed future demand for 'green' energy may increase the prices of biomass derived electricity, or more variable global agriculture output may increase food prices and food price variability. The potential effect of climate change on global food supply and therefore commodity prices is a complex area with agricultural output changes likely to change differentially depending on crop and are likely to differ between locations. For example maize yields may decline, while spring wheat and soybean yields are likely to improve due to CO_2 fertilisation effects (Deryng et al., 2014) and yields are predicted to decline in lower latitudes and generally increase in higher latitudes (Rosenzweig and Parry, 1994; Wheeler and von Braun, 2013). Farmers adjust their mix of inputs depending on the relative prices of inputs and outputs and their expectations about the growing season. Future research could extend the analysis presented in this research to examine the simultaneous effects of global climate change on not only biophysical conditions but market prices for input and output commodities and include the option for the landholder to adjust inputs according to a seasonal weather projection.
- The effect of subsidy payments was examined in Chapter 3 of this research. In order to make the model tractable, a time unlimited subsidy was offered for below ground carbon accumulation. While feasible in the presence of extant or future carbon markets, other

subsidies may be important for the establishment of a biomass industry in the study area, such as investment subsidies. These payments are unlikely to be time unlimited. Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014a) state that the presence of a time limited subsidy may hasten land use conversion as ultimately, the opportunity costs would be reduced over time with the declining remaining lifetime of the subsidy payment and the decision to convert would be shifted more toward a 'now-or-never-decision'. Future research could examine the effects of various time limited incentive payments, however this would require the use of a different model to the one presented in this research, and would require a finite investment horizon to be implemented along the lines of Odening et al. (2005). It would therefore also be interesting to investigate the effects of a time limited investment horizon in comparison to an infinite investment horizon.

- The research presented here uses wheat as a representation of the agricultural farming system in the region. While reducing the agricultural system to one regime is not without precedent (Sanderson et al., 2016; Wolbert-Haverkamp and Musshoff, 2014a) it is a simplification. Rainfed mixed farming systems, which involve livestock as well as a variety of crops (wheat, barley, oats, beans, lupins, peas, oilseed) of which wheat is just one, predominate in the study area. Kandulu et al. (2012) showed that in some locations, diversification of farming systems in the study area can reduce the variability of returns from agriculture and help manage short-term risk due to variance in market input costs and commodity prices. Future research could address this by incorporating other crops in order to examine the effect of varying levels of diversification on the uncertainty surrounding agricultural returns and in turn the effect on conversion thresholds using ROA.
- Finally, the use of ROA can be complex and daunting. While the methods undoubtedly provide important information for policy makers and natural resource managers, the complexity of the models may prove to be too much of a barrier for wide spread adoption and application. Specifically, the parameterisation of the models can be daunting. For example, the statistical analysis required to identify time-series models can require advanced statistical analysis and fraught, as the choice of stochastic process has been seen to significantly affect the results of the ROA analysis. The complexity of the parameterisation of the models will undoubtedly prove to be a barrier to wide spread adoption of ROA. Future research could investigate the feasibility of summary models to provide policy makers and natural resource managers with approximations of option values and estimates of 'true' conversion triggers in relation to those calculated using NPV models.

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APPENDIX A

1 APPENDIX A

1.1 The ROA model

A detailed explanation of the model used in this paper can be found in Tubetov et al. (2012), Musshoff (2012), Wolbert-Haverkamp and Musshoff (2014a).

1.2 Model data and assumptions

Eucalyptus socialis was the modelled species as it is commonly found in the Mallee areas of South Australia (Brooker and Kleinig, 1983). The average biomass accumulation rate of *E. socialis* in the study area is 7.5 green kg plant^{-1} year^{-1} (Hobbs and Bennell, 2005). The planting density is assumed to be 1000 trees ha^{-1} and the useful lifetime of the plantation is 20 years (Hobbs, 2009a). Investment costs associated with planting an *E. socialis* plantation are AU$1334 ha^{-1} while variable costs are AU$159.75 ha^{-1} based on a yield of 7.5 green tonnes year^{-1}, including haulage (Hobbs, 2009a). If a farmer returns to agriculture after the useful lifetime of the tree crop a recultivation cost of AU$1200 ha^{-1} is incurred.

Following Wolbert-Haverkamp and Musshoff (2014b) we assume a “normal forest” model. The assumption of a normal forest is made for pragmatic reasons and allows the modelled landholder to harvest an average yield of biomass every year.

The costs associated with the cultivation of annual wheat production in South Australia were obtained from State Department of Agriculture gross margin guides (Rural Solutions SA, 2013) and average yields for the Mallee district were calculated from State Department of Agriculture crop and pasture reports 2002-2013 (PIRSA, 2014). Inflation adjusted historical wheat prices from 1970 to 2014 (The World Bank, 2014) were used to forecast the annual wheat GM in the stochastic GM model and are presented in Figure 8.

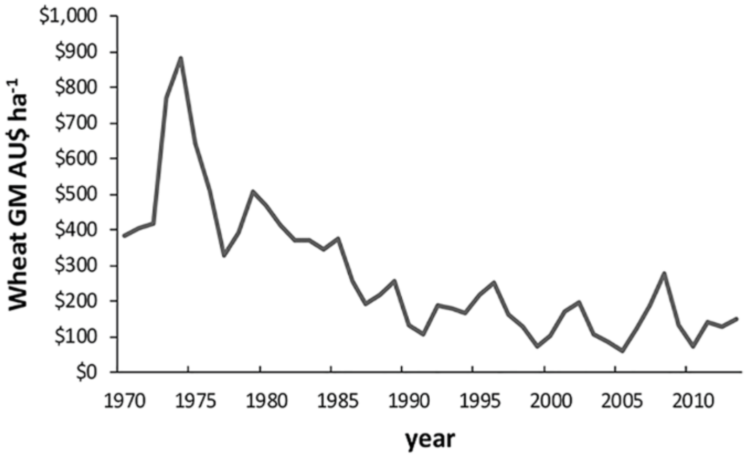

Figure 8 – Historical GM of wheat 1970-2013.

