A new approach to farm optimisation modelling enhances strategic and tactical livestock management in Western Australian mixed farm businesses

by

Michael Young

B.Sc. (Bachelor of Science, Hons)

This thesis is presented for the degree of Doctor of Philosophy of The University of Western Australia

School of Agriculture and Environment

Agricultural Economics

2023
Summary

Farm profits can be made or lost depending on the chosen management practices. Accordingly, much research effort has focused on the best way to manage farm businesses in Australia. However, agriculture is constantly evolving through new innovations, changing farm sizes, adapting to pests and diseases, the impacts of a changing climate and fluctuations and trends in input and output prices. Many models designed to aid farm management often contain significant simplifications of reality, and risk creating potentially misleading advice.

To contribute to the literature on farm management modelling, the objectives of this thesis were, firstly, to quantify important limitations in methodologies that have been applied to identify optimal livestock management. Secondly, to develop and apply an improved methodology that expands our knowledge about optimal strategic and tactical management of livestock within mixed enterprise farm businesses. These objectives are addressed in four stages.

Firstly, literature on the critical decision of stocking rate is reviewed to identify gaps in our knowledge and to identify the best method for building on previous research. This review confirmed the importance of livestock management within a mixed enterprise farming system. Furthermore, the review identified that previous farm models used to aid farm stocking rate analysis contain various limitations, including the major steady-state assumption. However, little research quantifies the importance of these limitations (Young et al., 2022). Hence a gap in our knowledge exists regarding how important it is to use detailed farm models that more accurately represent a farm system.

Secondly, to address the knowledge gap identified regarding the appropriate modelling method, we leveraged recent advances in computer technologies to develop and document a farm model called AFO (Australian Farm Optimisation). AFO is a functionally flexible model containing three sub frameworks that vary in detail and their reflection of reality. AFO overcomes many of the limitations identified with prior whole-farm optimisation models. The development and application of AFO is a major accomplishment and forms a significant contribution of this PhD thesis.

Thirdly, over two later chapters, three modelling frameworks housed within AFO are compared. These frameworks represent different levels of weather-year uncertainty and help build our knowledge regarding the relative importance of inclusion of additional detail in whole-farm optimisation models. In this thesis the key focus is on weather-year uncertainty because the inclusion of uncertainty (e.g. in prices, resource availability, weather-year variation) in whole farm optimisation models exponentially increases the model size. In the vast majority of previous
optimisation models that focus on Australian mixed enterprise farming systems weather-year variation is typically excluded. Yet the modelling results presented in this thesis reveal significant differences in farm profit and optimal farm management occur when weather-year variation and relevant management tactics are considered.

Lastly, this thesis builds on our limited knowledge regarding how best to employ short term tactical livestock management on a mixed enterprise farm when exposed to a variable environment. Results show that short-term adjustments to the overall farm strategy, in response to unfolding weather conditions, can generate substantial improvements in expected profit on farms in the study region of this thesis. Farm profits can increase by about 18%. These profit enhancements arise from capitalizing on the knowledge about how the farming system’s enterprises can differently respond under varying weather scenarios and management choices. The findings in this thesis are likely to have practical relevance to farms in the study region where livestock remain an important feature of many farm businesses.
## Table of contents

Summary ................................................................................................................................. 2
Thesis declaration .................................................................................................................. 7
Authorship declaration ......................................................................................................... 8
Acknowledgements ............................................................................................................... 10

**Chapter 1: General Introduction** .................................................................................. 11

**Chapter 2: Optimal Sheep Stocking Rates for Broad Acre Farm Businesses in Western Australia: A Review** ........................................................................................................... 14

  - Introduction ....................................................................................................................... 14
  - Defining stocking rate ....................................................................................................... 15
  - The stocking rate challenge in Australia: early research ..................................................... 19
  - Seasonal variation and risk ............................................................................................... 22
  - Feed supply ....................................................................................................................... 25
  - Sheep Production .............................................................................................................. 28
  - Environmental factors ...................................................................................................... 29
  - Modelling approaches to determine optimum stocking rate ............................................... 30
  - Stocking rate: Generalisations from studies ..................................................................... 34
  - Recommendations and future improvements to stocking rate analyses ............................. 35
  - Conclusion ......................................................................................................................... 37

**Chapter 3: Methodology** ............................................................................................... 39

  - Introduction ....................................................................................................................... 39
  - Linear programming introduction .................................................................................... 41
  - AFO Overview ................................................................................................................... 43
    - Key improvements ........................................................................................................... 46
  - Rotations ............................................................................................................................ 46
  - Cropping ............................................................................................................................. 49
  - Feed budget ....................................................................................................................... 51
  - Feed supply ....................................................................................................................... 52
    - Pasture ............................................................................................................................. 53
    - Crop residue .................................................................................................................... 55
    - Supplement ...................................................................................................................... 56
    - Crop grazing ..................................................................................................................... 56
    - Salt land pasture .............................................................................................................. 57
  - Livestock ............................................................................................................................ 58
  - Finance ............................................................................................................................... 61
  - Labour ............................................................................................................................... 63
Chapter 4: Improved whole-farm planning for mixed-enterprise systems in Australia using a four-stage stochastic model with recourse ........................................ 73

Introduction.................................................................................................................. 73
Method ............................................................................................................................. 76
Farm system modelled..................................................................................................... 76
Model overview .............................................................................................................. 77
Tactical decisions in the 4-SPR model.......................................................................... 79
Weather-years ................................................................................................................. 81
Production assumptions ............................................................................................... 82
Weather-year prices ....................................................................................................... 83
Results .............................................................................................................................. 83
Discussion ....................................................................................................................... 86
Conclusion ....................................................................................................................... 88
Appendix One ................................................................................................................ 89

Chapter 5: Representing weather-year variation in whole-farm optimisation models: Four-stage single-sequence vs eight-stage multi-sequence ........................................ 91

Introduction .................................................................................................................. 91
Method ............................................................................................................................. 93
Farm system modelled..................................................................................................... 93
Model overview .............................................................................................................. 94
Weather-years ................................................................................................................. 99
Production assumptions ............................................................................................... 101
Weather-year prices ....................................................................................................... 101
Results .............................................................................................................................. 101
Discussion ....................................................................................................................... 104
Conclusion ....................................................................................................................... 107

Chapter 6: Identifying high value tactical livestock decisions on a mixed enterprise farm in a variable environment ........................................................................... 108

Introduction .................................................................................................................. 108
Thesis declaration

I, Michael Young, certify that:

This thesis has been substantially accomplished during enrolment in this degree.

This thesis is my own work and does not contain any material previously published or written by another person, except where due reference has been made in the text or Authorship Declaration.

This thesis does not contain material which has been submitted for the award of any other degree or diploma in my name, in any university or other tertiary institution.

In the future, no part of this thesis will 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 Western Australia and where applicable, any partner institution responsible for the joint-award of this degree.

This thesis does not violate or infringe any copyright, trademark, patent, or other rights whatsoever of any person.

UWA Ethics Approval number: ET000181.

Signature

Date: 4/05/2023
Authorship declaration

Bibliographic details of publication/manuscript 1


Location in thesis:
Chapter 2

Student contribution to work: The student made the primary and substantial contribution to this paper.

May 4, 2023      May 1, 2023

Bibliographic details of publication/manuscript 2

YOUNG, M., YOUNG, J., KINGWELL, R. S. & VERCOE, P. E. 2023. Improved whole-farm planning for mixed-enterprise systems in Australian using a four-stage stochastic model with recourse

*This chapter has been submitted for publishing in the journal of Australian Farm Business Management*

Location in thesis:
Chapter 4

Student contribution to work: The student made the primary and substantial contribution to this paper.

1 May 2023      1 May 2023      4 May 2023
Bibliographic details of publication/manuscript 3

YOUNG, M., YOUNG, J., KINGWELL, R. S. & VERCOE, P. E. 2023. Representing weather-year variation in whole-farm optimisation models: Four-stage single-sequence vs eight-stage multi-sequence

*This chapter has been submitted for publishing in The Australian Journal of Agricultural and Resource Economics*

Location in thesis:

Chapter 5

Student contribution to work: The student made the primary and substantial contribution to this paper.

1 May 2023  1 May 2023  4 May 2023

Student signature

Date: 3/05/2023

I, Philip Edward Vercoe certify that the student’s statements regarding their contribution to each of the works listed above are correct.

Coordinating supervisor signature:

Date: 04/05/2023
Acknowledgements

Firstly, I would like to thank my supervisors Ross Kingwell and Phil Vercoe for their continual support throughout my PhD journey. Their guidance, insights, and mentorship have been invaluable, and I am grateful for their continual availability to provide a sounding board for my ideas. Their feedback has helped me improve the quality of my work and enabled me to overcome many challenges during the research process.

I would also like to thank my unofficial supervisor John Young, who is also my dad, for his ongoing analysis feedback and huge help in building AFO. We have created a tool that will truly benefit the agricultural industry in years to come.

And of course, I would like to thank my partner Katy Bruinsma for always reviewing work that was thrown her way and patiently listening to hours and hours of practice speeches.

Lastly, I would like to acknowledge that this research was supported by an Australian Government Research Training Program (RTP) Scholarship. I would like to further thank the Department of Primary Industries and Regional Development for their funding through the Sheep Industry Business Innovation project. Without their financial support this project would not have been possible.
Chapter 1: General Introduction

In mixed farming systems livestock and associated pasture production complement cropping activities by utilising crop residues, providing disease and pest breaks, providing weed management options and improving labour and machinery use efficiency during the year. As such livestock and pasture production are key components of many farm businesses and farming systems in Australia. In Western Australia, for example, livestock revenues comprise 21% of average farm total income (Planfarm/BankWest, 2019). Which is likely to be a greater proportion of the total profit as the livestock enterprise typically incurs lower costs than cropping (Planfarm/BankWest, 2019).

The management of livestock within mixed enterprise farming systems can significantly affect business outcome. For example, Young et al. (2020) showed that choice of sheep flock structure altered farm profit by $630 000 per year between the least and most profitable flock options. It can be challenging, however, to identify and implement optimal livestock management because of the large number of decisions farmers face. Mixed enterprise farm systems often encompass a range of soil types, crop options and livestock options (Young et al., 2020, Mosnier et al., 2022). Farmers’ enterprise choices are often constrained by a range of factors including labour availability, an existing complement of farm machinery and animal production infrastructure (e.g. dams, yards and fences), access to finance, managerial preferences and past decisions that influence current resource status and feasible future actions (Ewing et al., 2004). Furthermore, price and climate variability can cause significant business uncertainty (Laurie et al., 2019, Feng et al., 2022), complicating the management of the system.

So complex and challenging is the task of managing mixed enterprise farms in Western Australia that many farm businesses employ professional farm management and agronomic consultants to advise them on key aspects of farm management, crop management and farm planning. Such professional support is often useful as the agricultural industry is ever changing through new innovations, technological advances, changing farm sizes, evolving pests and diseases, changing climate conditions and fluctuating input and output prices. Furthermore, many industry resources have been devoted to researching the best way to manage mixed enterprise farm businesses in Western Australia. The industry has established a long history of whole farm planning, starting from work such as Morrison et al. (1986), Kingwell and Pannell (1987) and Pannell and Pol (1987). The success of such work has shown through its continuation and expansion (e.g. Young et al., 2020, Walsh and Kingwell, 2021). Some notable recent examples of farm management research projects include the Lifetime Ewe Management program, which has, and continues to have, a direct impact on over 4000 farmers (LTW, 2021, Trompf et al., 2011, Young et al., 2011). The Australian Herbicide Resistance
Initiative (AHRI) researches and extends solutions for farmers to minimise the adverse impact of herbicide resistance. Since 2010 it has received on-going government and industry funding to combat herbicide resistance in farmers’ cropping programs.

The intricacies of a mixed enterprise farming system suggest that whole-farm modelling may aid agricultural decision-making (Apland and Hauer, 1993, Pannell, 1996). Agricultural or farming systems in Australia, and internationally, are most frequently modelled either by dynamic simulation (Anderson, 1974, Rozman et al., 2013) or mathematical programming (Kingwell and Pannell, 1987, Annetts and Audsley, 2002, Roughsedge et al., 2003, Schäfer et al., 2017). Dynamic simulation (DS) aims to replicate the behaviour of a system. It is frequently applied to represent biological systems within the farming system (Thomas et al., 2018) or a component of the farming system (Keating et al., 2002, Robertson et al., 2002). Mathematical programming (MP) is a group of optimisation techniques that represents a system using variables, constraints and an objective (Norton et al., 1980, Kingwell and Pannell, 1987). Both DS and MP often achieve more than their simple categorisation implies, as it is feasible to specify an objective in a DS model and search for an optimal solution, and MP techniques can represent simulated biological detail (Kingwell and Pannell, 1987, Young et al., 2011). Although, research and improvement in livestock management often has been undertaken using modelling methods with known limitations. For example, Kingwell and Pannell (1987), Pannell (1996), Kopke et al. (2008), Bathgate et al. (2009), Kingwell (2011), Young et al. (2011), Thamo et al. (2013), Young et al. (2020) have used steady-state whole-farm MP to investigate a range of livestock management issues in the mixed enterprise farming system of Western Australia. However, persistent sole reliance on the steady-state modelling approach highlights a gap in the literature which is the consideration of other modelling frameworks that highlight other important features of farm management such as the responses to price and weather-year variation and the role of farm management tactics in response to unfolding conditions. Australian farm management modelling literature is dominated by the steady-state modelling approach and there is a need to appraise the applicability and utility of other modelling frameworks.

We focus on MP throughout this thesis due to it past and continuing prominence in whole farm agricultural research within Australia. Which can be attributed to its ability to efficiently optimise farm resources subject to various constraints. This is important for identifying how best to incorporate a new technology or practice into the farming system or comparing two practices on a like for like basis. Given the variables in a farming system this is highly important. progressing on the notable work of Kingwell et al. (1991), Kingwell (1994), Kingwell (1996), Schilizzi and Kingwell (1999) who focused on the inclusion of uncertainty in farm systems analysis. However, their work was
completed several decades ago when computer capacity was much more limiting and restrained the wide adoption of stochastic model in agricultural research.

We place a particular emphasis on the MP approach throughout this thesis, acknowledging its historical and ongoing significance in whole farm agricultural research in Australia. The enduring prominence of MP can be attributed to its capacity to efficiently optimise farm resources, subject to a range of constraints. This holds significant value when it comes to evaluating the integration of novel technologies or practices into farming systems or making comparisons between two practices on a like-for-like basis. Given the complexities of farm systems and the large number of inherent variables within the system, accurate optimisation is unique and powerful.

Throughout this thesis we build upon the noteworthy contributions of Kingwell et al. (1991), Kingwell (1994), Kingwell (1996), Schilizzi and Kingwell (1999), who delved into incorporating uncertainty into mathematical programs of farm systems. Their work was conducted several decades ago when computational capabilities were significantly more limited. Furthermore, their work was primarily cropping focused. As a result, there remain gaps in our knowledge regarding how best to optimise livestock systems using MP. Hence, the objectives of this thesis are twofold. Firstly, to identify and quantify important limitations of the steady-state methodology when used to identify optimal livestock management. Secondly, to develop and apply an improved methodology that can increase our knowledge of optimal strategic and tactical management of livestock within mixed enterprise farm businesses in Western Australia. The general hypothesis tested in this thesis is that the steady state assumption embedded in many published whole farm optimisation models leads to inaccurate estimation of profitability and a potential non-optimal allocation of farm resources.

We begin the research investigation by first reviewing the literature on a key farm management decision, choice of stocking rate, to identify and compare current and past farm decision methodologies and thereby identify gaps in our knowledge that especially apply to livestock management.
Chapter 2: Optimal Sheep Stocking Rates for Broad Acre Farm Businesses in Western Australia: A Review

This chapter is published in the journal of Animal Production Science and remains in its published form with the exception of the removal of the Abstract.


Introduction

Choice of sheep stocking rate affects the profitability and sustainability of mixed enterprise farms (White and Morley, 1977, Warn et al., 2006a). Sheep stocking rates that are lower than the optimum underutilise available pasture or crop residues, foregoing potential profitability. Similarly, a stocking rate above the optimum can incur excessive costs due to an increased requirement for supplementary feed (Hinton, 2007) and can leave paddocks at risk of wind and water erosion when left bare from overgrazing (Saul and Kearney, 2002). Determining the optimal stocking rate is clearly beneficial to farm businesses (Chisholm, 1965, Lloyd, 1966, Young et al., 2020) and the environment, but it can be particularly challenging to determine because it is intertwined with many aspects of the farming system, such as; length and nature of the growing season and its associated pasture production, the myriad of options regarding flock structure and sheep management, the farm manager’s skill and risk attitude, season and price variation and the availability of family and hired labour (Dillon and Burley, 1961, Lloyd, 1966, McArthur and Dillon, 1971, Dunlop et al., 1984, Warn et al., 2006a). In this paper we review the literature on sheep stocking rate to provide insights about the nature and role of stocking rate decisions and their effect on farm profitability.

The key issues linked to stocking rate decisions that are a focus of this review are:

- Definition of stocking rate.
- Determining the optimal stocking rate.
  - Season and price variation and their interaction with different levels of risk aversion.
  - The nature of feed supply, including supplementary feeds.
  - The biology of sheep production and the role of flock structure.
Greenhouse gas emission policy impacts on sheep economics.

Future improvements for determining optimal stocking rate.

Defining stocking rate

The definition of stocking rate is highly important for comparable communication between personnel in the agricultural industry. Ensuring that research relevant to stocking decisions is interpreted and applied correctly by farmers, for example, is especially important. The following section discusses the current definition of stocking rate, its evolvement and potential limitations.

Stocking rate is a metric of the grazing pressure applied on a farm (Meat and Livestock Australia, 2020b, Scarnecchia, 1990). A common approach is to use a component that represents the carrying capacity associated with the feed supply and a second component is grazing requirement of the different livestock classes, such that the resulting stocking rate is a number of grazing units per unit area. Optimum stocking rate is the stocking density that maximises long-term, expected whole farm profit.

A useful metric should be:

(i) relative and consistent within a property so that different flock structures or livestock enterprises can be compared. The optimum stocking rate for all classes of stock need to be the same when grazing the same feed supply;

(ii) relative and consistent across properties so that a stocking rate achieved by one farmer is comparable to the stocking rate achieved by another farmer. This is important for practices such as benchmarking, which compare farming businesses often using stocking rate as a key metric. Additionally, a relative and comparable stocking rate is important for accurate interpretation and application of research findings to different situations;

(iii) amenable to explanation, especially when stocking rate differences are observed. Ideally, rules of thumb should be generated to aid farmers and advisers to understand why a particular stocking rate is appropriate.

(iv) easy to calculate. Stocking rate metric is used widely because it is simple to calculate, adding complexity may be counterproductive.

The metrics of stocking rate vary depending on the country and era in which the research was conducted and published. Historically the main reported measure was the number of sheep per acre
(Chisholm, 1965, Dillon and Burley, 1961). The major limitation of this definition is that it did not discriminate between the age and sex of sheep. Lambs were equated with adult sheep and large old rams were equated to young hogget ewes; yet the feed requirements of these different types of sheep differed greatly. Later studies used improved definitions of stocking rate by defining a standard livestock unit that allowed different classes of livestock to be compared (McLaren, 1997, Redfearn and Bidwell, 2003). In Asia, America, and Europe a standard livestock unit is determined based on cattle. In Europe, for example, a standard animal unit is defined as a 500 kg cow (Flessa et al., 2002, Takai et al., 1998). However, in southern Australia and New Zealand a standard animal unit is based on sheep (Sandhage-Hofmann, 2016). The standard livestock unit adopted in Australia is known as a dry sheep equivalent (DSE) (Saul and Kearney, 2002, Warn et al., 2006b, Young et al., 2011, Young et al., 2020), which was defined as the maintenance energy requirement of an adult wether (McDonald and Orchard, 2015). The DSE measure allows different categories of sheep to be compared based on their relative energy requirement (Robertson et al., 2020), for example see Table 1. Energy required is used rather than feed intake because feed quality varies significantly and affects intake (Freer et al., 2007). A similar concept, adult equivalent (AE), has been adopted in cattle dominated areas such as northern Australia (McLennan et al., 2020). The AE, like the DSE, rates an animal by the ratio of its maintenance energy requirements relative to a standard animal. An AE is a 2.25-year-old, 450 kg B. taurus steer maintaining its body weight whilst walking 7 km/day (McLean and Blakeley, 2014). The DSE and AE metrics are both based on the maintenance energy requirements of a standard animal. Thus, once the standard animals are defined, a constant conversion factor can be used to describe other classes of animals. While the DSE classification is widely accepted in Australia there is variation in the definition of an adult wether and the time over which the energy requirement is measured. A DSE has been defined as the annual energy requirement of a 45 kg wether (McLaren, 1997), but also as a 50 kg wether (Meat and Livestock Australia, 2020b, McDonald and Orchard, 2015). McLennan et al. (2020) support the former suggesting that the standard animal is a 45 kg wether, with zero weight change, no wool growth additional to that included in maintenance, and walking 7 km/day. This equates to an energy requirement of 8.7 MJ ME/day. Defining a DSE according to energy required means that the number of DSEs can be used as a measurement of grazing pressure applied at a point in time or for a period of time (McLennan et al., 2020). Thus, as discussed below, the energy requirement used to calculate the DSE of animals is often based on their energy requirement during the feed-limiting period of a year.
Table 1: Comparative feed requirements of different classes of sheep expressed as a dry sheep equivalent (McDonald and Orchard, 2015).

<table>
<thead>
<tr>
<th>Class of stock</th>
<th>DSE at specified liveweights</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>15kg</td>
</tr>
<tr>
<td><strong>Weaned lambs:</strong></td>
<td></td>
</tr>
<tr>
<td>Gaining 100 g/day</td>
<td>0.8</td>
</tr>
<tr>
<td>Gaining 200 g/day</td>
<td>1.3</td>
</tr>
<tr>
<td><strong>Mature sheep:</strong></td>
<td></td>
</tr>
<tr>
<td>45kg</td>
<td></td>
</tr>
<tr>
<td>Dry ewes, wethers (maintain weight)</td>
<td>0.9</td>
</tr>
<tr>
<td>Dry ewes, wethers (gaining 50 g/day)</td>
<td>1.2</td>
</tr>
<tr>
<td>Dry ewes, wethers (gaining 100 g/day)</td>
<td>1.5</td>
</tr>
<tr>
<td>Pregnant ewes last 6 weeks bearing singles</td>
<td>1.4</td>
</tr>
<tr>
<td>Pregnant ewes last 6 weeks bearing twins</td>
<td>1.8</td>
</tr>
<tr>
<td>Ewes with single lamb at foot</td>
<td>2.4</td>
</tr>
<tr>
<td>Ewes with twin lamb at foot</td>
<td>2.8</td>
</tr>
</tbody>
</table>

The unit of land area that underpins stocking rate has also varied between country and era. Historically the land area was measured in acres, though in Australia this has been replaced by the metric equivalent of hectares. In southern Australia, with its winter dominant pattern of rainfall, winter and spring pastures are the principal sources of cost-effective feed. The feed supplied by these pastures most affects the size of a farm’s sheep carrying capacity (Moore et al., 2009). In southern Australia pasture growth during winter is much less than during spring (Cullen et al., 2008) and hence the winter feed period is most likely to constrain the number of sheep carried on farms. Additionally, on mixed farms, areas sown to crop further limit feed during the winter period. Therefore, the basis for measuring the area has been the winter-grazing (WG) area for livestock and the time for the relative energy requirement has been the winter period. Hence, the abbreviated measure often reported is DSE per WG hectare (Kenny et al., 2019, Kingwell et al., 1992).

However, there are limitations with using only the winter period, because although this is the main feed-limiting period of the year, in a winter rainfall environment the feed demand and feed supply at
other times of the year can also affect optimum stocking rates. For example, on mixed crop and livestock farms the winter-grazing area fails to account for the feed supplied from grazing crop residues after harvest or the ability to graze dual-purpose crop areas. There is evidence that differences in the number of sheep carried between farms can be attributed to different crop intensities and therefore different availabilities of crop residues as feed sources (Thomas et al., 2010, Dove and Kirkegaard, 2014). Thus, the optimum stocking rate is not solely associated with the feed required during the feed-limiting period of the year. This has implications for the recommendations about stocking rate that can be applied to farms with different circumstances, and there needs to be adjustment rules for different feed supplies (e.g. how optimal stocking rate changes with stubble area).

In summary, the current definition of stocking rate represents the grazing pressure applied per hectare in the feed-limiting period. The definition is consistent across different flocks and properties, overcoming many of the issues identified by Macdonald et al. (2008). However, as shown by Young et al. (2020), if 10 DSE/ha is the most profitable stocking rate for a wether dominant flock, it does not mean 10 DSE/ha is the most profitable stocking rate for a ewe dominant flock. This is because in an environment where supplementary feeding can occur or grazing management can be altered to adjust grazing intensity during the year, optimal carrying capacity is affected by factors additional to energy requirements, such as timing of energy requirements throughout the year and livestock income. For example, it may be profitable to run a higher stocking rate and feed more supplement to a flock structure that then generates a higher income. Hence, for a specific feed situation, the optimal stocking rate for a wether dominated flock may be 10 DSE/ha but the optimal stocking rate for a ewe dominated flock may be 13 DSE/ha.

Sheep management factors such as time of lambing can also impact farm profit and optimal stocking rate (Robertson and Friend, 2020). Robertson and Friend (2020) used whole farm simulation modelling to evaluate the profitability of farm systems that varied by time of lambing and stocking rate. Their results indicated that April joining resulted in an optimal stocking rate of approximately 2 sheep/ha greater than February joining because the better match of pasture demand and supply reduced feed costs. This corresponded to a 15% larger gross margin, reinforcing the importance of considering the whole farm system when evaluating the optimal stocking rate, but also indicating that relative stocking density changes with time of lambing and the distribution of the energy requirement of the flock during the year. Thus, the DSE metric only represents the relative energy requirement at a given point in the year. Yet in practice the energy requirements of different classes of sheep can change greatly across a production year. Hence, the DSE metric only partially captures
important differences in the patterns of energy requirements of different classes of sheep. As a consequence, using the DSE metric in reporting a stocking rate, although useful, has important limitations that are not always widely recognised. Two main uses for reporting on stocking rate are:

(i) to aid discussion with farmers regarding their farm management decisions.
(ii) to facilitate analyses of sheep enterprise gross margins in order to compare the prospective profitability of different animal production systems or flock structures (NSWDPI, 2020).

In both cases, the discussions or gross margin analyses are likely to be further aided if either a range of stocking rates is considered or that the definition of a DSE is changed to reflect important differences in the patterns of energy requirements of different classes of sheep. The concept of the new definition of DSE is similar to substitution ratios as discussed by Scarnecchia (1990) and McLennan et al. (2020).

The stocking rate challenge in Australia: early research

In previous decades a variety of economic evaluation approaches have been applied to determine the optimal sheep stocking rate. Chisholm (1965), Dillon and Burley (1961), Lloyd (1966), McArthur and Dillon (1971) all showed the importance of making sound decisions about stocking rate and provided a useful economic basis for determining stocking rate. Dillon and Burley (1961) proposed a simple model of the grazing complex. They discussed a range of factors that ought to be considered when analysing stocking rate, such as livestock production and feed consumption, pasture production and deterioration, pasture conservation and the quantity and cost of fertiliser inputs for pasture production. However, the focus of their research was an examination of key factors affecting stocking rate, rather than the estimation of the optimal stocking rate.

Chisholm (1965) took a different tact and split the stocking rate problem into two parts. First, he determined the most profitable stocking rate for an average season; and then, he assessed the optimal stocking rate and fodder reserves needed to account for long-term fluctuations in pasture production. He investigated three methods for determining the optimal stocking rate:

(i) Direct data from farms that had altered their stocking rate but kept all other inputs constant. This was deemed infeasible because few, if any, farms could fulfil these requirements.

(ii) Derive whole farm production functions by which the marginal revenue of livestock was predicted by a multiple regression model in which the number of livestock was a farm input.
This was also deemed infeasible as previous work determined that including the value of livestock as an input produced nonsensical values (Duloy, 1964).

(iii) Use of experimental data to determine a relationship between stocking rate, wool cut, and gross margin. This was selected as the most feasible option for the analysis.

The third method was tested by Chisholm (1965) for the New England region of NSW and replicated by Dunlop (1984) in the Great Southern region of WA. Both discovered a negative linear relationship between stocking rate and wool cut. For Chisholm, each additional sheep per hectare reduced the wool cut by 0.67 kg/head. Using this relationship, the optimal stocking rate was estimated for an average farm in New England to be approximately 5 sheep/acre (i.e. 12 sheep/hectare) in an average year. Chisholm noted that fluctuations in pasture production associated with variation in climate greatly complicated the stocking rate problem. Attempting to account for the impact of seasonal variation, 38 years of rainfall data and three years of pasture records were analysed. Using this data, each year was classified into one of six pasture production classes and their probability of occurrence was estimated. Using this information and assuming that in poor seasons supplementary feed would be required, the gross margin of sheep production was calculated for poor, average and good season types for a range of stocking rates and wool prices. The results from the study showed that the poor years reduced profits more than the good years increased profit, and therefore the optimal long-term stocking rate was lower than that calculated when only average seasons were assumed. Applying his findings to farmers in the New England region Chisholm suggested that increases in stocking rate by up to 50% could offer significant improvements in profit.

Lloyd (1966) used the same relationship between stocking rate and wool cut as Chisholm (1965) and also used hypothetical long-term averages (due to lack of experimental data) to investigate the marginal value of product for different stocking rates in southern Australia. His results indicated that a stocking rate of approximately 15 sheep/ha maximised profit. However, Lloyd stated that this stocking rate was unlikely to be completely optimal because the following four factors were not represented in the calculation of stocking rate:

(i) Feed reserve cost (cost to obtain and store feed to cover feed shortage in drought conditions) would likely increase more rapidly as stocking rate increased. Lloyd stated that this factor could reduce the optimal stocking rate by 2.5 sheep/ha.

(ii) It was unreasonable to assume overhead costs per hectare would be constant over a range of stocking rates. He stated that this factor could reduce optimal stocking rates by over 1.25 sheep/ha.
(iii) The risk attitude of farmers was not considered. For example, if the optimum stocking rate was X sheep/ha but X-1 sheep/ha was nearly as profitable and much less risky, then the optimal stocking rate for a risk averse farmer would be lower than the optimal calculated without consideration of the farmer’s risk attitude. The author stated that this factor could reduce optimal stocking rates by 2.5 sheep/ha.

(iv) The possibility of regular seasonal feeding was not considered. This area of research had not been considered at this time, but Lloyd believed that with access to reasonably priced supplementary feed, it was likely to be a profitable activity.

McArthur and Dillon (1971) proposed that if farmers were risk averse and they maximised their expected utility, then their resource allocation would be suboptimal compared to that of expected profit maximisation. This indicated that in the face of uncertainty, such as climate and price variation, farmers would tend to run lower stocking rates than those farmers that maximised long term average profit.

Optimal stocking rates were also considered by White and Morley (1977) who argued that previous analyses had not considered changes induced by stocking rate on wool value per kg, as opposed to just the weight of wool cut (kg). Although an increased stocking rate decreased wool growth it also decreased fibre diameter, which received a premium in the market. White and Morley (1977) and Curtis (1988) showed that as the relationship between wool price and fibre diameter increased, the optimal stocking rate also increased. For example, if a decrease in fibre diameter of one micron received a 10 cent premium, the optimal stocking rate would increase by approximately 12%. In addition, they created and used a simple cash flow simulation model to generate the optimal stocking rate for a 500 hectare farm producing wool over a random sequence of years. Instead of estimating the risk aversion of a particular farmer like McArthur and Dillon (1971) had done, White and Morley (1977) provided an indication of financial risk by calculating the stocking rate that maximised the minimum profit over number of years. Their results showed that the stocking rate that maximised the minimum profit was between 0.5-1.0 sheep/ha less than the stocking rate that maximised average profit. They also showed that reducing stocking rate by more than 10% from the optimum could result in a large decrease in the long-term minimum profit. These findings suggested that attempting to minimise the chance of financial hardship by running a low stocking rate might in fact have the opposite effect.

Many assumptions underpinned this earlier research in order to simplify the farming system to facilitate its analysis (Chisholm, 1965, Dillon and Burley, 1961, Lloyd, 1966, McArthur and Dillon,
1971, White and Morley, 1977). For example, there was no consideration of regular supplementary feeding, no drought management strategies other than supplementary feeding, a uniform soil type was assumed as well as a single livestock class and no optimisation of pasture production through grazing management was permissible. These assumptions were made partly due to the limited availability of experimental data, and partly due to a lack of computing power, which made it difficult to undertake detailed modelling. Nonetheless, the results from this period of research identified that choice of stocking rate could have large economic impacts and therefore, to maximize profits, farmers needed to consider stocking rate carefully, and output per hectare rather than production per head. This point was and is often overlooked in partial farm analyses that do not include the land, which is the biggest resource constraint. Highly productive animals may need to be run at a low stocking rate creating less profit. There is an optimal balance between production per head and stocking rate that maximises profit per hectare. In summary, the results from this early work provided insights into important factors to consider such as:

1. **Seasonal variation and risk** – seasonal and price variation coupled with the farmer’s risk attitude and the farmer’s drought management tactics could simultaneously impact the optimal stocking rate and hence must be considered jointly. McArthur and Dillon (1971) proposed that risk aversion lowers the stocking rate.

2. **Feed availability** – feed availability was a key driver of stocking rate, therefore optimising stocking rate required a full understanding of the nutrition available to sheep and its cost. More feed meant higher stocking rates. However, feed reserves had to be kept to handle poor seasons, which could reduce stocking rate by 15-20% (Lloyd, 1966).

3. **Sheep production** – determining the optimal stocking rate required understanding the trade-off between stocking rate and sheep production. Early work showed negative relationships between stocking rate and wool production and positive relationships between stocking rate and wool value (Chisholm, 1965, White and Morley, 1977).

**Seasonal variation and risk**

Year-to-year seasonal and price variation causes large variance of farm profit (Darbyshire et al., 2020, Kingwell, 1994) resulting in more complicated decision making (Kingwell et al., 1992). In addition, in Australia, empirical studies of farmer behaviour indicate the majority of farmers are slightly risk averse, meaning they would sacrifice some expected profit to reduce yearly profit variation (Bardsley and Harris, 1991, Bond and Wonder, 1980, Ghadim et al., 2005). Thus, there are
two issues; (i) year to year variation; and (ii) farmer risk attitude that warrant consideration when determining an optimal stocking rate strategy.

Seasonal variation is concerned with the probability of each season type and price scenario, the production associated with each season type, and the seasonal tactics that can be implemented to boost expected utility by lessening downside risk in less productive years and increasing the upside in productive years. To attempt to capture the impact of seasonal variation on stocking rate Trompf et al. (2014) ran MIDAS (whole farm optimisation model, described in detail below) multiple times with different production inputs to represent a poor, average and good season in a low rainfall and medium rainfall zone in Western Australia, and a higher rainfall zone in south west Victoria. They used a weighted average of the season types to determine the overall optimal stocking rate. Their results showed that across the rainfall zones the optimal stocking rate in the poor years was between 57% and 87% lower than the optimum long term average stocking rate, and the optimum stocking rate in the good years was 31% to 35% above the long term average. They then discussed strategies and tactics that farmers could use to flexibly alter the stocking rate on farm. Similarly, Donnelly et al. (1994) used GrassGro (a partial farm simulation model, described in detail below) and found that in both Wagga Wagga (NSW) and Hamilton (Victoria) the gross margin per hectare varied significantly (up to $214/ha and $255/ha respectively) between years. Their results showed that income variation was greater at higher stocking rates, varying up to 56% more when stocking rate was increased by 25%. This indicates that the type of weather season significantly affected choice of stocking rate and farm risk.

Commodity price variation adds further risk to farm businesses. The relative profitability of sheep production is linked closely to the prices of key farm products and their inputs (Kopke et al., 2008, Warn et al., 2006a). The key commodities’ prices that impact the livestock enterprise are grain, meat, and wool. Changes in meat and wool prices directly affect the profitability of the sheep enterprise. Changes in grain prices also impact sheep enterprises in two main ways. First, they affect the price of grain feeding. Second, they impact the profitability of cropping enterprises, which may alter the optimal area of cropping, the type of crop, and consequently, the area of pasture available and the quantity and quality of stubble. Kopke et al. (2008) found that as grain prices increased, the optimal area of land allocated to pasture decreased and the number of sheep declined. Further, as wool and meat prices increased so did the optimal number of sheep. There was evidence that as the profitability of the sheep enterprise increased, both the area of pasture and the stocking rate increased (Kingwell et al., 1992), however there has been little subsequent research to quantify such changes.
Future seasonal conditions and commodity prices are not firmly known. Therefore, farmers must decide on a base stocking rate and use management tactics to handle variations as a season unfolds. There are various management tactics able to be implemented by farmers as a season unfolds. Trompf et al. (2014), for example noted the tactic of selling wethers as lambs rather than retaining them in the advent of a poor season could increase optimal stocking rate by one or two DSE/ha. Using MUDAS, Kingwell et al. (1992) found that altering the area of crop and pasture as a season unfolded, where possible, and agisting livestock in poor years were also viable seasonal tactics. In higher production seasons it was optimal to have up to 35% more crop and hence a higher stocking rate than in a poor production season. Additionally, in a poor season, it was optimal to further reduce stocking rate by agisting up to 30% of the DSE. Furthermore, Moore et al. (2009) suggests that management tactics such as fertilising pasture and grazing crops rather than adopting a long term strategic response could be especially worthwhile in environments where a feed gap was unpredictable in terms of its timing and magnitude. Thus, successful implementation of seasonal tactics by farmers can help reduce the impacts of poor seasons and maximise the benefits of good seasons and thereby affect the optimum stocking rate.