To obtain a biomass price time series, the inflation adjusted monthly coal price 1969-2014 (The World Bank, 2014) is divided by the average gross calorific value of black coal (GJ/fresh weight tonne^{-1}) multiplied by the average gross calorific value of *Eucalyptus Spp*. (GJ/fresh weight tonne^{-1}) (CSIRO, 2006). The coal derived biomass price is multiplied by the modelled average biomass accumulation rates to determine biomass revenue per hectare. The variable cost per hectare are subtracted from revenue per hectare to return the gross margin AU$ ha^{-1}. The coal derived BEC gross margin time series can be seen in Figure 9.

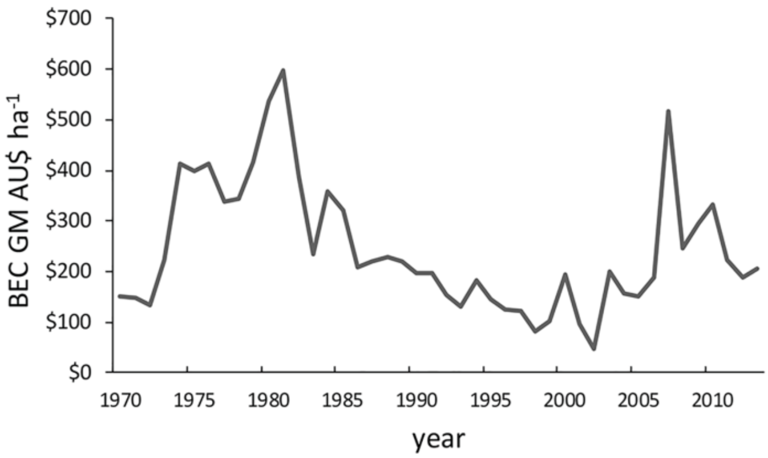

Figure 9 – Derived Historical GM of BEC 1970-2013

Time series analysis was used to gain information regarding the distribution attributes of the BEC and the wheat GM time series in order to fit the most appropriate stochastic process. We modelled future prices of BEC and wheat using an arithmetic Brownian motion (ABM) , as suggested by Wolbert-Haverkamp and Musshoff (2014b).

Times series stationarity was tested using both an augmented Dickey-Fuller test (Dickey and Fuller, 1979), the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) and a commercial statistical package's (Palisade @Risk) time series analysis function. The results of these tests suggest the BEC and wheat time series were initially non-stationary (p =.05).

In this model, we assume a risk neutral investor and future revenues are discounted using a risk free interest rate. The risk free interest rate was calculated from the average nominal returns of Australian 3-year Government Bonds 1995 to 2013 (The Reserve Bank of Australia, 2014) which equated to a discount rate of 5.41%.

To account for unequal risk profiles of different crops or land holder preference, previous studies have discounted the returns of different crops independently based on the volatility of their respective historical returns. The enterprise with the higher volatility in returns can be viewed as a riskier investment, and therefore discounted at a higher rate to compensate for increased risk (Musshoff, 2012; Wolbert-Haverkamp and Musshoff, 2014a, b). This has not been addressed in this model.

1.3 Further results

Several expected GM_W were tested to represent current, improved and deteriorated conditions for wheat producers. Expected GM_W ranging from AU\$178ha^{-1} to AU\$478ha^{-1} were tested. In this model, GM_W was treated as deterministic, that is, in every year of the model the farmer would receive the expected GM_W, while the GM BEC was treated as a stochastic variable.

As the GM_W increases from AU\$178ha^{-1} to AU\$478ha^{-1}, the conversion trigger under both the NPV and ROA models rises by the same magnitude (Figure 10). This is due to the GMs of wheat and BEC being discounted at the same rate. In this case, the change in conversion trigger, under a deterministic wheat price, can be seen to be influenced solely by the change in the GM of wheat.

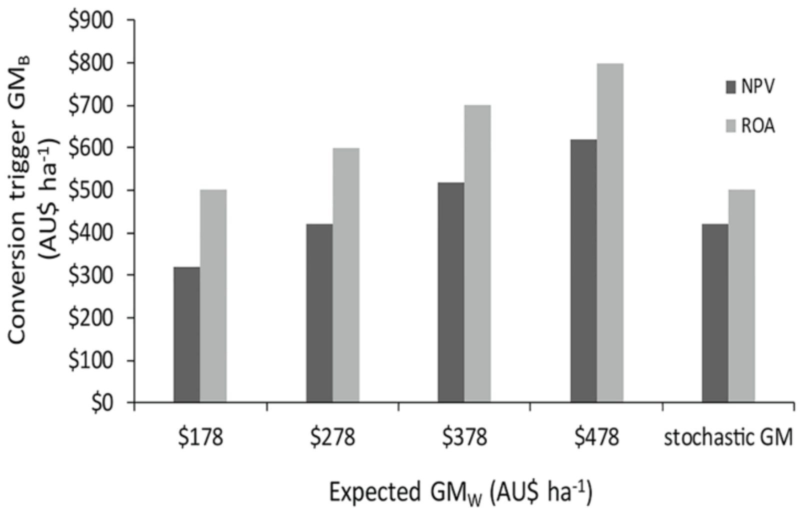

Figure 10 – GM_B required to trigger land use conversion from wheat following NPV analysis and ROA at four different test gross margins for wheat and under stochastic wheat and BEC gross margins.