Farmer risk attitude is the behaviour of farmers in response to year-to-year variation. Price and climate variation result in a high variability of yearly profit for farmers. Risk averse farmers opt for a farm management strategy that attempts to lower the profit variability albeit at some cost to expected profit. Kingwell (1994) used MUDAS to examine farm management decisions of moderate and highly risk averse farmers. His results showed that risk aversion only reduced the expected profit by 2-6%, yet the key management changes involved shifting resources away from cropping towards livestock enterprise due to the greater variability of profits associated with crop production. Pasture area, stock numbers and stocking rate were all increased for the risk averse strategies, with the increase in optimal stocking rate being due to an increased area of pasture on the most productive land management units because that generated lower variation in farm profit. Kingwell’s findings showed the important interplay between soil types, enterprise selection on those soils and seasonal tactics applicable to enterprises on some of those soil types. However, other studies have shown that increased stocking rate is associated with greater variation in farm profit (Trompf et al., 2014, Warn et al., 2006b). At lower wool prices Kingwell (1994) found stocking rate increased 5% and 9% respectively for moderate and high risk aversion. This was magnified in a price scenario where wool was relatively more profitable than grain. In this scenario, the sheep stocking rate increased 16% and 23% under moderate and high risk aversion. It must be noted, however, that these findings were generated during a period when sheep flock structures were dominated by wethers and the price of livestock products were lower relative to cropping than now. The switch to younger flock structures
(Young et al., 2020) and the knowledge of the importance of good ewe condition on farm profit (Young et al., 2011) may mean that switching resources towards the sheep enterprise to minimise profit variation is less effective now.

In summary, farming is very uncertain with weather and price changes effecting choice of stocking rate (Kopke et al., 2008, Pannell et al., 2000, Trompf et al., 2014, Kingwell et al., 1992). Pannell et al. (2000) discussed the inclusion of risk attitudes and production and price risk in farm analyses and concluded that the most important aspect of risk to be modelled is not farmers’ aversion to risk, but rather their short-term tactical responses to variation in weather and prices. For stocking rate decisions that are often impacted by tactical decisions as the season unfolds (Kingwell et al., 1992), we support the idea that year to year variation and associated management tactics need to be represented. However, the need to include risk aversion is less clear. Australian farmers are shown to be only slightly risk averse (Bardsley and Harris, 1991, Bond and Wonder, 1980, Ghadim et al., 2005). As argued by Pannell et al. (2000), representation of aversion is often not a high priority. However, Kingwell (1994) did find that risk aversion affected decisions around choosing stocking rates. Therefore, regarding livestock enterprise management, inclusion of risk aversion may warrant some investigation.

Feed supply

The main feed sources for sheep in Australia are pastures and crop residues with supplements of grain, hay, and silage. The seasonality of supply in most regions means that there is often a mismatch between supply of newly grown forage and the daily demands of livestock (Bell et al., 2008, Macdonald et al., 2008). Imbalances between feed supply and demand suggest that there are inefficiencies in production in terms of excess feed wasted, or unmet animal demand. Farmers supplement sheep diets during periods when the marginal value of extra feed is high because pasture and crop residues are insufficient in quantity or quality to meet the production targets of the animals being run (Hinton, 2007). Agistment is another useful tactic when the marginal value of feed is high (Kingwell et al., 1993). For example, over the summer period, a livestock dominated farm can, for a cost, agist their livestock on stubble from a crop dominated farm. Supplementary feeding also allows farmers to defer pastures at the break of season to increase leaf area and subsequent growth rate, which allows an increase in the number of sheep carried through the winter period (Brown, 1976). However, supplementary feed is often expensive and is the main contributor to the increase in the marginal cost of increasing stock numbers on farms. This is an important contributor to the determination of the optimum stocking rate, because at the optimum
stocking rate the marginal cost of the extra animal must equal the marginal benefit to the farm enterprise.

Crop residues (i.e. stubbles) are a summer feed source for sheep on mixed crop-livestock farms. Stubbles are a cheap source of feed for the livestock enterprise, resulting in a lower marginal value of feed over the summer period. Thus, as mentioned above, increasing the area of crop tends to support higher stocking rates. Cropping complicates the analysis of stocking rate decisions for these mixed enterprise farms, as feed availability is also linked to crop production and crop area. The introduction of dual purpose crops over the last decade on mixed farms also enhances the influence of cropping on the optimal sheep stocking rate, as does the introduction of summer active perennials (Kingwell and Squibb, 2015). An analysis by Moore et al. (2009) concluded that grazing of cereals is the most promising means to alleviate winter feed gaps. Hence, the relationship between the crop enterprise and feed availability must be included when determining the optimal stocking rate.

Understanding pasture production is also crucial to determining optimal stocking rate, however, the interaction between pasture production and grazing is complicated and multi-faceted. The quantity and quality of pasture available depends on a multitude of factors such as time of year, rainfall distribution, grazing intensity, soil fertility and pasture composition (Dunlop et al., 1984, Saul and Kearney, 2002). The average digestibility of pasture is greater at low levels of feed on offer (FOO) because most of the pasture is new growth and its digestibility decreases as FOO and lignification increases, or when pasture senesces later in the growing season and over summer. Pasture growth increases as FOO increases, and decreases as grazing pressure increases, caused by defoliation (Dunlop et al., 1984). Animal production also varies with FOO and digestibility because voluntary feed intake increases with higher FOO and the capacity for selective grazing to achieve a higher quality diet than the sward average digestibility is increased with increasing FOO (Freer et al., 2007). Therefore, it is vital to consider biological relationships between pasture quality and quantity and, pasture growth rate and animal production when determining the optimal grazing strategy.

Between 1993 and 1997 a large project was undertaken across properties in south-eastern Australia comparing standard pasture management (low input) with improved pasture management (increased fertiliser inputs). Saul and Kearney (2002) analysed the data from the project using a regression model and showed that for each additional month of pasture growth, stocking rate could be increased by 3.4 DSE/ha, and for each additional mg/kg of Olsen Phosphorus in the soil, stocking rate could increase by 0.17 DSE/ha. Their results showed the potential impact of improved pasture production and increased length of the growing season on stocking rate and illustrated, perhaps
expectedly, that it was feasible to run higher stocking rates on improved pastures. These findings however did not account for any economic factors such as the cost of improved pastures, so the level to which pastures should be improved to maximise profitability was not assessed by Saul and Kearney (2002).

Young et al. (2004) used a revised version of the farming system model MIDAS (Kingwell and Pannell 1987) to evaluate the economic impact of including lucerne, fescue and highly productive perennial ryegrass on a typical farm in the Hamilton region in south-west Victoria. The model allowed the management of farm resources to be optimised, including factors such as pasture deferment, supplementary feeding, and stocking rate. They found the inclusion of improved pastures increased profit per hectare for all flock structures by up to $271/ha, accompanied by stocking rate increases of up to 67%. Although carried out for a similar region as the study of Saul and Kearney (2002), the increase in stocking rate was greater than what would be predicted using their relationship. This indicates that other factors associated with pasture production also influence optimum stocking rate. In Western Australia, Bathgate and Pannell (2002) found lucerne, which extends the growing season, to only be profitable in certain environments. The additional summer feed provided by the perennial increased optimal stocking rate, but the cost of establishment reduced its overall economic attractiveness.

MIDAS was also used to determine the whole-farm economic impact of pasture improvement in the central wheatbelt zone of Western Australia (Bathgate et al., 2009). Pasture improvement involves sowing of new pasture to increase growth and quality (Alcock and Hegarty, 2006, Bathgate et al., 2009). In this agricultural zone, pasture improvement led to a 26% increase in farm profit, but had little impact on optimal stocking rate, which remained at 6 DSE/ha. Bathgate et al. (2009) concluded that this was due to the optimisation of rotation selection, with improved pasture causing more of the farm area to be optimal for grazing rather than cropping, and hence there was less crop residues available for grazing during the summer-autumn period. Alcock and Hegarty (2006) used GrassGro to simulate the impact of pasture improvement for a cross-bred lamb farm in Cowra, NSW. Their simulation found that the sustainable stocking rate (i.e. the stocking rate at which total herbage mass fell below 800 kg DM/ha in autumn only once in every 5 years) was double when improved pastures were used and the gross margin increased three-fold due to the increased stocking rate and greater sheep production. Some of the differences in results between Cowra in NSW and the central wheatbelt in Western Australia could be attributed to the shorter growing season in the central wheatbelt region, which reduced the time to capitalise on the benefits from improved pastures and thus reduced the value of pasture improvement. However, some of the difference could also be due
to the different methods used to determine optimum stocking rate, with the MIDAS model calculating an economic optimum that included animals being fed a full ration in confinement if F0O fell to a threshold value whereas the GrassGro modelling required the animals to remain on the pasture paddock and the stocking rate was determined by the frequency of F0O being reduced below an accepted threshold. Furthermore, the GrassGro analysis did not include impacts on the cropping enterprise or factor in additional labour requirements as a result of improved pastures.

Determining the optimal feed management strategy and stocking rate is a complex process, requiring the biological characteristics of each feed option and their interactions with other aspects of the farming system to be represented and examined. For example, pasture production depends on stocking rate and grazing management yet stocking rate itself depends on pasture production. These mutual relationships and interactions need to be accurately described and evaluated simultaneously. This is a complex modelling challenge but is made possible by modern computational power.

**Sheep Production**

A sheep’s energy intake profile throughout the year, which reflects in the animal’s liveweight profile, has significant impacts on sheep productivity because it can influence key traits such as lambing percentage, lamb survival and wool quality and quantity (Thompson and Young, 2002). It is important therefore to consider the trade-offs between nutrition profile and production when determining the optimal stocking rate, particularly for ewes where their liveweight profile can impact the productivity of both the ewe and her progeny.

Ferguson et al. (2011) and Oldham et al. (2011) found that production of ewes and their progeny could be predicted by the ewe’s liveweight profile throughout the year. Using these relationships Young et al. (2011) modelled a range of liveweight patterns for properties in Victoria, Western Australia and southern New South Wales, and found that the optimum liveweight profiles for ewes lambing in spring were similar in all three regions, and were insensitive to changing commodity prices, pasture productivity and management. For ewes, the optimum profile was to join at approximately 90% of their standard reference weight (i.e. the weight of a sheep when mature, not pregnant, bare shorn and in medium condition), allow them to then lose a small amount of weight after joining and regain that weight in late pregnancy to return to their joining weight by lambing. In the Western Australian region, their results showed that whole farm profit increased with stocking rate increases up to an optimum of 14.3 DSE/ha. Additionally, optimal ewe liveweight management increased farm profit at all levels of stocking rate. These results implied that the economic priority
for allocating available feed to different animal classes varied during the year. This is consistent with the findings of Young et al. (2016) who examined the profitability of using ultra-sound pregnancy scanning to identify the pregnancy status and litter size of ewes. They showed that the optimum nutrition profile changes and that profit could be increased if extra feed was allocated to the ewes carrying 2 foetuses. These results suggested that when calculating optimum stocking rate, feed should be allocated throughout the year to ensure sheep met their optimal liveweight profile. This is in accord with economic theory whereby the optimum stocking rate, and hence optimum liveweight profile, occurs at the point where the marginal cost of providing extra feed equals the marginal revenue, and that the marginal revenue is equal for each class of stock. This is a theoretically simple concept but computationally difficult to identify.

Environmental factors

Most decision-making models used in farm planning reflect the basic economic criterion of profit maximization with little concern for environmental factors such as greenhouse gas (GHG) emissions (Sintori, 2014). However, both farmers and the general public are becoming more aware of the adverse effects of GHG on the environment and agriculture’s contribution to GHG emissions (Kopke et al., 2008, Sintori, 2014). In response the Australian government, like many governments, is adopting policies and initiatives to reduce emissions of GHGs (Thamo et al., 2013).

Petersen et al. (2003) considered GHGs emitted from four sources in the farm system: nitrogen fertiliser, fuel use, stubble burning and sheep. Their results indicated that, on a livestock dominated farm (85% pasture), 97% of total farm emissions were from sheep in the form of methane. They found that the relatively high GHG emissions from the sheep enterprise meant that the inclusion of emission abatement policies resulted in a shift towards cropping. Without changes in farm technology, the introduction of emission abatement policies is likely to render farm systems with a high livestock dependency unprofitable. Thamo et al. (2013) found, in the more crop dominated region of the Western Australian grainbelt, introduction of emission policies reduced farm profit by 14.4 – 30.8%. This is a significant reduction in profit. However, with some small technological changes, farming systems could remain viable. Petersen et al. (2002) and Kingwell (2009) determined that planting trees to sequester carbon is a viable technological option for farm systems, mostly at high emission prices. Furthermore, Thamo et al. (2017) examined the impact of climate change on farm profit by simulating farm production under a range of future climate scenarios. Their findings were that in the majority of scenarios profit decreased, indicating that globally reducing
emissions to limit climate change could potentially benefit farms by helping them avoid future losses.

Although prospective environmental changes are likely to restrict sheep production and limit stocking rates, it is not yet clear what future emission policies might be and therefore their additional impact on sheep production and stocking rates is unclear. A likely scenario is that the joint influence of environmental change and emissions policy will lower optimal stocking rates. For example, if there is a tax on emissions then the marginal cost of each sheep increases, reducing the incentive to feed supplements, resulting in a lower stocking rate. However, if the policy is simply an emission restriction then another plausible scenario is that the optimal stocking rate could remain similar, although it may also be necessary to shift toward cropping or allocate some land to plant trees, thereby reducing the total DSE count. However, as the marginal cost of each DSE/ha is likely to remain similar, the result would be a similar optimal stocking rate. The marginal cost and revenue of each DSE would remain similar provided the feed supply remained similar. However, this may not be the case if the area foregone to the cropping enterprise was significantly better pasture-producing land, because it would leave land with much poorer pasture production that results in higher supplementary feed requirements and a lower winter-grazing stocking rate.

The other topical area of research is the development of GHG-reducing technologies and practices applicable to cattle and sheep production. Patra et al. (2017) and Honan et al. (2021) describe the current suite of feed additives currently under review. Adoption of feed additives and altered feed management to reduce emissions will be governed by their ease of use, their efficacy in reducing emissions, their cost and the advantages they produce. Depending on how animal performance is affected, the optimal stocking rate in turn will be affected.

**Modelling approaches to determine optimum stocking rate**

There are many approaches to evaluate farm management ranging from simple field experiments, benchmarking (Kahan, 2013) and gross margins (NSWDPI, 2020) to more complex system modelling (Kingwell and Pannell, 1987, Moore et al., 1997). Benchmarking can provide general insights about farm management by comparing productivity of different businesses. However a key limitation is quoted by Malcolm (2000) “there are no benchmarks for yet to be introduced change”. Additionally, benchmarking using gross margins can be misleading because gross margins do not capture fixed costs, which can change between farms due to resource and management differences (NSWDPI, 2020). Simple gross margins provide a snapshot of the costs and benefits at a point in time. Although a simple framework, correctly applying gross margins can be challenging as obtaining relevant and
accurate information to underpin the analyses is not always a simple task. For example, if gross margins were used to examine stocking rate, inputs would need to capture the relationship between grazing pressure and wool per head. The choice of approach depends on the problem at hand. For each problem there is an optimum degree of generality (Malcolm, 2000).

As discussed in previous sections, the stocking rate problem is highly complex, which makes it difficult to evaluate using field experiments and other simple appraisal tools. Thus, most recent work has been conducted using various farm or partial farm models. There are four models used widely in Australia and that have been applied to evaluate sheep stocking rate:

(i) Model of an Integrated Dryland Agricultural System (MIDAS) (Kingwell and Pannell, 1987) – MIDAS is a steady state whole farm linear programming model with a joint emphasis on biology and economics, it represents multiple land management units and a self-replacing flock with all classes of stock. However, MIDAS assumes an average season so there is no inclusion of year to year variation (Young et al., 2020)

(ii) Model of an Uncertain Dryland Agricultural System (MUDAS) (Kingwell et al., 1991) – MUDAS is a whole farm discrete stochastic programming model that explicitly accounts for climatic risk and dryland farm management responses to such risk.

(iii) GrassGro (Moore et al., 1997) – GrassGro is a partial farm simulation model that couples the GRAZFEED feed intake and ruminant nutrition models (Freer et al., 1997) for a single class of animal with a daily simulation model of pasture growth and dynamics.

(iv) AusFarm (Moore et al., 2007) – AusFarm is a whole farm simulation model, representing the detail of GrassGro with multiple sheep classes along with the crop enterprise.

The stocking rate that is optimum has been variously defined by different authors and it is usually aligned with the modelling method used. Authors using MIDAS (Bathgate et al., 2009, Trompf et al., 2014, Young et al., 2020) generated an optimum stocking rate by maximising expected profit subject to minimum ground cover constraints while allowing confinement feeding of livestock. Using MUDAS Kingwell et al. (1992) found an optimal stocking rate through maximising expected utility across a range of season types subject to the same constraints as the MIDAS analyses. Authors using simulation modelling such as GrassGro and AusFarm (Alcock and Hegarty, 2006, Donnelly et al., 1994, Warn et al., 2006b) generate an optimum stocking rate that is associated with a long term median profit, subject to environmental and production risk criteria relating to pasture mass and probability of feeding supplements. This approach has the outcome that the optimum stocking rate is the maximum stocking rate that can be carried while achieving the specified environmental outcome in low production years. Each of the above methods would generate a different ‘optimum’ stocking rate for
a specified flock in a given environment even if the models were otherwise identical. Therefore, further work is required to determine which is the most useful approach or measure for farmers.

Each of the modelling approaches has its pros and cons. MIDAS has been used frequently to evaluate the impact of various factors on whole farm profit in southern Australian farming systems, particularly those in Western Australia (Kingwell and Fuchsbichler, 2011, Kopke et al., 2008, Thamo et al., 2017, Trompf et al., 2014, Young et al., 2004a, Young et al., 2020). MIDAS captures the complex biology of pasture and livestock production and allocates the farm resources in such a way that optimises whole farm steady state profit. However, as mentioned previously, a key weakness of MIDAS is its steady-state framework that assumes an average season and expected price scenario (Kingwell et al., 1992). MIDAS also does not represent a farmer’s risk attitude nor their seasonal tactics.

MUDAS was developed in the early 1990’s to analyse the impact of seasonal variation and price risk in Western Australian farming systems (Kingwell et al., 1991). However, the complexity and lack of ease in updating MUDAS meant it quickly fell into disuse. Moreover, the model was built when computational power was limited, resulting in long solution times and an arduous error-checking and calibration process. Due to these limitations MUDAS has not been updated since the late 1990’s. Since then farm management and farming systems have changed significantly. For example, farm practices, in both cropping and livestock management, have altered substantially; farm sizes have increased, as has the work rates of farm machinery; crop types and yields have altered, and relative prices of farm commodities and farm inputs have changed; the relative profitability of the sheep enterprise has increased, and more information is available about the importance of adhering to sheep management liveweight targets; there is increased computing technology and availability of farm data, and greater sophistication in biophysical simulation modelling now allow farm modelling to be more detailed and accurate; and the probabilities of the various types of seasons that underpin MUDAS have changed since the 1990s as climate change has been observed to worsen with more frequent warmer and drier years. Consequently, it is likely that many of the findings from the early analyses based on MUDAS are no longer relevant or accurate and therefore require reassessment.