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APPENDIX B

1 APPENDIX B

1.1 Rainfall distributions used in wheat and biomass yield forecast models

The future stochastic yields for both wheat and biomass are modelled based on APSIM modelling (wheat) and Carbon Sequestration from Revegetation Estimator (Hobbs et al., 2013**).** Frequency distributions of annual primary productivity (wheat and biomass) for each region were created using @Risk software (Palisade Corporation, 2014). Project Evaluation and Review Techniques (PERT) distributions were used to sample and simulate wheat and biomass production variability in the ROA model. The distributions used are presented below (Figs.11 to 20).

1.1.1 Wimmera

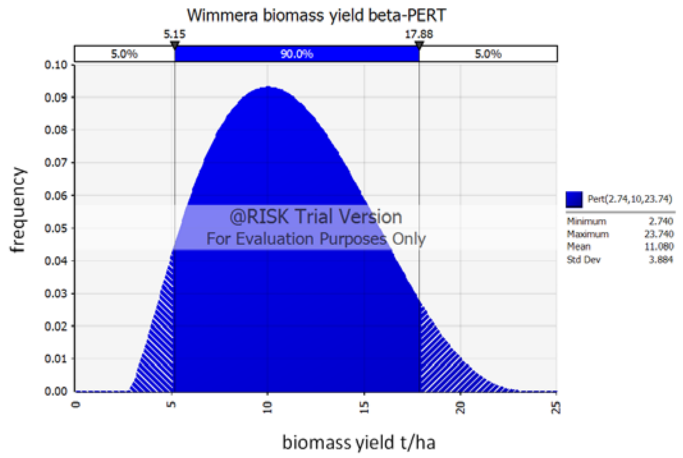

Figure 11 –Distribution of modelled biomass yields for Wimmera.

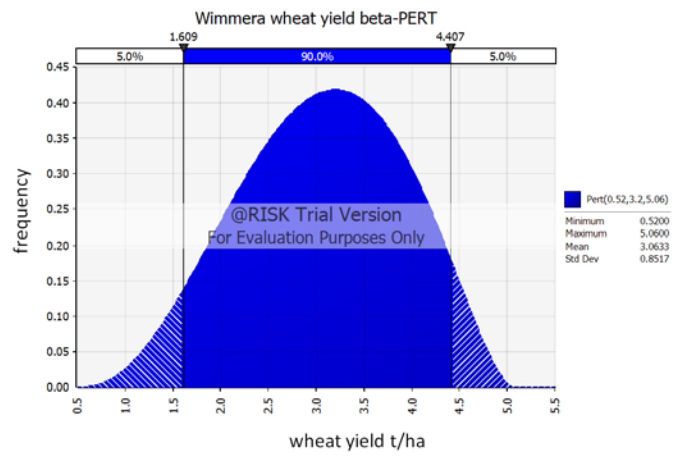

Figure 12 – Distribution of modelled wheat yields for Wimmera.

1.1.2 Natimuk

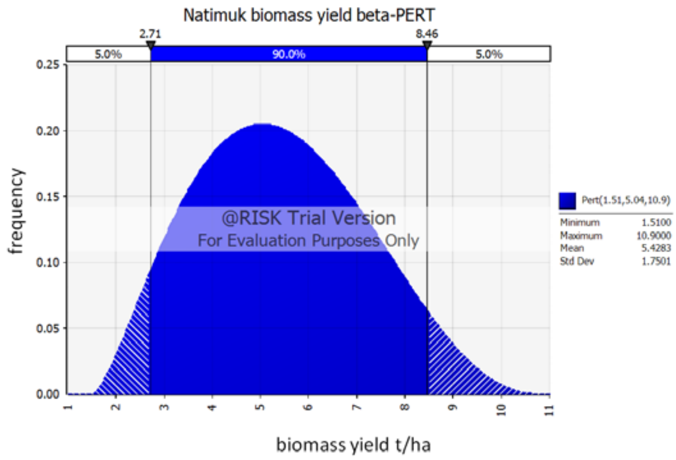

Figure 13 – Distribution of modelled biomass yields for Natimuk.

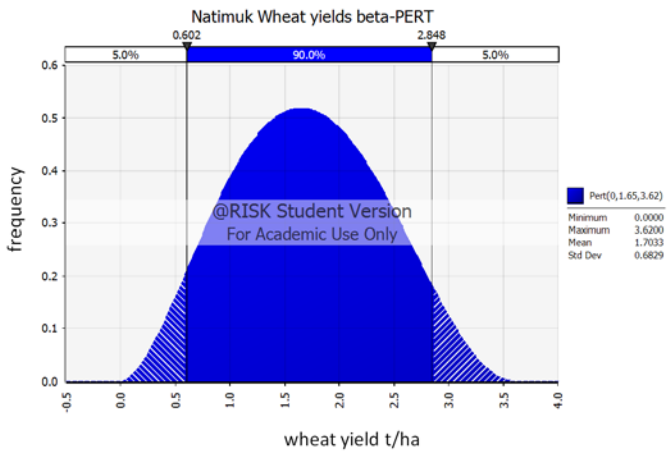

Figure 14 – Distribution of modelled wheat yields for Natimuk.

1.1.3 Manangatang

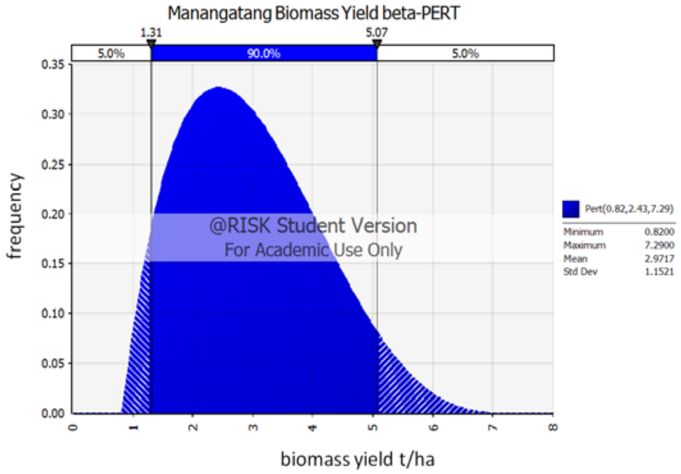

Figure 15 – Distribution of modelled biomass yields for Manangatang.