Simulation models have also been widely used to evaluate stocking rate. They represent the biophysical aspects of the farm in more detail than the bio-economic models such as MIDAS. They also represent the year-to-year variation in climate by using historical weather data. These features mean that different management can be evaluated in detail. Some simulation models, for example AusFarm, includes the capacity to develop flexible management rules and hence can represent tactical management adjustments in response to varying seasons. However, bio-physical models are often developed without a strong economic focus and rely on the skill of the user to incorporate the
economics (e.g. Thomas et al. 2010). Furthermore, optimisation of simulation models is inefficient (Doole and Pannell, 2008). Without optimisation, the results are highly dependent on the skill of the user and the management rules implemented. For example, the level of supplementary feeding is often determined by a minimum condition score for the sheep rather than the marginal cost relative to the marginal revenue of the feeding decision. Similarly, the allocation of paddock feed is often not related to the marginal benefit of feed for the different livestock classes but rather to a fixed grazing rule (e.g. McGrath et al. 2016). If the goal of the work is to better understand the system, then in some cases optimisation may not be a prerequisite for the desired modelling framework, in which case bio-physical simulation modelling can be highly useful (Thomas et al., 2018). However, as discussed in the previous sections, stocking rate is highly complex with a large number of contributing factors. Therefore, without an optimising mechanism, evaluating an optimal stocking rate is extremely challenging.

In addition to the modelling frameworks that have been widely applied to sheep systems in Australia, the technological development in the recent years has open the doors to a range of novel and emerging modelling techniques including artificial intelligence (AI), bayesian belief networks (BBN) and agent based modelling (ABM). AI can make sense of complex systems however it needs significant data to be trained which is challenging for farm systems management where there is no data source that specifies farm outcome under different management regimes (Tung and Yaseen, 2020). BBN is a probability based model that predicts the likelihood of a given outcome based on input parameters. However it does not provide direct guidance on the optimal decisions to make (Randall et al., 2022). and similarly ABM is based around system simulation and system understanding rather than actually optimising decisions (Bonabeau, 2002). In the immediate term their roles may be of complementation rather than of substitution to the more widely use whole farm modelling techniques. For example, an AI decision tool was recently developed by MLA to examine the implications of mating ewe lambs. The AI decision tool was trained using output from a whole farm mathematical program (MLA, 2023).

There have be numerous farm modelling frameworks developed ranging in complexity and scope (Janssen et al., 2016). Most have been used to examine stocking rate in some form or another. We argue that although each model has served a purpose, none fully captures the intricacies of the stocking rate problem. Simulation models such as GrasGro and AusFarm capture the biology of the farm system in detail yet lack the capacity for optimisation (Doole and Pannell, 2008, Thomas et al., 2010, Thomas et al., 2018). Conversely, mathematical programming models like MIDAS provide a framework for efficient optimisation but are resource constrained and lack detailed representations of aspects of biology and uncertainty (Kingwell et al., 1991, Trompf et al., 2014, Young et al., 2020).
To accurately determine optimal stocking rate requires an optimisation framework or model that includes the important bio-physical details of the farm but also represents seasonal variation and can optimise strategic and tactical management.

Stocking rate: Generalisations from studies

Most research on the optimal stocking rate for sheep production has been conducted in eastern Australia (Warn et al., 2006b, Gicheha et al., 2014, White and Morley, 1977, Young et al., 2004b). Unfortunately, the results from these studies are not easily generalized to all other regions of Australia. For example, Western Australia, unlike many parts of New South Wales and Queensland, has a different climate and seasonal conditions. Hence there is a gap in the research about stocking rates especially for Western Australia. This gap in the literature has only been partially addressed by Trompf et al. (2014) and Young et al. (2020). Both used MIDAS, yet as outlined above, MIDAS has limitations when applied to certain aspects of determining the optimal stocking rate.

The case for many years is that most farmers consistently run relatively conservative stocking rates compared to calculated optimums (Young et al., 2020, Lloyd, 1966). For example, zonal benchmarking shows that the average stocking rate in the south-west of the Western Australian Wheatbelt was 8.5 DSE/ha with the top 25% running 11.8 DSE/ha and the bottom 25% running 6.2 DSE/ha (Planfarm/BankWest, 2016). By contrast, Young et al. (2020) indicated an optimal stocking rate in the region was between 10 and 13.7 DSE/ha. Farmers’ rationale for selecting lower stocking rates may be explained by a host of factors not captured by MIDAS as used by Young et al. (2020).

The weaknesses of MIDAS are that it does not account for:

(i) Risk attitude – risk averse farmers may run lower stocking rates to lessen the variability of profit. Running a lower stocking rate reduces the losses in a poor year yet reduces the upside in good years, thereby lessening profit variance. However, running a lower stocking rate is a suboptimal strategy for risk neutral and slightly risk averse farmers (Kingwell, 1994, White and Morley, 1977).

(ii) Preference - high stocking rates demand more monitoring and a greater speed of reaction to seasonal and price conditions. However, farmers are time-pressed (Kingwell, 2011) and often have a preference for cropping, making sheep management a subsidiary rather than complementary activity, leading farmers to prefer a simple livestock management regime (Rose, 2011).

(iii) Seasonal variation and management tactics – as a steady-state model, the role of variation in seasons, prices and farmers’ tactical reactions is not featured in MIDAS, the assumption...
being that the cost of the poorer seasons is exactly matched by benefits in the better seasons. However, farmers’ abilities to react to changes in seasonal and market conditions is often an important source of protecting or boosting farm profits.

Recommendations and future improvements to stocking rate analyses

Stocking rate is often used as a summary measure of sheep production and sheep management, and as previously discussed, even when underpinned by the concept of a DSE, it lacks precision in capturing the managerial interplay between sheep classes, their nutritional needs and the availability of different feed sources throughout a production year. To determine what is an optimal stocking rate for any particular farm business is a complex task.

As previously discussed, most analyses that aim to identify an optimal stocking rate have been conducted using one of few modelling frameworks. However, each framework has limitations that caution the accuracy and generalisation of its findings. There is no current framework or model that fully and accurately captures the current decision-making environment for mixed enterprise farmers, especially in Western Australia. Thus, there is a gap in the current literature regarding the optimal sheep stocking rate on Western Australian mixed farm enterprises, noting that Western Australia supplies about 21% of Australia’s wool production and contains about 22% of the nation’s sheep flock.

The research challenge is to develop a method that appropriately represents how a farmer’s choice of the optimal stocking rate is influenced by seasonal risk, price risk, risk attitude, tactical management, flock management and the vast array of crop and pasture management options; alongside improvements in seasonal forecasting and greenhouse gas emission policies. This gap in our knowledge needs to be addressed to improve the validity and applicability of advice to farmers regarding opportunities to alter their stocking rate choices.

One option is improvements to an existing model or models, such as MIDAS, AusFarm and GrassGro. There are arguments for and against the development of more detailed models than these. Malcolm (1990) cogently argued that complex modelling had been of virtually no direct use for farm decision making. The main reason being that all models only partially represented a farmer’s reality. Therefore, it was more beneficial to use more simple methods that captured all the important parts of the problem. However, in the decades following Malcolm’s assessment, computing power and the ease of model construction has increased enabling more detailed models to be more quickly constructed and validated, thereby allowing additional components of a farmer’s decision-making
environment to be described. For example, detailed whole farm modelling was a core component behind the successful Lifetime Ewe Management extension program, which has, and continues to have, a direct impact on over 4000 farmers (LTW, 2021, Trompf et al., 2011, Young et al., 2011).

Another factor discussed in detail by Pannell (2006) is that in many cases, deviations from the optimum decisions make little difference to a farmer’s payoff. He stated that modelling in the 1980s found whole farm profit to be within 10% for a range of cropping percentages. Young et al. (2020) show a similar more recent example for stocking rates whereby farm profit varied by less than 10% for stocking rates within 20% of the calculated optimum. However, Trompf et al. (2014) shows that stocking rate can vary from the average by up to 87% in poor seasons and 37% in good seasons. So although the payoff function is somewhat flat, under an average season assumption, the exclusion of seasonal variation in Young et al. (2020)’s analysis could result in a less valid determination of the optimal stocking rate. Reworking data from Young et al. (2020) indicates that stocking rates 30% from the optimum are sacrificing approximately $50 per hectare so there could be economic justification for a more complete analysis of a farmer’s decision-making environment regarding the determination of an optimal stocking rate.

Typically, these more complex models are mostly developed and applied research tools to aid research prioritisation, policy decision making (e.g. Kingwell 2009) and to a lesser extent farm management (e.g. Young et al. 2016; Young et al. 2020). To be generalisable for farm management decision-making, complex models usually require user-friendly interfaces.

An additional refinement for more complex modelling of stocking rate might be to include seasonal forecasting. Such forecasting is becoming increasingly accurate (Asseng et al., 2012), although Darbyshire et al. (2020) highlight some important limitations to the economic worth of improved seasonal forecasting. To the extent that some types of seasonal forecasts are accurate and valuable, farmers can profitably adjust their seasonal tactics (Mitchell and Brown, 2019).

Additional factors to consider in creation of a more complex model are:

(i) transition costs incurred when moving from one stocking rate strategy to another. These are often unaccounted for in modelling approaches, particularly steady state frameworks that generally provide only the final outcome (e.g. Young et al. 2020). However, stocking rate guidance is often medium to long term, so any error associated with assuming no transition costs is diluted. There is a gap in literature regarding inclusion of transition costs. A thorough solution would be to use a multi-period framework that has a specified starting point.
Farmers’ preferences regarding management complexity. Some farmers may prefer to forego profit to reduce management complexity (Kingwell, 2011). Again, this is different for every farmer and would require a multilevel sensitivity analysis. We hypothesise that a lower preference for complexity would reduce the optimal stocking rate because the higher the stocking rate, the higher and more complex is the workload.

Conclusion

Optimising stocking rate requires an understanding of the quantity and quality of feed available throughout a year, the optimal live weight profile throughout a year, the impact of seasonal variation, the impact of labour availability, the risk preference of the farmer, the array of crop and pasture options available to the farmer, the tactical management options farmers can embrace, the accuracy of seasonal forecasts they can draw upon to facilitate their decision-making, relative prices of inputs and outputs and GHG abatement policy settings that might alter the costs of running livestock. To account for this diverse array of factors researchers have relied on the use of computer models.

However, a review of the relevant literature reveals a current gap insofar as there is no model or decision framework currently available that captures most of these factors and that broadly informs farmers and researchers as to what constitutes the likely optimal sheep stocking rate and how sensitive that rate is to various changes in the panoply of factors, especially for mixed enterprise farms in Western Australia, a region containing just over a fifth of Australia’s sheep population (Meat and Livestock Australia, 2020a).

The models, MIDAS, AusFarm and GrassGro, which have been used widely to estimate the optimal stocking rate, have key limitations. Another model, MUDAS, has fewer limitations but is no longer operational and does not accurately reflect modern farm practices and seasonal and commodity price conditions. Hence, stocking rate recommendations based on applications of these models lack credibility because some key factors likely to affect a farmer’s stocking rate choices are not captured by these models.

Due to the greater ease of model construction and of dealing with numerical complexity that is now possible, we propose that more complex optimisation models should be constructed to represent more features of a farmer’s decision-making environment. It is feasible to construct such models more quickly to reveal optimal stocking rates and grazing management that ensures that the cost
and revenue of the marginal animal are equal, and the cost and revenue of the marginal feeding
decisions for different classes of stock during a year are equal, as well as representing year-to-year
variation to ensure optimal management tactics are identified. Such modelling can remove the need
to rely on the DSE concept, which has some important limitations when determining an optimal
stocking rate.
Chapter 3: Methodology

Introduction

The initial justification for an improved farm analysis tool was outlined in the previous chapter. In this current chapter the need for a new whole farm bio-economic modelling method is further justified, and the resultant modelling approach is described.

Agricultural or farming systems are most frequently modelled either by dynamic simulation, one example being APSIM (Anderson, 1974), or by mathematical programming, one example being MIDAS (Kingwell and Pannell, 1987). Dynamic simulation (DS) aims to replicate the behaviour of a system. It is frequently applied to represent biological systems encompassing the whole farm (Thomas et al., 2018) or a subsection of the farm (Keating et al., 2002, Robertson et al., 2002). By contrast, mathematical programming (MP) is a group of optimisation techniques that represents a system using variables, constraints and an objective (Kingwell and Pannell, 1987, Norton et al., 1980, Young et al., 2020). Both DS and MP often achieve more than their simple categorisation implies, as it is feasible to specify an objective in a DS model and search for an optimal solution whilst MP techniques can represent simulated biological detail (Kingwell and Pannell, 1987).

Heuristic techniques are a branch of optimisation procedures that can be used with DS, including genetic algorithms (Raju and Kumar, 2004) and simulated annealing (Kuo et al., 2001). These methods use various computational algorithms, often inspired by physical processes, to identify solutions in complex search spaces (Lindfield and Penny, 2019). Such procedures are valuable for the optimisation of simulation models in which analytical gradients cannot be efficiently computed. However, these techniques are not mathematically guaranteed to find the optimum, and can be limited in their capacity to consistently incorporate resource constraints (Doole and Pannell, 2008). For example, Doole and Pannell (2008) combined an agricultural weed simulation model called Ryegrass and Integrated Management (RIM) with the heuristic technique of compressed-annealing and determined that compressed-annealing was a suitable algorithm to identify near-optimal configurations in constrained simulation models of weed populations. RIM encompassed around 500 parameters and solely considered weed management. Doole and Pannell (2008) noted that including additional detail greatly increased the model’s solution time. Heuristic techniques such as used by Doole and Pannell (2008) are conceptually interesting, but are computationally challenging and very time consuming, especially if applied to represent a detailed whole farm system. The lack of optimisation capability can be a significant limitation of simulation modelling for evaluating the economics of on-farm decision making. For example, the profitability of mating ewe lambs is
dependent on many factors such as ewe live weight before, during and after mating, pasture supply, time of lambing and relative prices (Tocker et al., 2020). Thus, even for a skilled simulation user it is possible to generate a local optimum that unfortunately could result in inaccurate economic advice regarding optimal management of ewe lambs.

While MP is not as flexible as DS in representing biological and dynamic features, it does provide a more powerful and efficient optimisation method. Although MP is not as efficient at representing biological and dynamic features, this limitation should not be overstated. Firstly, at the whole farm level, representing precise biological and dynamic relationships is often not of high importance because the overall relationships can be represented at a higher level whilst still capturing the necessary detail. Secondly, in the hands of skilled practitioners, it is possible to use MP techniques to represent or closely approximate complex nonlinear biological and dynamic features (Pannell, 1997). Thirdly, DS and MP are somewhat complementary because they are suited to different tasks. For example, DS models developed to imitate the biological features of a farm sub system may generate data for use in whole farm MP models (e.g. Young et al., 2010, Young et al., 2014). For these reasons MP has been used successfully to model farming systems in Australia (Kingwell et al., 1991, Kingwell and Pannell, 1987) and in other countries (Annetts and Audsley, 2002, Schäfer et al., 2017, Roughsedge et al., 2003, Norton and Hazell, 1986, McCarl and Spreen, 1997), and so MP as applied to whole farm systems is the focus of this chapter.

Due to lack of available computing power, software, time and knowledge, previous MP models that represented farming systems were developed with a fixed, inflexible modelling framework and were simplified depictions of reality. For example, MIDAS (Model of an Integrated Dryland Agricultural system), a prevalent whole farm MP model used to examine broadacre farming systems principally in Western Australia (Flugge and Schilizzi, 2003, Gibson et al., 2008, Kopke et al., 2008, Thamo et al., 2013, Young et al., 2011, Young et al., 2020), excludes price and weather uncertainty. Yet the farming system of the Western Australian region is a dryland farming system in which variation in rainfall between weather-years can cause dramatic changes in crop and pasture yields (Feng et al., 2022). Failure to represent this variation in MIDAS weakens the credibility of some of its results. Furthermore, these previously developed models were built in Microsoft Excel, which although easy to learn, has large computational overheads, size restrictions and its tabular structure makes scalability challenging. Although it is unlikely that a computer program will ever fully reflect reality, frequent improvements in computing power, improved solving algorithms and a greater ease of coding enable increasingly sophisticated models to now be constructed. Moreover, generating and capturing farm-level data is increasingly feasible, and cost-effective, which allows more detailed farm models to be constructed.
Linear programming introduction

The model described below uses linear programming (LP), a form of mathematical programming. Here we first provide a basic understanding of LP to set the scene for the following chapter. For a more detailed exposition of LP the reader is referred to Pannell (1997).

LP is a mathematical technique that optimises a linear objective function subject to a set of linear constraints. In other words, it is a method used to find the maximum or minimum value of a particular function, given a set of conditions or constraints. This technique is widely used in various fields, such as economics, engineering, and computer science, to solve a wide range of optimization problems.

A LP model comprises a set of decision variables (also called activities), a linear objective function indicating the contribution of each decision variable to the desired outcome, a set of linear constraints describing the limits on the values of the variables and parameters (also called coefficients) that link the decision variables and the constraints. The parameters are often expressed as a matrix with the decision variables being columns of the matrix whilst the constraints are the rows of the matrix. The matrix is completed with the inclusion of the objective function above the first constraint and the right hand side coefficients of the constraints are listed after the last decision variable. The “answer” to a linear program is a set of values for the decision variables that result in the best (largest or smallest) value of the objective function consistent with all the constraints.

The decision variables in a linear program are a set of activities and quantities that need to be determined in order to solve the problem; i.e., the problem is solved when the values of the variables (i.e. activities) that maximise or minimise the objective function have been identified. Typically, the decision variables represent the amount of a resource to use or the level of an activity to carry out. For example, a variable may represent the number of hectares of a particular crop or the number of days of labour required.

Constraints define the possible values that the decision variables of the LP model may take. Constraints can be:

(i) logical, e.g. the quantity of an input used must not be greater than the quantity purchased;

(ii) limitations on available physical resources, e.g. the total area of the land uses must be less than the farm area;

(iii) limits on financial, labour or time resources;
(iv) technological restrictions, e.g. the area planted is the days of seeding multiplied by the machinery work rate;
(v) biological restrictions, e.g. the productivity of an animal is linked to the amount and quality of feed consumed.

The objective of a LP model is to maximise or to minimise some numerical value. For example, to maximise farm profit or minimise farm greenhouse gas emissions. The objective function indicates how each variable contributes to the value to be optimised in solving the problem.

A simple example is provided below:

A farmer wishes to maximise their profit from either growing canola or having pasture and running ewes.

Canola yields 2.0 tonnes per hectare, sells for $800 a tonne and the chemicals, fertiliser, seeding operation and harvest costs are $500/ha.

Ewes are purchased for $100/hd and are sold at the end of the year for $80/hd, having each produced a lamb for sale at $150/hd and produced $40/hd of wool. The costs of husbandry, mating, shearing and supplementary feed are $45/hd. Pasture fertiliser is $50/ha and 8 ewes can be carried per hectare of pasture.

The total farm area is 1000 hectares.

Canola can only be grown after a 2 year break for disease management (i.e. for every hectare of canola there must be two hectares of pasture).

Variables are:
1. Hectares of canola (x1)
2. Hectares of pasture (x2)
3. Number of ewes (x3)

Constraints are:
1. \(x_1 + x_2 \leq 1000\) (area constraint)
2. \(2x_1 - x_2 \leq 0\) (non-consecutive canola)
3. \(-8x_2 + x_3 \leq 0\) (carrying capacity of pasture)
4. \(x_1, x_2, x_3 \geq 0\) (non-negativity)

The objective is: \(Max(1100x_1 - 50x_2 + 125x_3)\)
The above problem is simplistic. Further detail could be added such as including other land uses, linking crop yields, costs and pasture carrying capacity to the land use history, representing a self-replacing flock and including interactions between the enterprises such as the benefit of grazing crop stubbles. These additions would make the representation of the farming system more realistic but would require far more complex matrices.

Although the word linear features in the term linear programming, it is technically possible to represent non-linear relationships within a LP framework. This occurs by applying what is known as piecewise representation where non-linear relationships are closely approximated by linear segments. Linear segmentation of non-linear relationships is one of the features of the following LP model of a farming system. This newly constructed model is called the Australian Farm Optimisation Model (AFO).

AFO Overview

The Australian Farm Optimisation Model (AFO) is described in detail below. Further details can be found at https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html. In summary, AFO is a Python based, whole farm LP model. AFO leverages a powerful algebraic modelling add-on package called Pyomo (Hart et al., 2011) and IBM’s CPLEX solver to efficiently build and solve the model. The model represents the economic and biological details of a farming system including components of rotations, crops, pastures, livestock, stubble, supplementary feeding, machinery, labour and finance. Furthermore, it includes land heterogeneity by considering enterprise rotations on any number of soil classes. The detail included in the modules facilitates evaluation of a large array of management strategies and tactics.

AFO has been built with the aim of maximising flexibility. Accordingly, depending on the problem being examined, the user has the capacity to:

- Change the region or property.
- Select the level of dynamic representation. For example, the user controls the number of discrete options for seasonal variation and price variation.
- Add or remove model components such as the number of land management units, land uses, novel feed sources such as salt land pasture, times of lambing for the flock and flock types (pure bred, 1\textsuperscript{st} cross or 2\textsuperscript{nd} cross).
- Adjust the detail in linearising the production functions (e.g. the number of livestock nutrition profiles).
• Make temporary changes to production parameters and relationships. For example, altering the impact of livestock condition at joining on reproductive rate.
• Constrain management. For example, fix the stocking rate or crop area.
• Include or exclude farmer risk aversion.

To facilitate user flexibility and support future development, AFO is built in Python, a popular open source programming language. Python was chosen over a more typical algebraic modelling language (AML) such as GAMS or Matlab for several reasons. Firstly, Python is open source and widely documented making it easier to access and learn. Secondly, Python is a general-purpose programming language with over 200,000 available packages with a wide range of functionality (Van Rossum, 2007). Packages such as NumPy and Pandas (McKinney, 2012) provide powerful methods for data manipulation and analysis, highly useful in constructing AFO which contains large multi-dimensional arrays. Packages such as Multiprocessing (Singh et al., 2013) provide the ability to run the model over multiple processors taking advantage of the full computational power of computers to significantly reduce the execution time of the model. Thirdly, Python supports a package called Pyomo which provides a platform for specifying optimization models that embody the central ideas found in modern AMLs (Hart et al., 2011). Python’s clean syntax enables Pyomo to express mathematical concepts in an intuitive and concise manner. Furthermore, Python’s expressive programming environment can be used to formulate complex models and to define high-level solvers that customize the execution of high-performance optimization libraries. Python provides extensive scripting capabilities, allowing users to analyse Pyomo models and solutions, leveraging Python’s rich set of third-party libraries designed with an emphasis on usability and readability (Hart et al., 2017).

The core units of AFO are:

1. Inputs: The model inputs are stored in three Excel spreadsheets. The first contains inputs likely to change for different regions or properties such as farm area. The second file contains inputs that are ‘universal’ and likely to be consistent for different regions or properties such as global prices of exported farm products. The third file contains structural inputs that control the core structure of the model.
2. Precalcs: The precalcs are the calculations applied to the input data to generate the data for the Pyomo parameters (in other terms, the conversion of the inputs to the parameters for the LP matrix). The precalcs for each individual trial (trial is the name for a single model solution) can be controlled by the user with the ‘experiment’ spreadsheet which allows
inputs from the three input spreadsheets to be temporarily adjusted, or the intermediate calculations in the precalcs to be temporarily adjusted.

3. Pyomo and solver: This is the LP component of the model (matrix generation). It defines all the decision variables, the objective function, the constraints and parameters then utilises them to construct the model’s equations (i.e. constraints). Components of the LP model can also be temporarily adjusted by the user via the ‘experiment’ spreadsheet. Pyomo formulates all the equations into a linear program format and passes the file to a solver. AFO has multiple compatible solver options. Most frequently used are CPLEX (Cplex, 2009) and GLPK (Makhorin, 2014). When tested both solvers resulted in the same answer. CPLEX has some advanced features unavailable in GLPK. However, GLPK is open source whereas CPLEX is costly proprietary software (Cplex, 2009).

Simply put, the LP component of AFO sees a range of activities (variables) that can be selected so long as all the constraints are met. In many cases this is easy to visualise for example AFO can select as many or as few labour sources as it likes so long as all on-farm tasks can be completed by a suitably skilled staff member. However, in some cases it is a little more complex. For example, in the pasture module where an activity represents a current state (e.g. FOO at the start of the period 1), a management option (e.g. level of grazing during period 1) and a future state (e.g. FOO at the end of the period 1). The pasture activities in period 1 are then transferred to period 2 using constraints that ensure that the FOO at the start of period 2 is equal to the FOO at the end of period 1. The calculations that determine the future states of an activity based on a starting point and a range of management options are conducted in the precalcs. These are similar to that of simulation calculations.

The procedure for building and solving AFO is that firstly, the inputs are read in from the Excel files. The experiment spreadsheet is read that includes the temporary adjustments (sensitivities) for the model parameters. Furthermore, the spreadsheet allows the user to group trials into an experiment to be run as a batch. For example, the user may be interested in the impact of increasing prices, hence an experiment examines several price levels. Secondly, each module containing precalcs is executed. The parameters produced are stored in a python data structure called a dictionary. Then the Pyomo section of the model creates the decision variables, formulates the model constraints, populates the parameters with the coefficients from the precalcs and passes the information to a linear solver. The results from the solver reveal the maximum farm profit and the optimal levels of each decision variable that maximises the farm profit (or some other objective function). From here the user can create a range of reports.
Key improvements

Some of the key improvements of AFO over previous optimisation models include;

i. Inclusion of price and weather uncertainty, the associated short-term management tactics and farmer risk attitude.

ii. Increased rotation options.

iii. Extra detail on the biology of livestock production that allows:
   a. Inclusion of optimisation of the nutrition profile of livestock during the year.
   b. A larger array of livestock management options such as time of lambing and time of sale.

iv. Improved pasture representation that includes production effects of varying grazing intensity.

v. More detailed representation of crop residue that includes multiple feed pools based on quality and quantity.

Additionally, developing AFO in Python has resulted in a flexible framework that overcomes many previous structural challenges such as scalability. The structure allows the user to alter the biological detail to balance computer resource requirement against model realism in different aspects of the farm system. For example, the user of AFO can easily alter the number of discrete options represented in different sections of the model so that detail can be added to aspects that are important for a particular analysis while simplifying the less important. Furthermore, AFOs usability and detailed representation of the farm system means it can be applied to a plethora of current and future farming system opportunities and problems.

Rotations

Modelling of cropping or crop-pasture rotations to date has primarily been based on a predetermined restricted set of rotations represented as “activities” in a LP matrix (Wimalasuriya and Eigenraam, 2000). However, this approach often limits the potential rotations to be selected and does not capture the flexible nature of real-life rotation selection especially in the face of unfolding seasonal conditions. For example, using a fixed rotation structure, it is not possible to alter the rotation in response to the timing of early season rainfall. It also results in the necessity to build entirely new modules for each agro-climatic region due to differences in crop and rotation choices that are available and applicable to each region.

In AFO, we adopt an alternative method proposed by Wimalasuriya and Eigenraam (Wimalasuriya and Eigenraam, 2000), where the “activities” in the model are rotation phases. A rotation phase is a
land use with a specific sequence of prior land uses (‘history required’). A constraint is included to ensure that for the model to select a given rotation phase, the ‘history required’ must match the ‘history provided’ from another rotation phase. The model solves for the optimal rotation through a selection of rotation phases. This is an unrestricted approach that supports a large range of possible rotations and allows greater flexibility for adding new land uses. Additionally, the approach aligns closer to reality, facilitating a more detailed and accurate representation of the effects of weather-year type on rotation choice.

Each rotation phase requires a history and provides a history. As a simple example, consider the rotation phase barley – wheat: canola in which canola is the current land use. Barley followed by wheat is the history required and wheat followed by canola is the history provided. Based on the current land use and the land use history the level of production (grain and stubble production from crop phases and, seed set and germination from pasture phases), the costs, the machinery requirement and the labour requirement are determined.

The rotation phases are designed to be as simple and general as possible while still capturing important performance and management variants. The system employed is to generate all possible combinations of the land use sequences over a set number of years, then the infeasible options are removed and the remainder are generalised where possible e.g. wheat, barley and oats may be generalised to cereal in the phase history if the type of crop does not affect subsequent productivity or costs.

The length of the rotation phases and the level of generalisation is determined so that the impacts of the history on the current land use production and costs are captured. These can be summarised by:

1. The need to track the number of crop phases to determine if an annual pasture needs reseeding.
2. The need to track the effect of a land use on the productivity or costs of subsequent land uses. This can be either:
   a. Fixing of soil nitrogen and its subsequent effect on following crops. This requires tracking:
      ▪ The number of years of the legume as it affects the quantity of organic nitrogen.
      ▪ The number of years since the legume to determine the remaining nitrogen.
   b. Impacts on disease levels.
Impact on weed seed levels.

3. The impact of cropping on subsequent annual pasture seed bank and germination.

The impacts and assumptions of land use history on production and costs that are being captured in the rotation phases developed are:

1. Annual pasture will be resown if the four most recent land uses in the history are crops. Resowing impacts the current year and the succeeding year.

2. Lucerne (or Tedera) will be resown if the immediately preceding land use is not Lucerne (or Tedera).

3. The impacts of spray-topping and manipulating pastures lasts for two years.

4. Germination of annual pasture is affected by:
   a. The two most recent land uses in the history.
   b. The crop type immediately prior to the annual pasture. Specifically:
      - Germination is higher after an oat fodder crop.
      - A pulse crop increases growth of annual pastures (which is represented by an increase in germination).

5. A history of legume pasture (annual, Lucerne and Tedera) provides organic nitrogen for subsequent non-legume crops (cereal or Canola).
   a. The amount of organic nitrogen increases up to four years of consecutive legume pasture.
   b. The impact of the organic nitrogen lasts for a maximum of three years.

6. Pulse crops provide organic nitrogen for subsequent non-legume crops.
   a. The impact of the organic nitrogen lasts for a maximum of three years.

7. Leaf disease and root disease builds up for each land use and reduces productivity for consecutive land uses.
   a. It is assumed that the maximum level of disease is reached after 4 consecutive years of a land use.
b. There is variation in the length of the break (interval in years between the same land use) required and the duration of the benefits of a break.

To capture all the factors listed above, the length of the rotation phases represented in AFO is defined to five years, allowing a history of four pastures to be tracked. To reduce the number of rotation phases, land uses in the history that are assumed to have the same impact on the production and cost of the current land use are grouped into ‘land use sets’ (see the online documentation).

Some of the rotation phases constructed will be illogical and are removed. For example, annual pasture is only resown after four years of continuous crop therefore any rotation phases that are generated with resown annual pasture that do not have four years of crops preceding it can be removed. To further reduce the possible number of rotation phases in the model, unprofitable and unused land sequences are removed. See RotGeneration for the full list of rules.

**Cropping**

Cropping is often a large component of broadacre farming in Western Australia (Planfarm, 2022). Crops are primarily established with a goal of harvesting and selling the grain for human or animal consumption. However, crops can also be used as fodder for farm livestock. Using a range of user inputs, the crop module calculates the crop production, the associated costs, the labour requirements and the machinery requirements. The inputs include crop yield, fertiliser and chemical requirements, frost damage, seeding rates, soil type, machinery size, paddock efficiency of seeding and harvesting, proportion of helper labour required, crop residue management, proportion of arable area, commodity prices, fees and levies. To accurately reflect rotation history, soil type and weather effects on crop production and management, many of these user inputs vary by rotation phase history, soil type and weather conditions. For example, the rotation phase history can influence the soil fertility, weed burden and disease and pest levels. These factors impact the potential yield and the level of fertiliser and chemicals.

Each phase provides a certain amount of biomass based on the inputs above. Accordingly, AFO can optimise the area of each rotation phase on each LMU and the best way to utilise the biomass of each rotation phase. Biomass can be either harvested for grain, baled for hay or grazed as standing fodder. AFO does not currently simulate the biology of crop plant growth under different technical management. Thus, AFO does not optimise technical aspects of cropping such as timing and level of fertiliser applications. However, the user has the capacity to do this manually by altering the inputs.
(à la management of inputs in simulation modelling) or by including additional land uses which represent varying levels of inputs and production.

There are two methods that can be used to generate cropping inputs for the model:

1. Manually enter the inputs for selected rotation phases: The user can manually input the fertiliser and chemical requirements and resulting yield of each rotation phase. To do this accurately requires an in-depth knowledge of cropping in the location being modelled. Thus, the process is often done in collaboration with a consultant or specialist in the field. This input method can be limiting if the user is hoping to include a large number of rotation phases or land uses that are not well established in the given location because it can be difficult to determine accurate inputs.

2. Generate using simulation modelling (e.g. Thamo et al., 2017): APSIM is a whole farm simulation model widely used in Australia. APSIM has detailed modules which use robust relationships to simulate plant growth. The parameters used in APSIM can be altered to represent plant growth in many different situations. For example, different rainfall or soil conditions. AFO users can use APSIM to generate yield of crops in a given rotation under a specified fertiliser and chemical regime.

Although both methods can be sources of yield estimates; only the first method is a source of estimates of required fertiliser and chemical at a particular location.

The crop management decisions that are optimised can include:

1. Area of each rotation phase on each soil type in each weather year depending on paddock history.
2. Area of each crop harvested, baled or grazed.
3. Contractual services for seeding or harvesting.
4. Labour allocation.
5. Time of sowing.

The model can also represent and compare (but not optimise in a single model solution):

1. Fertiliser application rate and timing.
2. Chemical application rate and timing.
3. Seeding rate.
4. Alternative cultivars.
5. Seeding technology.
Feed budget

Energy is the primary nutritional constraint for extensive ruminant livestock enterprises (Rickards and Passmore, 1977). As such, energy is the only nutritional element that is constrained in AFO to ensure that feed supply is greater than or equal to the feed demand of the livestock (as measured by metabolisable energy). There is also a volume constraint that limits the minimum diet quality to ensure that the voluntary feed intake capacities of the livestock are sufficient to consume the quantity of feed selected. The volume of each feed source (kg of intake capacity / kg of feed dry matter) varies depending on the feed quality (relative ingestibility) and feed availability (relative availability) using relationships from Freer et al. (2007).

The feed supply from pastures, crop residues and supplementary feeds, is represented by changes in the type, amount and quality of feed available during the year. The feed demand of livestock is represented as the requirement for metabolisable energy and the feed intake capacity. The year is partitioned into 10 feed periods. A feed budget is carried out for each feed period to ensure that the feed demand of the flock can be met from the feed available on the farm. The dates of the feed periods during the growing season are selected to group periods that have similar supply and demand characteristics. During the growing season this is driven by the response of pasture growth to defoliation and the periods are shorter after the break of season and just prior to senescence. During the dry feed phase the dates are selected to minimise feed variation within each period and are shorter after pasture senescence and prior to the break of season. The selection of the period definitions is likely to alter depending on the region being modelled.

Any of the 10 periods can be the period that limits the farm carrying capacity. This is representing far more detail than underpins a typical gross margin analysis that considers a pre-defined feed limiting period of the year. Furthermore, AFO includes the capacity to alter the live weight (LW) profile and hence feed demand of any class of stock in any feed period with a concomitant change in production per head. This links to the capacity for supplementary feeding the livestock to optimise the number of livestock carried on the farm. As such AFO is much more detailed than a typical gross margins analysis of livestock profitability. If AFO is compared to a simulation model the feed periods are equivalent to the time-steps in the simulation model, however, they are much longer than a typical simulation model that often considers daily time-steps. As such AFO represents the feeding options in less detail than is possible in a dynamic simulation model, however, AFO has the advantage of optimising the grazing management of the pastures and crop residues and optimising the target nutrition for each class of stock during the year.
Cross subsidisation of volume is a problem that can occur in the feed budgets of linear programming models. Cross subsidisation occurs if animals with divergent quality requirements are constrained by single energy and volume constraints; the single constraint is termed a feed pool. For example, consider two animals, one losing 100 g/hd/d and one gaining 150 g/hd/d. The first animal can achieve its target on low quality feed whereas the second animal needs high quality feed. However, if both of these animals were constrained using a single feed pool, then the total energy requirement and total intake capacity is combined, such that feeding medium quality feed to both animals meets the constraints. This is likely to be the optimal solution because the cost of feed by quality is a convex function and therefore the cost-minimising solution is to provide an average quality to both classes of stock. However, this is not a technically feasible solution. To reduce the possibility of cross-subsidisation of volume while still limiting model size, the energy requirement and maximum volume constraints are applied in multiple nutritive value pools, each spanning a small range of nutritive value (where nutritive value = ME requirement / volume capacity). This is more efficient in reducing model size and complexity than having a feed pool for each animal class.

Feed supply

The main sources of feed considered in the model are; pasture (annual and/or perennial), crop residue (stubble) and supplement (grain concentrates and conserved fodder). AFO also includes some novel feed sources such as early season crop grazing, grazing standing fodder crops and salt land pastures.

The feed management decisions that are optimised can include:

1. Area of each pasture variety on each soil type.
2. Area of reseeded pasture based on paddock history.
3. Area of pasture manipulated and/or spray-topped based on paddock history and setting up for future land uses.
4. Grazing intensity of different pasture varieties on different soil types at different times of the year which manifests as a FOO profile of the pasture.
5. Timing and extent of pasture deferment.
6. Level and timing of supplementary feeding of hay or grain to each class of stock.
7. Grazing management of stubbles.
   a. The time to start grazing of each stubble.
   b. The class of stock that grazes the stubble.
   c. The duration of grazing.
d. The amount of supplementary required in addition to stubble (to meet alternative LW profiles).

8. Area of fodder crops established and their grazing management.
9. Tactical grazing of standing crops in place of harvesting.
10. Amount of early season crop grazing.
11. Salt land pasture grazing management.
12. Conserving surplus pasture as hay or silage.
13. The level of growth modifier (e.g. nitrogen fertiliser) applied to pasture.

The model can also represent and compare (but not optimise in a single model solution):

1. The level of phosphate fertiliser application to pastures.
2. The impact of varying pasture conservation limits.
3. Altering pasture cultivars on different land management units.