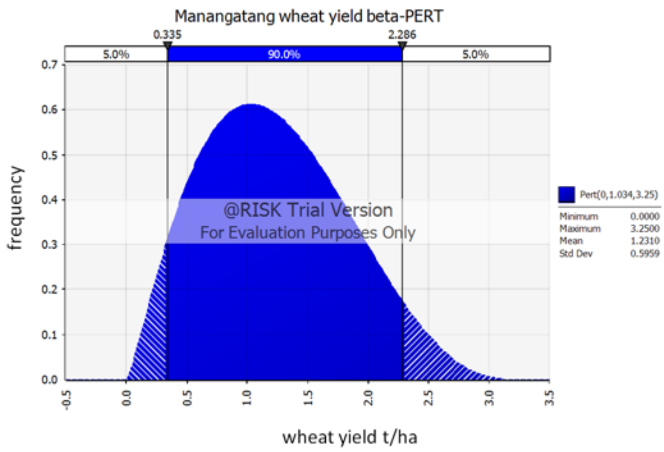

Figure 16 – Distribution of modelled wheat yields for Manangatang.

1.1.4 SA Murray Mallee

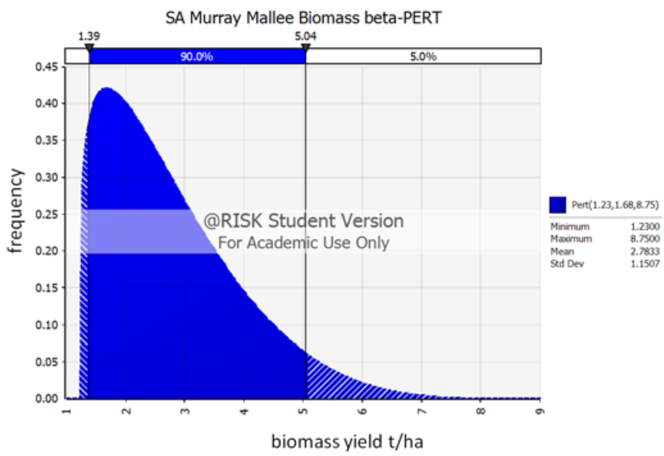

Figure 17 – Distribution of modelled biomass yields for SA Murray Mallee.

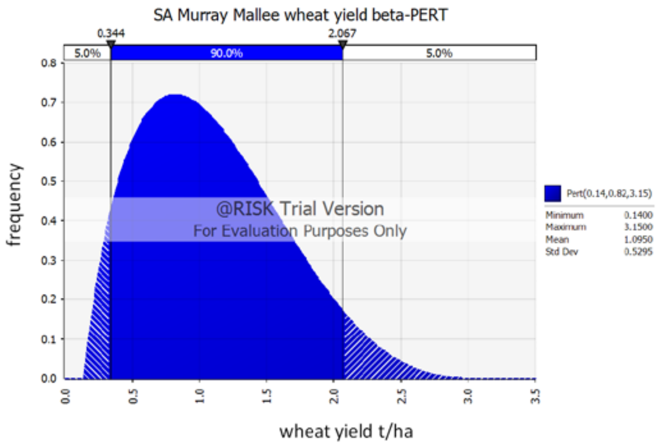

Figure 18 – Distribution of modelled wheat yields for SA Murray Mallee.

1.1.5 Florieton

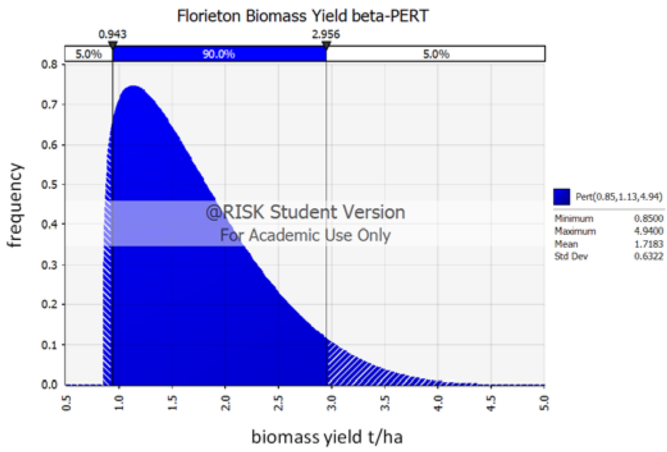

Figure 19 – Distribution of modelled biomass yields for Florieton.

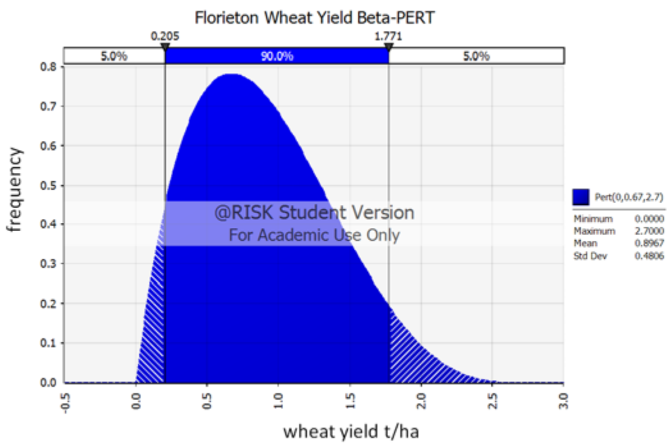

Figure 20 – Distribution of modelled wheat yields for Florieton.