**Pasture**

Pasture is the primary livestock feed source because in an extensive farming system it is a cost-effective source of energy available for the entire year. Different pasture types can be represented by altering the inputs for each pasture type. The default pasture type is “annual pasture”. However, by altering the inputs, perennial pastures and mixed swards can be represented.

Pastures are often included in a rotation to provide a break from cropping, which can rejuvenate soil conditions, provide disease and pest management and provide a cheap feed source for livestock. The pasture module generates the pasture production (as discussed below) and the costs and labour associated with seeding, monitoring, fertilising and spraying. Similar to cropping, the inputs vary based on rotation history, soil type and weather. AFO can then optimise the area of each pasture phase to include on each land management unit (LMU).

Pasture feed sources can be supplemented with concentrates, and in a mixed crop-livestock farm system the pasture can be complemented with dry residues from crop production (stubbles). The biology and logistics of pasture growth rate that are represented in AFO is:

- Pasture growth rate (PGR) is dependent on pasture leaf area, which is quantified by the level of feed on offer (FOO, kg of DM/ha). Additionally, PGR for each pasture type varies with the phase during its life cycle, soil moisture, sunlight and level of growth modifier applied. All are quantified by their land management unit (LMU), time of year and weather-year.

- The average FOO during a feed period depends on FOO at the beginning of the period, the grazing intensity and the PGR during the period.
The mobilisation of below-ground reserves (germination) of annual pastures at the break of season is dependent on the seed bank. The seed bank is controlled by the rotation in which the pasture is grown and varies with LMU.

The mobilisation of below ground reserves of perennial pastures at the break of season can also be adjusted by rotation. However, perennials usually are not grown in rotation with crops.

The maximum intake of animals grazing pasture depends on FOO and diet dry matter digestibility (DMD). Intake can be less than maximum which implies that the optimum solution can include rationing of animal intake via rotational grazing.

The digestibility of the diet selected by animals grazing green pasture depends on the sward digestibility and the animal’s capacity for selective grazing. Sward digestibility varies depending on the pasture species, the time of year, the LMU and the FOO of the pasture. Selectivity depends on FOO and grazing intensity.

Dry pasture that is not consumed is deferred to later in the year, with a reduction in both its quality and quantity. Livestock can select a higher quality diet when first grazing the dry pasture but quality reduces with extra grazing.

Livestock trample both green and dry pasture while foraging in proportion to the amount consumed.

The risk of resource degradation increases when ground cover is lower so there is a user defined minimum limit to ground cover during both the green and dry phases of the year.

The decision variables optimised in AFO, that represent the above biology are the:

- rotation phases in which pasture can be grown on each LMU.
- FOO profile during the year that is represented by a discrete range of FOO levels at the start of each feed period.
- grazing intensity and the variation across feed periods during the year is represented by a discrete range of the severity of defoliation in each feed period.
- level of growth modifiers (nitrogen or gibberellic acid) applied to the pasture.
- quantity of dry feed consumed from each of 2 dry feed quality groups in each feed period.
The nutritive value of pasture is determined by the metabolisable energy per unit of dry matter, the relative ingestibility and the relative availability. This varies with:

1. Feed period.

2. The level of FOO. The greater the FOO, the lower the average digestibility of the sward. Lower digestibility of a high FOO sward is associated with the lignification that occurs in older foliage. Higher digestibility of a low FOO sward is associated with the higher digestibility of new growth that constitutes a higher proportion of the sward. There can be some error associated with this assumption if the low FOO was generated by grazing a high FOO sward back to a low FOO, in which case most of the DM would be stalk at the base of the plant which compares to a sward maintained at a low FOO level since the break of the season.

3. Grazing intensity. With heavy grazing there is little scope for selection, so the diet digestibility equals the sward digestibility. With light grazing there is scope for selection and diet quality that approaches that of high quality leaf. Note, increasing the energy content of the feed also improves the ingestibility of the feed (Freer et al., 2007).

Pasture on non-arable areas in the crop paddocks is modelled as above with a few additions. Firstly, pasture on non-arable area is represented as a continuous annual pasture. Secondly, non-arable pasture on crop paddocks is not available for grazing until after harvest and therefore it goes into the low-quality dry feed pool. Accordingly, pasture on non-arable areas of the crop paddocks does not receive any farm inputs.

Pasture grazed on the crop paddocks in the period before destocking for spraying and seeding is represented as a pre-specified quality and maximum quantity available each day on the area that is yet to be seeded, with the additional requirement that pasture must be destocked 10 days prior to seeding to allow time for an effective knockdown spray.

**Crop residue**

At the end of the growing season AFO has the option of harvesting or baling each crop, which leaves stubble for stock consumption, or crops can be left standing for fodder grazing. Stubble and fodder are modelled in the same ways, as follows. In general, sheep graze crop residues selectively, preferring the higher quality components. Thus, they tend to eat grain first, followed by leaf and finally stem. To allow the optimisation of the quantity of the stubble grazed, and to reflect selective grazing the total crop residues are divided into ten categories. The higher categories are better quality but generally lower quantity. Consumption of a higher quality category allows the
consumption of a lower category (e.g. sheep cannot consume any of category B until some of
category A has been consumed).

The total mass of crop residues at first grazing (harvest for stubble and an inputted date for fodder)
is calculated as a product of the biomass, harvest index and proportion harvested. Over time if the
feed is not consumed it deteriorates in quality and quantity due to adverse effects of weather and
the impact of sheep trampling.

Residue production can be positively impacted by frost because frost during the plants flowering
stage can damage cell tissue and reduce grain fill (Zheng et al., 2015). This results in less grain and
more residue due to not using energy resources to fill grain. Thus, the harvest index used to
calculate biomass to residue is adjusted by a frost factor.

**Supplement**

Supplementary feeding is the supply of additional feed to livestock, primarily grain and hay (which
are both represented in the model). Supplementary feeding is commonly used to help meet
production targets such as lamb growth rates prior to sale, or to fill the feed gap to allow higher
stocking rates during the summer and autumn months when pastures and crop residues are limiting.
Additionally, feeding supplements can be used as a tactic to allow pastures to be deferred early in
the growing season which increases subsequent pasture growth rates through increasing leaf area
index.

AFO represents a range of supplements including, oats, lupins and hay. Grain and hay as
supplementary feeds can either be grown on farm or purchased from another farmer at a farm-gate
price (i.e. net price of a product after selling costs have been subtracted) plus the transaction and
transport costs. Supplementary feeding incurs a depreciation cost associated with storage
infrastructure and variable costs associated with insurance, silo preparation, insect management,
grain shrinkage/losses and machinery usage when feeding the supplement. The costs are calculated
per tonne to allow for variations in grain density and amounts fed. Supplementary feeding also
incurs a labour requirement for time spent traveling to and from the silo, filling the sheep feeder,
emptying the feeder, and transporting between paddocks.

**Crop grazing**

Crop grazing is an option that allows stock to graze green crops, by default, from June until August
(user customisable range). Green crops have a high energy content and grow erect allowing for
easier grazing. Therefore, crops can meet livestock energy needs at a lower FOO than an equivalent
pasture. However, for every kilogram of crop biomass consumed yield is reduced by 150 grams per
hectare (user customisable), with a corresponding effect on stubble production.
**Salt land pasture**

Salt land pastures (SLP) are a novel feed source that consists of saltbushes and a grazable pasture understory. SLP establishment requires labour, specific machinery and a significant financial outlay, however it comes with numerous characteristics which make it attractive for certain situations. These characteristics include:

1. Saline tolerance and can therefore be established on land management units that would have had very low productivity (Barrett-Lennard et al., 2003).

2. Draw-down of the water table (Barrett-Lennard and Malcolm, 1999). This drawdown allows salts to be flushed from the topsoil of the moderately saline land, thereby creating growing conditions more suited to higher productivity annual pastures and perhaps leads to long term rehabilitation of the area.

3. Edible leaf for livestock consumption (O’Connell et al., 2006).

4. Livestock shelter – shelter provided by shrubs can be used by stock at vulnerable times such as lambing which helps increase animal survival.

5. Increased wool growth due to additional nutrients provided by grazing saltbush (Norman et al., 2010).

6. Reduced erosion risk due to the wind protection provided by the saltbushes year-round (Barrett-Lennard et al., 2003).

The salt land pasture land use is a combination of saltbush and understory. The saltbush module represents the saltbush component and the understory component is calculated in the pasture module.

The saltbush module includes the:

- cost of salt land pasture establishment and maintenance.
- productivity of saltbush during the year based on grazing management.
- feed value of saltbush during the year.
- diet selectivity of salt bush versus understory.
- impact of salt consumption on animal intake.
Livestock

A powerful and advanced feature of AFO is its ability to optimise livestock liveweight/nutrition profiles. AFO does this by generating production parameters for animals following a range of nutrition profiles (up to 2000 profiles for each class of sheep can be concurrently evaluated). These are represented as different decision variables which allows the optimisation of a wide range of management decisions. The total feed requirement and the minimum diet quality can vary for each feed period for each livestock decision variable. The range of nutrition levels are represented by profiles that are continuous for the entire year. At the end of the nutrition cycle (year) the range of final liveweights are ‘condensed’ back to a range of starting weights for the start of the next nutrition cycle. This capacity allows AFO to differentially feed animals based on reproduction, sale goals and feed supply based on land use selection while minimising model size and computing resources required.

AFO includes a livestock data generator that generates the production parameters for livestock for a user specified number of nutritional profiles. It is based on the relationships that underpin the GrazPlan suite of models as described by (Freer et al., 2007) and updated with production relationships developed in other research projects. Data is generated for the following components:

- Animal liveweight and sale values.
- Energy requirement profile and the nutritive value to achieve the target whole body energy profiles.
- Fleece production data; both quantity and quality (including the impact of the ewe liveweight profile during pregnancy on the lifetime performance of the progeny).
- Dam reproductive rate; represented by the proportion of ewes that are empty, single-, twin- and triplet-bearing.
- Perinatal survival of single, twin and triplet born lambs.
- Perinatal ewe survival associated with pregnancy toxaemia, dystocia and lambing difficulties.
- Mortality rates of dams, progeny and dry animals related to nutrition level.
- Foetal growth rates and birth weights for progeny.
- Milk production and progeny weaning weights.
- Husbandry cost and labour requirements.
• Methane emissions.

The values above are calculated for each ‘class’ of stock, for its lifetime. The feed supply offered to the animals is not based on simulating a growing pasture, rather the FOO, digestibility and supplement offered are inputs to the data generator. The outcome is the parameters required to define the production possibilities that are included in the matrix of the AFO model.

The data generator model simulates the sires, dams and offspring from weaning to their latest possible sale age and simulates the young at foot from birth to weaning. The initial animal for the sires, dams and offspring are based on input values for liveweight, clean fleece weight and fibre diameter.

The prediction equations included in the data generator can be selected from a range of equation sources. Currently those source are:

1. GrazPlan equations as documented in Freer et al. (2012), which are an improved version of the Australian Feed Standards (SCA 1990).

2. Research trials carried out by Murdoch University, DPIRD and DPI Victoria that have quantified the impact of changing nutrition on production. This research began with the Lifetime Wool Trial (Oldham et al., 2011, Thompson et al., 2011) but has continued with a suite of other projects including Lifetime Maternals (Behrendt et al., 2019) and Mob size (Lockwood et al., 2019).

3. A selection of other sources that have developed equations to predict animal performance including:
   b. NGGI for emissions including methane and nitrous oxide (DISER, 2021).
   c. Hutton Oddy’s group (NSW DPI) for alternative equations for heat production associated with maintenance and liveweight gain (Oddy et al., 2019).

In the full model the livestock management decisions that are optimised can include:

1. Number of animals carried (i.e. stocking rate) based on whole flock, whole year feed requirements and whole farm feed supply.
2. Sale age and weight of each animal group.
3. The proportion of the ewe flock mated to different sire genotypes (pure bred, maternal type or terminal)

4. The proportion of the ewe flock that is a first cross dam mated to a terminal sire (the dam cross is between the purebred and the maternal genotype)

5. The reproductive life of dams in the flock (based on whole flock feed requirements, value of wool variation by age, reproduction variation by age, the value of CFA dams at different ages, the selection pressure that can be applied on replacement ewes).

6. Whether to mate ewe lambs and the optimal proportion to mate.

7. A trading operation for dry animals. This can be either a short term trade with an aim to fatten animals or a multi-year trade to produce wool.

8. A ewe flock based on buying in ewes and mating all ewes to a terminal sire to produce first-cross lambs for sale. The age at purchase and sale can be optimised.

9. Diet selection for the animals based on the feed base options represented in the model including supplementary feeding.

10. Time in confinement and/or feed lot (note, this reduces the animals’ energy requirements due to reduced walking).

11. Nutrition profile of the animals during the year which is related to reproduction status, wool value, sale objectives and unfolding climate conditions.

12. Differential feeding of dams based on litter size, lactation number and foetal age, provided the dams are pregnancy-scanned or assessed for ‘gave birth and lost’

13. Optimal replacement policy based on:
   a. the change in reproduction and production over the animal’s lifetime,
   b. the potential to increase per head production through culling and a response in the current generation.

14. Optimal weaning age for each dam age group.

Furthermore, constraints can be applied to the model to limit:

1. Level of enteric greenhouse gas emissions and emissions of nitrous oxide from faeces and urine.

2. Bare ground during the summer/autumn period

3. Animal mortality or liveweight loss during the feed limiting period of the year

4. Animals to graze at their voluntary feed intake level (i.e. that intake reflects the FOO and DMD offered to the animals i.e. feed is not rationed through active management of the stock. This has little effect unless the pasture management is also constrained to limit variation of the FOO and quality profile)
The model can also represent and compare (but not optimise in a single model solution):

1. The length of the joining period (measured in the number of cycles mated); including the trade-off between the number of ewes conceiving and the distribution of size and energy requirements of the later born progeny.
2. The age that the young ewes are mated. For example, a 7 month mating versus a 8.5 month mating for ewe lambs.
3. Accelerated lambing where ewes are mated every 8 months and therefore have 3 lambing opportunities in 2 years.
4. Variation in timing of lamb, hogget and adult shearing.
5. More frequent shearing. For example, adopting a shearing interval of 6, 8 or 12 months.

Finance

The financial components of the model include:

- interest
- cashflow
- a limit on capital borrowings
- minimum return on expenditure
- opportunity cost of assets

Each module tracks its relevant financial components.

To support the sporadic nature of farming income, finance is often drawn from the bank throughout the year to fund costly operations such as purchasing fertiliser and chemicals. In AFO the total capital required for the given farm structure is tallied and can be constrained to a user specified level. This allows the user to examine how the business structure would change if finance is limited. This can also be used to ensure the model does not overdraw an unrealistic/undesired level of capital from the bank. Total farm capital required is calculated from the value of starting assets plus the sum of all the expenses minus any income, between the previous ‘main’ income (e.g. harvest or shearing) and the peak debt date. Peak debt is typically expected for an enterprise just before the main income is received for that enterprise, ensuring the main income for the enterprise is not included in the working capital constraint. The aim of the working capital constraint is to allow the user to constrain management practices which have high costs. If the main income was included in this constraint there would be no way to constrain high cost high reward management practices. The
default is to have one peak debt date per enterprise, just before the main income for that enterprise is received.

In an equilibrium model there is no start and end point. This complicates the calculation of interest because interest must be calculated for a given period. In AFO the interest period starts and finishes after the main income for the enterprise is received. This is logical from an expense point of view because the expense accumulates interest from the date it was incurred through to when the income associated with that cost is received. This ensures that expenditure is only incurred if the return exceeds the cost of interest.

Asset value is the value of all assets at the beginning of the interest period. The opportunity cost of investing in farm assets including livestock, machinery and infrastructure (sheds, yards etc) is captured in AFO. Asset value operates in conjunction with interest rate to represent the opportunity cost of holding assets. Its role is to ensure that all assets that are selected have a return more than the interest cost, this ensures the optimal solution does not include assets that return less than investing the same money in a savings account (or to reduce core debt). This structure makes an equilibrium model generate a result similar to a multi-period model that accounts for the interest cost of money. Livestock flock structure is the main ‘decision’ that is altered by the inclusion of an asset value. For livestock, it ensures that the flock structure optimisation accounts for the opportunity cost of interest foregone from holding an animal till it is sold.

The interest rate for credit and debit are different for farmers’ ‘real money’ in the bank. However, in AFO the same interest rate is used to represent debit and credit. The reasons are:

1. Many farmers often have a core debt, so the farm cash position is usually negative even though their short term operating account may occasionally be positive. The differential interest rates are only justified if the farmer does not operate with a sweep facility to pay down core debt and then redraw when required later.

2. As discussed above, the asset value and the cashflow operate together in the optimisation of flock structure. This implies that the interest rate for the cash flow should be the same as the discount rate for the asset value.

AFO tallies the total farm expenditure, adjusts it by a user defined return on expense factor and includes it in the objective to ensure the model achieves a minimum return on expenditure. The purpose of this is to represent farmer behaviour. It can also be used in the static equilibrium version to ‘fudge’ the risk associated with seasonal variation and reduce the optimal stocking rate to better align with on-farm values. The minimum rate of return on expenditure (MinROE) is specified by the
user and can be turned off. The current rate in the static equilibrium model (25%) was calibrated by a comparison of the model output with on-farm benchmarking (e.g. Planfarm, 2022).

There is no representation of a starting cash balance. If it is included, the model just selects the highest amount because that earns the most interest. The model can overdraw the working account if additional cash is required, so this does not affect the model solution.

Tax is also not represented for several reasons:

1. There are several mechanisms by which farmers seek to lessen their tax liabilities. Not all are ‘economically rational’ and not all are easily represented in a LP model.

2. Many farmers nowadays invest in farm management deposits and income-averaging as a means of taxable income averaging and to smooth working capital borrowings. If the FMDs could be used ‘perfectly’, then each year would have the same taxable profit. Thus, the optimal farm management is unaffected by the inclusion of tax.

3. AFO is a bioeconomic model with the aim of optimising farm management. It is not a finance model.

**Labour**

To capture the dynamics of labour, the year is broken into labour periods (Rose, 2011). The supply of labour in each period by each labour source is calculated, and the labour required by each farm activity is determined and assigned to the given period/s.

In addition to the labour requirement described in the other sections of the model, there is a fixed labour requirement which reflects the labour required for administration tasks such as BAS, tax and pay roll, farm planning and upskill activities such as attending conferences or field days.

The amount of labour available in each period depends on the number of labour units and the hours worked each day. Labour can be supplied by three sources:

1. Casual staff – In the unrestricted model, casual staff can come and go at any time throughout the year as required. However, the user can fix the number of casual staff employed during each period of the year.

2. Permanent staff – Permanent staff work on the property all year (with an allocation for leave).
3. Manager staff (commonly the farm owner) – The farm manager works on the property all year. They control the overall farm plan and thus spend a fixed amount of time each quarter on farm planning, learning, record-keeping, purchasing and selling, and other office work.