1.2 Development of future wheat and biomass price models

The most general class of models for forecasting a time series of variables such as biomass and wheat prices is the Auto Regressive Integrated Moving Average (ARIMA) (Iqbal et al., 2005). While other time-series processes certainly could have been used, and were tested for, initial statistical analysis of the data indicated that the ARIMA model was most appropriate for further investigation and statistical testing. The ARIMA model was determined according to four steps ; model specification, model estimation, diagnostic checking and forecast (Box and Jenkins, 1976; Enders, 2008; Iqbal et al., 2005). Within this framework the forecast biomass and wheat prices were determined using the Box and Jenkins (1976) linear time series model. Statistical analysis was done using the R programming language. Model specification involved interpreting the plots of the auto correlation function (ACF), partial auto correlation function (PACF) and the time plot of the log, differenced wheat (and biomass) price time series. The auto correlation function indicated the order of the autoregressive components *'q'* of the model, while the partial correlation function gave an indication for the parameter '*p'*. The first step was to check the stationarity of the data. The plot of the original time series showed a distinct decreasing trend indicating that the original time series was not stationary (Figure 11). The log of the original time series was taken to eliminate variance (Figure 12). The time series was then differenced to stabilise the mean.

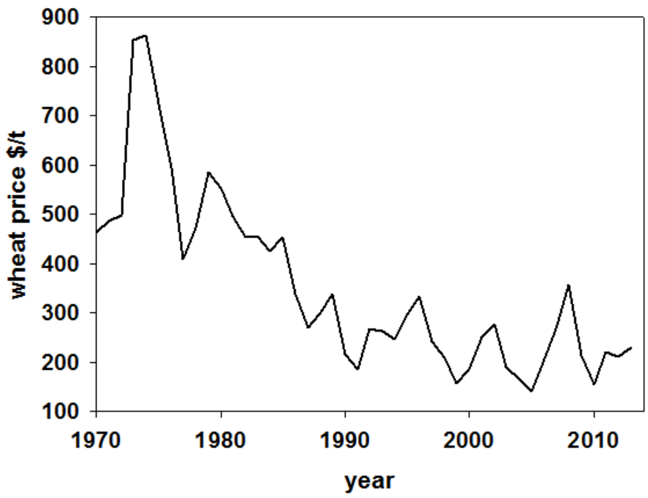

Figure 21 – Wheat prices (A$) per tonne 1970-2013.

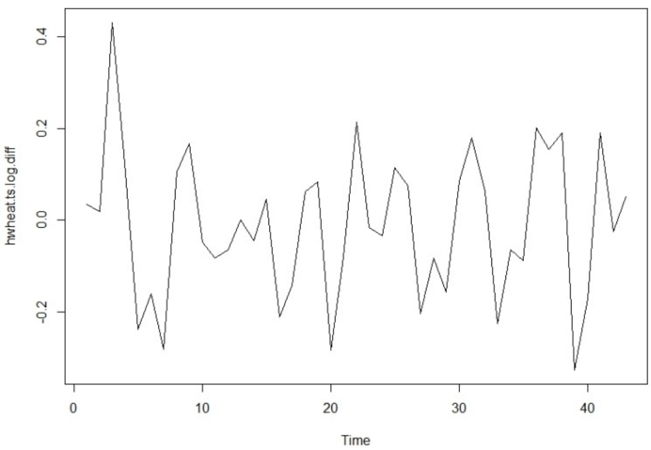

Figure 22– The log/differenced wheat price time series

Augmented Dickey-Fuller (Dickey and Fuller, 1979) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests were conducted to test for the stationarity of the log differenced time series. Both tests indicated the log differenced time series was stationary. As the time series was differenced once the *'d'* component of the *ARIMA(p,d,q)* model used was estimated to be 1.

Augmented Dickey-Fuller Test

Dickey-Fuller = -6.4116, Lag order = 3, p-value = 0.01

Alternative hypothesis: stationary

KPSS Test for Level Stationarity

KPSS Level = 0.0407, Truncation lag parameter = 1, p-value = 0.1

The ACF (Figure 13) and PACF (Figure 14) were used to estimate the autoregressive parameter *'p'* and the moving average component *'q'*. The correlogram of the ACF (Figure 23) of the log/differenced time series decreased quickly after lag 1. The value for the '*q'* component was therefore estimated to be 1.

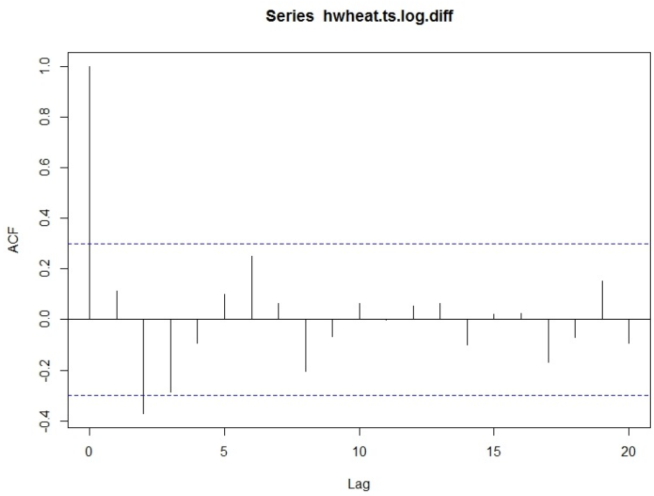

Figure 23– Correlogram showing the ACF of the log, differenced wheat price time series.