Farm labour tasks can be allocated to a specific labour source where required. For example, farm planning must be completed by manager staff. Any labour source can complete unallocated tasks. To realistically reflect the labour hierarchy, casual and permanent staff both require a certain amount of supervision from the farm manager. The proportion of supervision is specified separately for seeding and harvesting. This is because during seeding and harvest it is likely that less supervision is required. Casual staff are generally less experienced and/or acquainted with the farm operation than permanent staff and thus require more supervision.

The importance of timeliness and the high labour requirement of seeding and harvest means staff often work longer days during those periods (Rose, 2011). To accommodate this, the user specifies the hours worked by each type of staff on the weekdays and weekends for both standard periods and seeding and harvest periods.

The farm manager and permanent staff have four weeks of holiday each year. The holiday timing is flexible (optimised by AFO). This is because managers and permanent staff tend to have a less defined schedule, often taking multiple smaller holidays during the year or returning to the farm during holidays to check on things. Additionally, in AFO, permanent and casual staff require supervision from the manager which means if the manager is forced to take their holidays in one big chunk the model may not be able to access labour resulting in inconsistencies if the period dates change. All labour sources take days off for Christmas, New Year’s Day, and Easter. Permanent staff are also allocated a certain number of sick days per year. The user has the ability to alter the length and timing of worker leave.

Casual staff are paid on a per hour basis and the manager and permanent staff are paid an annual wage. All labour costs include superannuation and workers’ compensation insurance.

Machinery

There is great variation in the type, age and investment in machinery between farms (Kingwell and Pannell, 1987). To account for this, the model accommodates a range of machinery options. The model user can then select which machinery complement is appropriate for their analysis. The machinery option selected determines the fixed cost, variable cost and machinery work rate. For the seeding activity, the land management unit can also impact the variable cost rate and work rate. For example, work rates are slower on heavy clay soils.
A machinery cost applies to all farm activities that require machinery. However, for both seeding and harvest, the work rate of the machinery affects the timelines of completion. For example, with smaller machinery, seeding takes longer, potentially incurring a late seeding yield penalty. Additionally, the model can hire contract services for seeding and harvest, although this can be limited by the user.

There are operating costs and depreciation costs associated with machinery. Operating costs refer to expenses incurred during usage such as for fuel, oil, grease, repairs and maintenance. Depreciation costs represent the decline in the value of the asset. Depreciation is made up of two components. Firstly, a fixed component which represents depreciation even if the machine is not used and secondly, a variable component which represents that asset value reduces faster with increased usage.

**Uncertainty and short-term tactics**

The two main sources of uncertainty in Australian farming systems are the high variance of world prices for most agricultural commodities (e.g. Hazell et al., 1990) and climate variability, which results in significant production variability (Feng et al., 2022, Laurie et al., 2019). To deal with short-term variability within the system, farmers implement tactical adjustments that deviate from the long-term strategic plan. Tactical adjustments are applied in response to unfolding opportunities or threats and aim to generate additional income or to avoid losses (Pannell et al., 2000). In AFO price and weather variation is represented as a number of discrete options along with a range of relevant tactical adjustment options.

**Weather variation**

Weather uncertainty in AFO can be included or excluded and the representation of uncertainty can be more or less detailed. Variability or uncertainty is represented using the modelling approach of discrete stochastic programming (Cocks, 1968, Rae, 1971, Crean et al., 2013). Discrete stochastic programming is a formulation of a decision tree. It requires the explicit specification of management choices and their possible consequences. The nodes or event forks are usually represented by a relatively small number of discrete outcomes. The inclusion of uncertainty allows management decisions to be made as the year unfolds (Norton and Hazell, 1986, Hardaker et al., 1991), which has been noted as an important aspect of farm management (Pannell et al., 2000, McCown et al., 2006). The three different AFO frameworks are:

(i) A deterministic steady state expected weather-year framework (DSSE) (e.g. Kingwell and Pannell, 1987). In this framework the farming system is represented as a single discrete state
that is statistically the expected weather-year. Representing a farm system by such a single state of nature requires use of expected inputs and outputs (e.g. the wheat yield is the average of all years). It assumes every year is the same and the finishing state equals the starting state. Thus, only strategic (or year-in year-out) management is represented and management does not change between years because there is only one branch of the decision tree being represented. This model includes 83,271 variables and 49,364 constraints.

(ii) A four-stage single-sequence stochastic programming with recourse (4-SPR) (e.g. Kingwell et al., 1991). A 4-SPR model represents the farming system as subject to a portfolio of discrete states of nature where each state represents a different type of weather-year that has separate or unique inputs and outputs to reflect different prices, weather conditions and production outcomes. All states begin from a common point that is determined by the weighted average of the end of all the weather-years, but then these states separate at various nodes during the production year to unveil the particular nature of that weather-year (Note: To minimise misrepresentation associated with the starting weighted average, the start of the weather-years is defined as the earliest season break). Once a weather-year has been identified, subsequent decisions are differentiated based on the known information about that given weather-year. For example, one node is the start of the growing season or ‘break of season’. If that start is what is known colloquially as an ‘early break’, then after that starting point those types of weather-years can be managed differently to weather-years where the break occurs later. For example, in an early break it may be optimal to crop more area and run a higher stocking rate and vice-versa for a late break, although these decisions can only be made after the break of season is known. However, at the break of the season the subsequent conditions are uncertain (e.g. 30% chance of a poor spring and a 70% chance of a good spring). Thus, the decisions made at the break of season must factor in future uncertainty about the spring conditions. The 4-SPR model examines each possible outcome and its probability to determine the optimal decisions. These decisions are a suite of tactical adjustments made at each node that complement or adjust an overarching farm management strategy. The 4-SPR model is much greater in size, comprising 476,113 variables and 237,956 constraints.

(iii) A eight-stage multi-sequence stochastic programming with recourse framework (known as 8-SPR) (Xie and Huang, 2018). 8-SPR is similar to 4-SPR with the difference being that the discrete states represent a sequence of weather-years in equilibrium rather than a single year in equilibrium. Optimisation of management within the sequence of weather-years fully
accounts for the temporal effects of management change between years. In AFO, the production data in the 8-SPR is the same as the 4-SPR for the individual weather-years. The difference is that the 8-SPR framework more accurately represents carryover management implications from the previous year. For example, if stock were sold in the previous year the current year would start with a destocked position. This version of the AFO model includes 4,571,881 variables and 2,140,700 constraints.

Price variation

There are two main methods to include price variation in whole farm LP.

1. Expected price variation (e.g. Kingwell, 1994): Expected price variation represents price variation by applying a discrete distribution to cashflow items after management decisions have been made. This method of representing price variation assumes that there is no knowledge of the price state, prior to purchasing or selling a commodity. The only known information is the expected price (i.e. a farmer does not know if they are in a high or low price year until they purchase or sell). Therefore, price variation has no impact on farm management for a risk neutral farmer. However, for a risk averse farmer price variation can alter their management. For example, if the grain price is more variable than livestock prices, it may be optimal for a risk averse farmer to have a higher livestock focus because it will reduce the variation in farm profit between years.

2. Forecasted price variation (Apland and Hauer, 1993): Forecasted price variation is a more realistic method achieved by including discrete states based on forecast information, allowing decision-making to change based on the forecasted conditions. The forecasted states are adjusted using a discrete distribution to reflect the actual prices received at purchase or sale. This requires a stochastic programming approach that increases model size and complexity.

AFO currently uses method 1 because price variation has not been the focus of this doctoral thesis, Nonetheless, a likely valuable future improvement for AFO would be to include forecasted price variation. AFO's flexible structure would facilitate inclusion of such price variation.

Currently, price variation is approximated in AFO using a range of discrete price states for meat, wool and grain. The need to form discrete approximations of a continuous distributions is a necessary requirement for developing a LP model of farm management responses to price and weather-year states. By their nature, discrete stochastic programming models cannot consider all
possible price states as described by continuous distributions. Rather continuous variables such as price need to be approximated by discrete states.

The price state scalars and their probabilities are calculated by fitting a multivariate normal distribution to historical prices, then summarises as discrete states by dividing the multi-dimensional probability density distribution into segments. A multivariate distribution is used so that correlations between commodities are accurately represented in the resulting price states. Grain and wool prices are better represented by log-normal distributions (Kingwell, 1996). Thus, before fitting the distribution, grain and wool data were subject to a log transformation. Additionally, the historical prices were CPI adjusted and detrended using a long-term moving average. The reason for detrending the price data was that the price states represented in AFO serve the purpose of capturing yearly price variation (i.e. variations around the expected price for that year) rather than capturing within year price cycles.

Nonetheless, within year price cycles are accounted for in AFO for products such as sale sheep that can be sold at different times during the year. Including the within year price cycles ensures that optimisation of the nutrition of sale sheep represents that sale data has an effect on expected price. Representing the annual price cycle also ensures that strategic management such as time of lambing is also evaluated correctly given the impact of time of lambing on likely turn-off dates.

To reduce model size and simplify input calibration, all meat classes (lamb, shipper, mutton, etc) receive the same meat price scalar. The same thing happens for classes of wool and types of grain. This simplification should not compromise the accuracy of the results because subclasses of a given commodity tend to have a high correlation (e.g. between 2000 and 2021 the correlation between light lamb and mutton was 96%). A further simplification was excluding price variation for input costs because input costs tend to vary less (Kingwell, 1996) and therefore the additional model size was not justified. The resulting assumptions are that all animal classes are 100% correlated, all wool microns are 100% correlated, all grains are 100% correlated and all input commodities have no variation. This assumption is not entirely accurate (e.g. canola and wheat prices are not 100% correlated) however, if in future analysis, price variation is of high importance this can easily be rectified by expanding the inputs.

**Tactical management options**

There are many tactical or adjustment options represented in AFO that reflect a farmer’s reality. The tactics are similar to, but an expansion of those represented by Kingwell et al. (1992) and revolve around land use area adjustment, land use inputs, whether a crop is harvested, baled or grazed as a standing crop, intensity of machinery use, labour utilisation, seasonal sheep liveweight patterns,
tactical sale of sheep, grazing management of pasture and stubble, and supplementary feeding. The same tactical adjustments are made to all weather-years that are indistinguishable from one another at the time a tactical decision is implemented. Such weather-years are clustered at that decision point, as the node that later differentiates these weather-years is still in the future. By illustration, tactical adjustments selected at the early season break node have to be the same for all weather-years that have an early break, because at the time of making the break of season tactical decision the occurrence of follow-up rain and the spring conditions are unknown. Typical tactical adjustments include:

- **Rotation phase** - The area of each land use can be adjusted depending on the date of season break or other early indicators such as residual soil moisture from summer rainfall. Choice of rotation phase can also be delayed at the break of season, for example waiting to ensure it is not a false break. During this period of delay, pasture will germinate on these paddocks and is able to be grazed (the level of germination is dependent on the rotation history of the paddock). The potential for tactical adjustment of rotation phases depends on the land use history on each LMU because the choice for current land use is constrained by the land use history. Likewise, tactical adjustment affects subsequent rotation phase choice through its impact on altering the land use history provided.

- **Land use inputs** – In favourable weather-years additional chemicals and fertiliser can be applied to maximise yields and vice versa in poor weather-years. Note, in this analysis the input level for each land use on each land management unit in each weather-year is optimised by the user externally to the model, reliant on expert agronomist advice for the study region. The optimisation accounted for the clustering of the weather-years.

- **Fodder crops** - In adverse weather-years where either livestock feed is limiting or crops are frosted or are not worth harvesting, saleable crops can be turned into standing fodder. That is, instead of harvesting a crop it is grazed by livestock as summer feed.

- **Bale crops** - Crops planted with the expectation of being harvested for grain can be baled as hay. This may occur in adverse weather-years where either livestock feed is limiting or crops are frosted or are not worth harvesting.

- **Labour supply** - Permanent and manager labour is fixed (i.e. must be the same for all weather-years). However, casual labour can be optimised for each weather-year as it unfolds.
• Machinery contracting - If the timeliness of an activity is an issue, contract services can be selected to improve the work rate. This could be valuable in a late break weather-year to ensure the crops get the maximum possible growing season. Note, the assumption that contracting services are available can be changed.

• Dry seeding - A useful tactic to improve timeliness of seeding is to sow into dry soil, before the opening rains, to ensure crops experience the maximum possible growing season. If dry seeding is selected it is implemented for all weather-years that have yet to have the season break.

• Confinement feeding - Confinement feeding can be a good tactic to allow pasture deferment at the beginning of a growing season or to keep ground cover on paddocks in the late summer and autumn.

• Supplement feeding – In-paddock supplement feeding can be used as a tactic to help finish lambs for sale, ensure ewes reach target conditions for reproduction or to help meet energy requirements during weather-years with poor pasture growth.

• Changing liveweight - Altering livestock liveweight targets can be used as a tactic to handle varying feed availability due to seasonal variation e.g. animals can lose weight in poor feed years but this is associated with lower production per head.

• Not mating ewes - If the feed supply is sufficiently poor prior to joining then there is the option of not mating ewes. This might be most relevant if mating ewe lambs.

• Selling scanned dry ewes or other ewes at scanning – Sale of dry sheep can be a useful tactic if the year is unfolding unfavourably.

• Retain dry ewes - If the strategy is to sell dry ewes, and the weather-year is favourable, a tactical adjustment can be to retain the dry ewes until shearing, thereby generating wool income and then a further decision is to retain them for mating the following year.

• Selling at other times – The ewes and lambs’ sale time can be adjusted with the value received depending on the liveweight and condition of the animals at sale. In AFO there are ten selling opportunities throughout the year for ewes and eight sale opportunities for lambs and wethers.
Objective

The objective of the model is to maximise expected utility. In the case of risk neutrality, expected utility is equivalent to expected profit, meaning that the optimal farm management plan is that which maximises farm profit. In the case of risk aversion, utility increases at a diminishing rate as profit increases. Thus, when farm profit is low, an extra dollar of profit provides more utility than when farm profit is high. This means a risk averse farmer aims to reduce profit variation (i.e. increase profit in poor years at the cost of reduced profit in the good years). For example, if the crop and stock enterprise on the modelled farm are similar but grain prices are more volatile, then risk aversion will shift resources towards the stock enterprise to reduce risk (profit variation).

Constant absolute risk-aversion (CARA) and constant relative risk-aversion (CRRA) are two well known utility functions. Both have been previously used in stochastic farm modelling (Kingwell, 1994, Kingwell, 1996). Both methods are included in AFO. CARA is a negative exponential curve: \( U = 1 - e^{-\alpha x} \) where \( U \) is utility, \( \alpha \) is the Pratt-Arrow coefficient of absolute risk aversion and \( x \) is the return to management and capital. The Pratt-Arrow coefficient is a user input that controls the level of risk aversion. Kingwell (1994) used two levels: 0.000 003 and 0.000 005 to represent moderate and high levels risk-aversion. CRRA is a power function denoted by: \( U = \frac{W^{(1-R)}}{1-R} \) where \( U \) is utility, \( W \) is terminal wealth and \( R \) is the relative risk aversion coefficient. The relative risk aversion coefficient is a user defined input that controls the level of risk aversion. Kingwell (1996) used values within the range of 0.1 to 3.0 to represent low to high levels of risk-aversion.

Both methods have limitations, most of which can be minimised if the modeler is aware. A CARA specification implies there are no wealth effects on a farmer’s income and price security decisions. In practice, the CARA specification means that the farmer’s risk management decisions, particularly in favourable states of nature (e.g. good weather-years with high commodity prices) when a farmer’s wealth is boosted, will be different and more concerned with income stability than those that would arise with a CRRA specification. The limitation of the CRRA method is that it cannot handle a negative terminal state. Additionally, because CRRA is impacted by terminal wealth, MINROE and asset opportunity cost (discussed in the finance section) will affect the impact of risk aversion, which is not technically correct because these are not real costs incurred by the farmer.

The utility functions discussed above are non-linear. To accommodate this in AFO, a piecewise technique is applied which approximates the function using 13 linear segments.
Validation

As an optimisation model, the sort of validation strategies used for simulation models are not applicable. However, significant time has been spent by the authors with local farming experts examining the outputs of each module to ensure that results and behaviour of the model are realistic and well aligned with actual farms in the region. Additionally, AFO was constrained and benchmarked against regional data to ensure that for a given farm structure the results are realistic. Furthermore, AFO builds on many of the fundamentals used in MIDAS which have been extensively tested in Western Australia for around 40 years since its creation (Kingwell and Pannell, 1987).

Table 2: Comparison of regional benchmarking results with AFO output when stocking rate, pasture area and prices in AFO were fixed to the benchmarking averages.

<table>
<thead>
<tr>
<th></th>
<th>Sheep gross margin(^1) ($/WgHa)</th>
<th>Average wool cut (kg/hd)</th>
<th>Weaning %</th>
<th>Cropping gross margin(^1) ($/Ha)</th>
<th>Barley Yield (t)</th>
<th>Canola Yield (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regional(^2)</td>
<td>$652</td>
<td>4.03</td>
<td>99</td>
<td>$570</td>
<td>4.2</td>
<td>2</td>
</tr>
<tr>
<td>AFO</td>
<td>$620</td>
<td>4.15</td>
<td>100.5</td>
<td>$549</td>
<td>4</td>
<td>1.8</td>
</tr>
</tbody>
</table>

\(^1\) Only includes variable costs.

\(^2\) Regional results were from 2021, an above average production year (livestock prices were very favourable in 2021)

Conclusion

AFO is a detailed whole farm mathematical program consisting of numerous modules that represent each aspect of the farm system. The level of complexity included in each module is part of the art of building whole farm model. Enough detail must be included to ensure the research topic being evaluated is fully captured. However, it is often also subject to resource allocation and parameterisation data. For example, in the last decade, AFO and MIDAS have been more widely used in the livestock industry and as such the livestock and pasture representation in the model is more detailed than cropping. In the future, modules can easily be improved when the resources and data are available. For example, nutrient response curves could be added to the cropping modules that allow fertiliser application to be optimised or cattle could be included.
Overall, the development of AFO has been a big step forward for the farming industry. AFO is the first Western Australian whole farm optimisation model built in Python. Utilising modern programming concepts, it is able to represent a high level of farm biological, technical and economic details, including weather and price variation. This opens the doors to many different applications by model users. AFO has the capacity to answer questions that were not previously possible such as what is the importance of single year and multi-year stochastic farm modelling versus steady state farm modelling. Furthermore, AFO has several sets of inputs allowing it to be applied in different regions. Taking AFO to a new region requires the user to calibrate the relevant model inputs which can be a significant job (e.g. Young et al., 2020). However, with the use of simulation modelling, expert advice, research data, benchmarking data, on-farm data and satellite data this is an achievable task.

Additional features of AFO include segregated inputs, cloud integrated, version control and automated documentation. All these functions make AFO highly flexible, more scalable, more transparent and more user friendly.

Of course, with the desire to accurately evaluate a system so complicated as a farm, AFO, in its raw form, is inherently complex and requires a dedicated and skilled user. However, using the factors outlined above AFO has been developed to facilitate research adoption. AFO includes detailed instructional documentation and users have been given moderate control over the complexity represented in the model for a given analysis. Even so, users are still likely to require additional training in order to successfully adopt the model into their research work.