The partial auto correlation (Figure 24) function of the log differenced wheat price time series was used to estimate the 'p' parameter. The PACF had a peak at lag 2, hence the 'p' parameter was initially estimated to be 2, however in the interest of finding a parsimonious model, 'p' parameters of 1 and 0 were also tested. We tested the different ARIMA models and inspected their forecast trajectories. The models were compared according to their log likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

ARIMA(0,1,1)

Coefficients:

	MA1
	0.3741
s.e.	0.1815

Sigma^2 estimated as 5834: log likelihood=-247.53

AIC=499.05   AICc=499.35   BIC=502.57

ARIMA(1,1,1)

Coefficients:

AR1	MA1
-0.3909	0.7112
s.e. 0.3079	0.2342

sigma^2 estimated as 5625: log likelihood=-246.78

AIC=499.55 AICc=500.17 BIC=504.84

ARIMA(2,1,1)

Coefficients:

AR1	AR2	MA1
0.7230	-0.4766	-0.6096
s.e. 0.1803	0.1351	0.1671

sigma^2 estimated as 4784: log likelihood=-243.5

AIC=495.01 AICc=496.06 BIC=502.05

Table 1 – Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) of tested ARIMA models.

Model	AIC	BIC
ARIMA(0,1,1)	499.05	502.57
ARIMA(1,1,1)	499.55	504.84
ARIMA(2,1,1)	495.01	502.05

As can be seen by the results above, adding parameters can increase the likelihood of the model, however in adding parameters there is the danger of over fitting (Enders, 2008). In the interest of parsimony, the model with the least number of parameters should ideally be chosen. Given that the

AIC and BIC of the ARIMA models were very similar, we chose to model future wheat prices with an ARIMA(0,1,1).

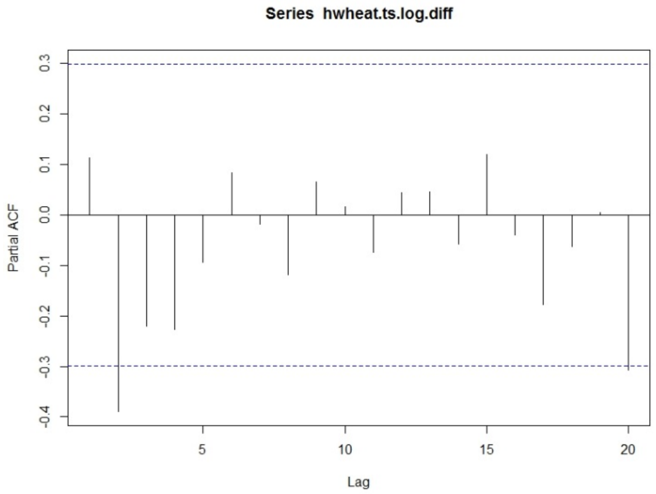

Figure 24– Correlogram showing PACF of the log, differenced wheat price time series.

Statistical checking of the estimated model and diagnostic checks were applied following Metcalfe and Cowpertwait (2009), Iqbal et al. (2005) and Open University (2007). Residual analysis was used in order to test the goodness of fit of the ARIMA(0,1,1) model (Metcalfe and Cowpertwait, 2009). Firstly we investigated the correlations between successive forecast errors. A correlogram of the forecast errors was created (Figure 25) and a Box-Ljung test (Ljung and Box, 1978) was performed on the forecast residuals (table3).

Table 2 – Results of Box-Ljung test

X-squared	14.0744
Df (lags)	20
p-value	0.8267

The correlogram (Figure 25) shows no significant autocorrelation between lags 1 to 20 and the Box-Ljung test p-value of 0.82 provides no evidence for non-zero autocorrelations in the forecast errors at lags 1 to 20.

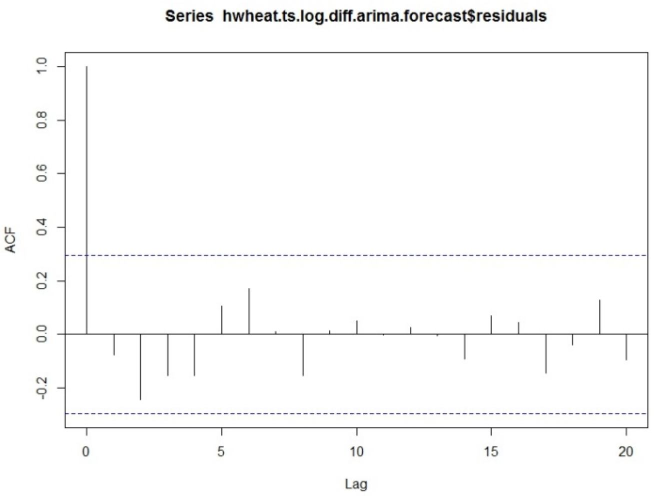

Figure 25– Correlogram showing ACF of sample forecast errors of ARIMA(0,1,1) model.

To investigate normality (whether the forecast errors are normally distributed with mean zero and constant variance) a histogram and time plot of the forecast errors were examined. If the histogram shows normality then the model can be considered a good fit (Iqbal et al., 2005)(Figure 26). To examine the variance, a time plot of the forecast errors was created (Figure 26). The results indicated that variance of the forecast errors appears constant.

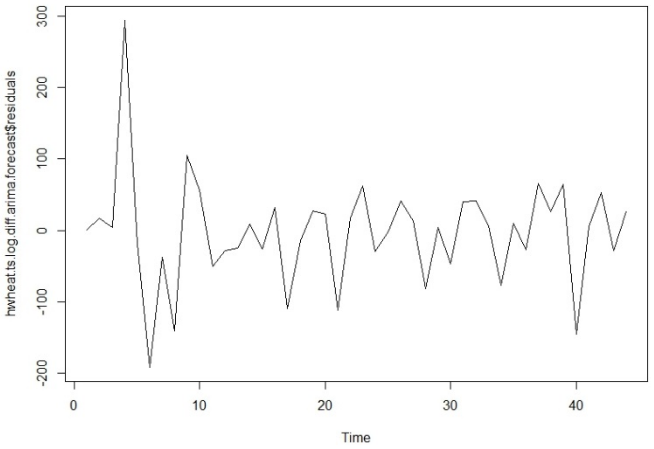

Figure 26 – Time plot of wheat time series forecast errors.

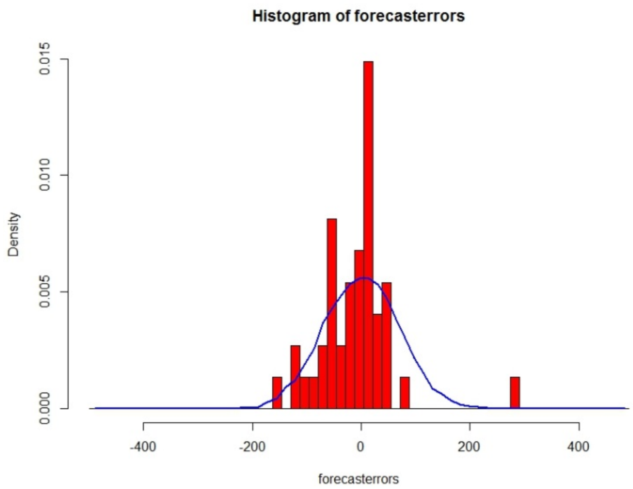

Figure 26 – Histogram of wheat time series forecast errors.

Given the histogram of the time series (Figure 26) shows that the forecast errors are approximately normally distributed and the mean appears close to zero, it is therefore plausible that the forecast errors are normally distributed with mean zero and constant variance. As a result, the ARIMA(0,1,1) model seems to provide an adequate predictive model for forecasts of wheat prices. The development of the model for future biomass prices was done analogously.

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APPENDIX C

1 APPENDIX C

1.1 Implementation of geometric Brownian motion

Geometric Brownian motion can be calculated in discrete time as follows:

$$p_t = p_{t-\Delta t} \times e^{[(\alpha - 0.5 \times \sigma^2) \times \Delta t + \sigma \times \sqrt{\Delta t} \times \varepsilon_t]} \quad (1)$$

Where p_t represents the commodity price at time t, α is the drift rate, σ is the standard deviation of relative logarithmic change in the value of the commodity price time series and ε_t is a standard normally distributed number with a mean of zero and standard deviation of one.

The use of GBM to model prices is not without issue. Unlike other processes a GBM has no tendency to revert back to a mean and values can become "explosive" (Hertzler et al., 2013; Sanderson et al., 2016). However several studies (Carey and Zilberman, 2002; Isik et al., 2001; Isik and Yang, 2004; Schatzki, 1998) have noted that agricultural output prices can be represented by a GBM, while Postali and Picchetti (2006) provide empirical evidence that GBM can approximate oil price development . An alternative is to model price development as a stationary Mean-Reverting-Process (MRP). However , the Augmented Dickey-Fuller test (Dickey and Fuller, 1981) was applied to analyse the stationarity of both commodity time series. The result of the test indicated neither time series was stationary. In addition, the literature states that MRP may only be able to be identified if very long (100 years) time series are available (Musshoff, 2012; Pindyck and Rubinfeld, 1998). In order to curtail the explosive nature of the GBM we follow Reeson et al. (2015) and constrain the price path of both wheat and biomass to prevent it going above AU$2500/t.

1.2 Implementation of ROA model

We adapted a numerical, simulation based real options model presented by Tubetov et al. (2012), Musshoff (2012), Wolbert-Haverkamp and Musshoff (2014b). The land use regime and returns from biomass (denoted as BEG in equations), in any year t, were calculated as follows:

$$R_t GM^{BEG*} = 0, \qquad if\ LU_t = 0 \wedge \mathrm{GM}_t^{\mathrm{BEG}} < \mathrm{GM}^{\mathrm{BEG*}} \quad (2a)$$

In any year t, the returns to biomass ($R_t GM^{BEG*}$) are 0 if the stochastic GM of biomass (GM_t^{BEG}) are lower than the trigger GM (GM^{BEC*}) being tested. The land will be used for wheat production ($LU_t = 0$) and the land will remain in wheat production in the next time period ($LU_{t+1} = 0$).

$$R_t GM^{BEG*} = \text{-EC} \times (1+r)^{-t}, \quad if \ \text{LU}_t = 0 \wedge \text{GM}_t^{\text{BEG}} \geq \text{GM}^{\text{BEG*}} \tag{2b}$$

The returns to biomass ($R_t GM^{BEG*}$) equal the present value of the establishment costs (EC) if the land is currently being used for wheat production ($LU_t = 0$) and GM of biomass in time *t (GM_t^{BEG}*) is higher than the trigger GM of biomass (GM^{BEC*}) being tested. In the next time period the land will be converted to biomass ($LU_{t+1} = 1$).

$$R_t GM^{BEG*} = \text{GM}_t^{\text{BEG}} \times (1+ r)^{-t} \text{- } \text{GM}_t^{\text{wheat}} \times (1+r)^{-t}, \quad if \ \text{LU}_t = 1 \wedge \text{H}_t < \text{LH} \tag{2c}$$

When land use is biomass ($LU_t = 1$) the returns to biomass ($R_t GM^{BEG*}$) correspond to the present value of the stochastic GM of biomass in time *t (GM_t^{BEG}*) minus the present value of the GM of wheat in time *t* (GM_t^{wheat}). This applies when biomass harvest (H_t) has not reached the last harvest (LH) within the plantation's useful lifetime (i.e. $t < 21$).

$$R_t GM^{BEG*} = (\text{GM}_t^{\text{BEG}}\text{-RC}) \times (1+ r)^{-t} \text{- } \text{GM}_t^{\text{wheat}} \times (1+r)^{-t}, \quad if \ \text{LU}_t=1 \wedge \text{H}_t = \text{LH} \wedge \text{GM}_t^{\text{BEG}} < \text{GM}^{\text{BEG*}} \tag{2d}$$

The returns to biomass ($R_t GM^{BEG*}$) correspond to the present value of the GM of biomass in time *t (GM_t^{BEG}*) minus the present value of the recultivation costs (*RC*), minus the present value of the GM of wheat in time *t* (GM_t^{wheat}). This applies when biomass has reached the last year of its useful lifetime and the stochastic GM_t^{BEG}received in the year of the last harvest (*t*=21) is less than the trigger GM of biomass (GM^{BEC*}) being tested. As the trigger GM of biomass (GM^{BEG*}) is not met, the land is returned to wheat production in the next period ($LU_{t+1} = 0$).

$$R_t GM^{BEG*} = (\mathrm{GM}_t^{\mathrm{BEG}}\text{-RC-EC}) \times (1+r)^{-t} \text{- } \mathrm{GM}_t^{\mathrm{wheat}} \times (1+r)^{-t}, \quad if\ \mathrm{LU}_t{=}1 \wedge \mathrm{H}_t = \mathrm{LH} \wedge \mathrm{GM}_t^{\mathrm{BEG}} \geq \mathrm{GM}^{\mathrm{BEG*}} \qquad (2e)$$

The returns to biomass ($R_t GM^{BEG*}$) correspond to the difference between the present value of GM of biomass in time *t* (GM_t^{BEG}) and the sum of the present value of recultivation costs (*RC*) and the establishment costs (*EC*), minus the present value of the GM of wheat in time *t* (GM_t^{wheat}). This applies when biomass has reached the last year of its useful lifetime (*t*=21) and GM of biomass (GM_t^{BEG}) received in the year of the last harvest (LH) is greater than the trigger GM of biomass (GM^{BEC*}) being tested. As GM^{BEG*} is met, the land is used for biomass in the next time period ($LU_{t+1} = 1$) and remains in biomass for another rotation.

The option value associated with each test trigger was calculated by summing the present value of future investment returns R_t during the planting period ($t = 0, 1, \dots, \infty$). The option value for each test trigger equals the average present value of farm returns for all simulated paths. In order to determine the optimal GM of biomass (GM^{BEG*}) that triggers investment, the function F_0 that corresponds to the maximum option value can be found:

$$F_0 = \sum_{t=0}^{\infty} R_t GM^{BEG*} \rightarrow max!\, GM^{BEG*} \qquad (3)$$

We followed Tubetov et al. (2012) and performed 50,000 simulations for each biomass test trigger GM (GM^{BEG*}). The initial test triggers were chosen from results from the NPV analysis. The NPV biomass trigger GM (GM^{BEG*}) acts as the lower limit, with which to start the iterative process outlined above.

1.3 Energy equivalence price calculations

In order to compare the competitiveness of biomass with existing fossil fuel energy sources we calculated the energy equivalent price of biomass.

The gross calorific value (GJ/dry t) of biomass, coal and crude oil (GJ/t) were taken from the CSIRO biofuels database (CSIRO, 2006) and are assumed to be as follows:

Mallee biomass = 19 GJ/dry t

Coal = 25 GJ/dry t

Crude oil = 43 GJ/ tonne of oil equivalent

Crude oil prices are quoted in $/barrel. One standard barrel of crude oil (BBL) contains 42 US gallons or 159 litres. Obtaining a definitive specific gravity of crude oil is problematic. The figure varies between the New York Mercantile Exchange, The National Energy Board of Canada and the Mexican State Oil Company. The specific gravity ranges from between 840 kg/m^3 and 893 kg/m^3 . We assumed the specific gravity of oil as 881 kg/m^3 . Therefore, under this assumption one barrel of oil weighs 140 kg. Therefore there are 7.15 barrels/ tonne of oil equivalent.

The current price for crude oil and coal (at the time of writing) was taken from the World Bank Commodities Price Data (The World Bank, 2016) and converted to Australian dollars and were as follows:

Crude oil = AU$41/barrel

Coal = AU$68/t

Given a crude oil price of AU$41/barrel;

AU$/tonne of oil equivalent = AU$41/barrel x 7.15

= AU$293/ tonne of oil equivalent.

Given an energy (GJ)/t ratio of 19:43 between biomass and crude oil, biomass would need to be priced below AU$129.54/DM t to be competitive with crude oil on an energy equivalence basis.

Given a coal price of AU$68/t, and an energy (GJ)/t ratio between biomass and coal of 19:25, biomass would need to be priced below AU$51.63 to be competitive with coal on an energy equivalence basis.

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Statement of Authorship

Title of Paper	**Regan, C.M., Bryan, B.A., Connor, J.D., Meyer, W.S., Ostendorf, B., Zhu, Z., Bao, C., 2015. Real options analysis for land use management: Methods, application, and implications for policy.**
Publication Status	☑ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	Journal of Environmental Management 161, 144-152

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Overall percentage (%)	**85%**
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By signing the Statement of Authorship, each author certifies that:

i. **the candidate's stated contribution to the publication is accurate (as detailed above);**
ii. **permission is granted for the candidate in include the publication in the thesis; and**
iii. **the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.**

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Statement of Authorship

Title of Paper	Regan, C.M., Connor, J.D., Bryan, B.A., Meyer, W.S., Ostendorf, B., 2016. Spatial real options analysis: informing better incentive policy for motivating biomass agroforestry in agricultural land.
Publication Status	☐ Published ☐ Accepted for Publication ☑ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Land Use Policy. Submitted, manuscript ID LUP_2016_139.

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Signature		Date	9-11-16

Statement of Authorship

Title of Paper	Regan, C.M., Connor, J.D., Raja Segaran, R., Meyer, W.S., Bryan, B.A., Ostendorf, B., 2016. Climate change and the economics of biomass energy feedstocks in semi-arid agricultural landscapes: A spatially explicit real options analysis.
Publication Status	☐ Published ☑ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted w ork w ritten in manuscript style
Publication Details	Journal of Environmental Management. manuscript ID JEMA-S-16-01136.

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Overall percentage (%)	80%
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
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