Chapter 4: Improved whole-farm planning for mixed-enterprise systems in Australia using a four-stage stochastic model with recourse

This chapter has been submitted for publishing in the journal of Australian Farm Business Management and remains in its submitted form with the exception of the removal of the Abstract.

Introduction

Australian mixed enterprise farm systems often encompass a range of soil types, crop options and livestock options (Young et al., 2020, Mosnier et al., 2022, Young and Young, 2022). Farmers’ enterprise choices are often constrained by a range of factors including labour availability, an existing complement of farm machinery and animal production infrastructure (e.g. dams, yards and fences), access to finance, managerial preferences and past decisions that influence current resource
status and feasible future actions (Ewing et al., 2004). Furthermore, price and climate variability can generate significant production and farm income variability (Laurie et al., 2019, Feng et al., 2022) that can complicate the management of the farming system. Furthermore, price and climate variability can generate significant production variability (Laurie et al., 2019, Feng et al., 2022), which can complicate the management of the farming system. In response, farmers tend to implement a long-term strategic plan tailored to their enterprise preferences, their perception of commodity price outlooks, their familial and financial resources and their existing investments in machinery complement and related infrastructure.

To deal with seasonal variability that affects their production possibilities, farmers implement tactical adjustments that are deviations from their year-in-year-out strategic or initial farm plan. Tactical adjustments are applied in response to unfolding opportunities or threats and aim to generate additional income or to avoid potential losses (Pannell et al., 2000). The combination of some or all of these factors and actions means Australian farming systems can be complex to analyse and manage (Price and Goode, 2009, Kingwell, 2011).

The intricacies of a mixed enterprise farming system suggest that whole-farm modelling may aid agricultural decision-making (Apland and Hauer, 1993, Pannell, 1996). Agricultural or farming systems in Australia, and internationally, are most frequently modelled either by dynamic simulation (Anderson, 1974, Rozman et al., 2013) or mathematical programming (Kingwell and Pannell, 1987, Annetts and Audsley, 2002, Roughsedge et al., 2003, Schäfer et al., 2017). Dynamic simulation (DS) aims to replicate the behaviour of a system. It is frequently applied to represent biological systems within the farming system (Thomas et al., 2018) or a component of the farming system (Keating et al., 2002, Robertson et al., 2002). Mathematical programming (MP) is a group of optimisation techniques that represents a system using variables, constraints and an objective (Norton et al., 1980, Kingwell and Pannell, 1987). Both DS and MP often achieve more than their simple categorisation implies, as it is feasible to specify an objective in a DS model and search for an optimal solution, and MP techniques can represent simulated biological detail (Kingwell and Pannell, 1987, Young et al., 2011).

MP is the focus of this paper because it can capture biological and economic interactions of a farming system and allow reliable and efficient optimisation techniques to be applied. In their review of the development and use of farm models for policy impact assessment in the European Union, Reidsma et al. (2018) observe that “the majority of articles used Mathematical Programming (MP) in their farm models MP is thus still the major technique for farm level assessments.” (p. 114).
MP methodologies previously applied to farming systems include the deterministic steady state expected weather-year framework (Young, 1995, Roughsedge et al., 2003). Perhaps the best-known Australian example of this framework is the model known as MIDAS (Model of an Integrated Dryland Agricultural System) that has been widely applied to a variety of farming system issues in Australia (Morrison et al., 1986, Kingwell and Pannell, 1987, O’Connell et al., 2006, Young, 1995). Another framework is stochastic programming with recourse, also known as state-contingent stochastic programming (Crean et al., 2013, Britz et al., 2014, Featherstone et al., 2019). The primary difference between these two frameworks is their representation of uncertainty. The deterministic steady state expected weather-year framework employs the key assumption that the same management decisions are repeated each year, with that year being an unchanging average, median or modal weather-year. Hence there is no representation of weather-year uncertainty. By contrast, stochastic programming with recourse represents multiple alternative states of nature, each with a given probability that allows weather-year uncertainty and relevant tactical state-contingent decisions to be represented (Rae, 1971, Crean et al., 2013). Stochastic programming with recourse is brought into equilibrium by making the initial activity levels equal to the probability-weighted average of ending levels (Kingwell et al., 1991, e.g. Cacho et al., 1999, Crean et al., 2012, Featherstone et al., 2019).

Previous research that has compared the output from a deterministic steady state expected weather-year model against that of a stochastic programming with recourse model has either been conducted with models that only represent a subsection of the farm system (e.g. Jones et al., 2006), or been conducted in a less comprehensive manner that excludes the many intricacies of a farming system and its management (e.g. Crean et al., 2013) or was conducted decades ago and, since then, farming systems, technologies, farm machinery and crop performance have changed greatly (e.g. Kingwell et al., 1992, Cacho et al., 1999). The changes that have occurred in farming systems bring into question how modern systems respond to variable weather conditions.

These studies identified that weather-year variability and sequential decision making significantly impacted farm management and farm performance metrics and so should not be ignored in farming system analyses. However, for various reasons, much whole-farm research is still conducted using deterministic steady state expected weather-year models (Kopke et al., 2008, e.g. Kingwell and Fuchsbichler, 2011, Young et al., 2016, Thamo et al., 2017, Young et al., 2020). Often these models are readily available, relatively easy to use and are regularly updated to maintain their relevance. Nonetheless, due to changes in computational capacity, farm size, farming systems, technologies, farm machinery capabilities, and crop and animal performance over the last three decades it is timely to re-visit the appropriateness of continued reliance on deterministic steady state expected weather-year models.
weather-year models and assess once again if stochastic programming with recourse models offer a more accurate and useful representation of farming systems and their optimal management.

Accordingly, in this paper, two modelling frameworks, a deterministic steady state expected weather-year model and a stochastic programming with recourse model are compared and contrasted to form insights about their relative utility to researchers, farm advisers and farm managers. In this paper, to limit the magnitude of the analysis, we only consider weather uncertainty. The impact of including price uncertainty warrants a separate analysis.

**Method**

**Farm system modelled**

The model, with 2 sub-frameworks, was calibrated to represent a typical farm in the medium rainfall zone of the Great Southern region of Western Australia. The Great Southern region was selected for two reasons. First, the region has been modelled previously for a variety of analyses (Young, 1995, Poole et al., 2002, Young et al., 2011, Trompf et al., 2014) and thus the farm data required is more readily available. Second, the Great Southern region contains 26% of Western Australia’s sheep flock (ABARES, 2016), so the selection of this region increases the relevance of the findings from the study to farm businesses dependent on sheep production in Western Australia.

The Great Southern region in Western Australia is characterised by a hot dry summer and autumn, with a winter and spring growing season of 400–650 mm rainfall. Farms are typically a mix of cropping and livestock enterprises. Furthermore, as discussed in the weather years sub section below, the timing of the start of the growing season, also known as the ‘break of season’, and the quantity of spring rainfall are key management indicators for farmers in the region.

The model was calibrated to represent current farm management technology regarding machinery complement, herbicides and fertilisers used based on discussions with local farm consultants. The tasks contracted and crop and livestock options considered are all consistent with those used currently by farmers in the modelled region (Tim Trezise *pers. comm.*, Ed Rigall *pers. comm.*).

The model represents a typical 2130 ha farm that includes three land management units to reflect soil heterogeneity in the region. The calibration of crop and pasture inputs was completed through a combination of simulation modelling and expert consultation. The growth rate of the pastures and yield of crops in each rotation were generated using AusFarm simulation modelling (Moore et al., 2007), with the output for each individual year simulated and then allocated to a weather-year category. The simulation model output grouped by weather-year categories was reviewed by a local agronomist who applied broad brush scaling to align the yields with farmer practice. Climate data
was sourced from the Kojonup weather station (BOM station 10582) for the period 1970 to 2020. Soil data representing the land management units was sourced from the APSOIL database (Dalgliesh et al., 2012b).

**Model overview**

Analyses in this study are derived from applying the model **Australian Farm Optimisation (AFO)**. A brief summary of the model is provided below. For a more thorough description see the model’s documentation: [https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html](https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html). In summary, AFO is a Python-based, whole-farm MP model that supersedes the popular farming system model known as MIDAS (Model of an Integrated Dryland Agricultural system) (Kingwell and Pannell, 1987, Pannell, 1996, Kopke et al., 2008, Bathgate et al., 2009, Kingwell, 2011, Young et al., 2011, Thamo et al., 2013, Young et al., 2020). AFO leverages a powerful algebraic modelling add-on package called Pyomo (Hart et al., 2011) and IBM’s CPLEX solver to efficiently build and solve the farming system model. The model represents the economic and biological detail of a farming system and includes modules for rotations, crops, pastures, sheep, crop residues, supplementary feeding, machinery, labour and finance. Furthermore, it includes land heterogeneity by considering enterprise rotations on a limited range of land management units.

A key aspect of AFO that makes it suitable for this analysis is its flexible representation of uncertainty. Uncertainty in AFO can be included or excluded. Variability or uncertainty is represented using the modelling approach of stochastic programming with recourse (Cocks, 1968, Rae, 1971, Crean et al., 2013, Kim et al., 2018). Stochastic programming with recourse is a formulation of a decision tree (e.g. Figure 1) consistent with state-contingent analysis (Chambers and Quiggin, 2000, Adamson et al., 2007, Mallawaarachchi et al., 2017). It requires the explicit specification of management choices and their possible consequences. The nodes or event forks are usually represented by a relatively small number of discrete outcomes. The inclusion of uncertainty allows the representation of tactical decisions as the year unfolds, which has been noted as an important aspect of farm management (Pannell et al., 2000, McCown et al., 2006). Furthermore, through the use of an expected utility function, AFO has the capacity to represent a farmer’s risk attitude in response to uncertainty or variability. However, in this study we assume a risk neutral attitude and the two different AFO frameworks used are:

- (iv) A deterministic steady state expected weather-year framework (DSSE) (e.g. Kingwell and Pannell, 1987). In this framework the farming system is represented as a single discrete state that is statistically the expected weather-year. Representing a farm system by such a single state of nature requires use of expected inputs and outputs (e.g. the wheat yield is the
average of all years). It assumes every year is the same and the finishing state equals the starting state. Thus, only strategic (or year-in year-out) management is represented and management does not change between years because there is only one branch of the decision tree being represented. This model includes 83,271 variables and 49,364 constraints.

(v) A four-stage single-sequence stochastic programming with recourse (4-SPR) (e.g. Kingwell et al., 1991). A 4-SPR model represents the farming system as subject to a portfolio of discrete states of nature where each state represents a different type of weather-year that has separate or unique inputs and outputs to reflect different prices, weather conditions and production outcomes. All states begin from a common point that is determined by the weighted average of the end of all the weather-years, but then these states separate at various nodes during the production year to unveil the particular nature of that weather-year (Note: To minimise misrepresentation associated with the starting weighted average, the start of the weather-years is defined as the earliest season break). Once a weather-year has been identified, subsequent decisions are differentiated based on the known information about that given weather-year. For example, one node is the start of the growing season or ‘break of season’. If that start is what is known colloquially as an ‘early break’, then after that starting point those types of weather-years can be managed differently to weather-years where the break occurs later. For example, in an early break it may be optimal to crop more area and run a higher stocking rate and vice-versa for a late break, although these decisions can only be made after the break of season is known. However, at the break of the season the subsequent conditions are uncertain (e.g. 30% chance of a poor spring and a 70% chance of a good spring). Thus, the decisions made at the break of season must factor in future uncertainty about the spring conditions. The 4-SPR model examines each possible outcome and its probability to determine the optimal decisions. These decisions are a suite of tactical adjustments made at each node that complement or adjust an overarching farm management strategy. The 4-SPR model is much greater in size, comprising 476,113 variables and 237,956 constraints.
Figure 1: An example of a decision tree associated with weather-year classification. The parallelograms are nodes that identify the type of weather-year and the diamonds are subsequent decisions. Note, the nodes reflect the Great Southern version of AFO, however, the decisions in AFO are not limited to what is depicted here.

Tactical decisions in the 4-SPR model

There are many tactical or adjustment options represented in the 4-SPR model. The tactics revolve around enterprise land use area adjustment, land use inputs, whether a crop is harvested or grazed as a standing crop, intensity of machinery use, labour utilisation, seasonal sheep liveweight patterns, tactical sale of sheep, grazing management of pasture and stubble, and supplementary feeding. The same tactical adjustments are made to all weather-years that are indistinguishable from one another at the time a tactical decision is implemented. Such weather-years are clustered at that decision
point, as the node that later differentiates these weather-years is still in the future. By illustration, tactical adjustments selected at the early season break node have to be the same for all weather-years that have an early break, because at the time of making the break of season tactical decision the occurrence of follow-up rain and the spring conditions are unknown. Typical tactical adjustments include:

- **Rotation phase** - The area of each land use can be adjusted depending on the date of season break or other early indicators such as residual soil moisture from summer rainfall. Choice of rotation phase can also be delayed at the break of season, for example waiting to ensure it is not a false break. During this period of delay, pasture will germinate on these paddocks and is able to be grazed (the level of germination is dependent on the rotation history of the paddock).

- **Land use inputs** – In favourable weather-years additional chemicals and fertiliser can be applied to maximise yields and vice-versa in poor weather-years. Note, in this analysis the input level for each land use on each land management unit in each weather-year was set externally by the model user who relied on the expert advice of experienced agronomists who work in the study region. Their advice accounted for the required clustering of weather-years.

- **Fodder crops** - In adverse weather-years where either livestock feed is limiting or crops are frosted or are not worth harvesting, saleable crops can be turned into fodder. That is, instead of harvesting a crop it can be grazed by livestock as summer feed.

- **Bale crops** - Crops planted with the expectation of being harvested for grain can be baled as hay. This may occur in adverse weather-years where either livestock feed is limited or crops are frosted or are not worth harvesting.

- **Labour supply** - Permanent and manager labour is fixed (i.e. must be the same for all weather-years). However, casual labour can be altered within each weather-year as it unfolds.

- **Machinery contracting** - If the timeliness of an activity is an issue, contract services can be selected to improve the work rate. This could be valuable in a late break weather-year to ensure the crops get the maximum possible growing season. Note, the assumption that contracting services are available can be changed.

- **Dry seeding** – This is a useful tactic to improve the timeliness of seeding by sowing into dry soil, before the opening rains, to ensure crops experience the maximum possible growing season.
• Confinement feeding - Confinement feeding can be a useful tactic to allow pasture deferment at the beginning of a growing season or to keep ground cover on paddocks in late summer and autumn.

• Supplement feeding – In-paddock supplement feeding can be used as a tactic to help finish lambs for sale, ensure ewes reach target conditions for reproduction or to help meet their energy requirements during weather-years with poor pasture growth.

• Changing liveweight - Altering livestock liveweight targets can be used as a tactic to handle varying feed availability due to seasonal variation.

• Not mating ewes - If the feed supply is sufficiently poor prior to joining then there is the option of not mating ewes.

• Selling scanned dry ewes or other ewes at scanning – Sale of dry sheep can be a useful tactic if the year is unfolding unfavourably.

• Retain dry ewes - If the strategy is to sell dry ewes, and the weather-year is favourable a tactical adjustment can be to retain the dry ewes until shearing, thereby generating wool income. A further decision can then be made regarding retaining them for mating the following year.

• Selling at other times – The ewes and lambs’ sale time can be adjusted, with the value received depending on the liveweight and condition of the animals at sale. In this analysis there were 10 selling opportunities throughout the year for ewes and eight sale opportunities for lambs.

Weather-years

Weather conditions influence crop and pasture growth (e.g. McCown, 1973, Ritchie and Nesmith, 1991). However, modelling the intricacies of weather events leads researchers to experience the “curse of dimensionality” where myriads of different weather events are possible (Burt, 1982). To lessen dimensionality problems associated with representing weather events and their effect on pasture and crop growth, discrete weather states were defined in AFO based on their potential to affect farm management. Following a process similar to Kingwell et al. (1991), the classification of weather-years arose, first, from discussions with farmers to identify which features of weather-years most influenced their main farm management decisions, and second, from detailed examinations of the meteorological and farm production characteristics of actual seasons from 1970 to 2020, using the crop growth simulation model, APSIM (Holzworth et al., 2018).

Of main importance to all farmers and advisers were rainfall events. This emphasis placed by farmers on rainfall events, rather than temperature or wind events, was not surprising because in Western
Australia rainfall is often the main limiting factor for crop and pasture yields (Pratley and Cornish, 1985, Anderson et al., 1992, Stephens et al., 1994). The particular rainfall events that explain the majority of the production variation between years are first, autumn rainfall events that affect pasture germination and crop sowing date; second, in the case of an early break, whether there are follow up rains or if a false break occurs and finally, the quantity of spring rainfall. Thus, in the 4-SPR framework, variance in weather-years was approximated by eight discrete states of nature (see Table 3). By contrast, the DSSE framework has a single discrete state that is an expected weather-year. The effects of each of these states of nature on major input-output relationships of enterprise options are represented in the model.

Table 3: AFO weather-years

<table>
<thead>
<tr>
<th>Code for weather-year</th>
<th>Definition of each weather-year</th>
<th>Probability of occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>z0</td>
<td>Early break(^1) with follow up rains and a good spring(^3).</td>
<td>24%</td>
</tr>
<tr>
<td>z1</td>
<td>Early break with follow up rains and a poor spring.</td>
<td>20%</td>
</tr>
<tr>
<td>z2</td>
<td>Early break that turns out to be a false break(^2) but is followed up with a good spring.</td>
<td>8%</td>
</tr>
<tr>
<td>z3</td>
<td>Early break that turns out to be a false break and is followed by a poor spring.</td>
<td>4%</td>
</tr>
<tr>
<td>z4</td>
<td>Medium break with follow up rains and a good spring.</td>
<td>14%</td>
</tr>
<tr>
<td>z5</td>
<td>Medium break with follow up rains and a poor spring.</td>
<td>16%</td>
</tr>
<tr>
<td>z6</td>
<td>Late break with follow up rains and a good spring.</td>
<td>4%</td>
</tr>
<tr>
<td>z7</td>
<td>Late break with follow up rains and a poor spring.</td>
<td>10%</td>
</tr>
</tbody>
</table>

\(^1\) Early break (i.e. start of the growing season): before the 5\(^{th}\) May; Medium break: between the 5\(^{th}\) May and 25\(^{th}\) May; Late break: after the 25\(^{th}\) May.

\(^2\) False break: pasture feed on offer reaches 500 kg/ha followed by 3 weeks of no growth.

\(^3\) Good spring: above the median (86 mm) rainfall for September and October; Poor spring: below the median rainfall.

Production assumptions

The production inputs were generated using the same process, data and assumptions for each framework. As a result, the main model inputs that differ between frameworks are pasture production and crop production. The inputs for the DSSE framework are the weighted average of the inputs for all the weather-years in the 4-SPR framework.
Weather-year prices

Analysis of commodity prices in different weather-years showed that the prices of agricultural products did not significantly correlate with the weather-years experienced in the study region. This is likely to be due to multiple reasons including the region’s outputs mostly being sold internationally and so the nature of any weather-year experienced in the region will unlikely affect the international prices received for the region’s farm products. In previous decades, such as the 1990s when the state’s sheep population exceeded 30 million head (ABARES, 2010) it was more likely, for example, that a drought year would cause a dramatic lowering of sheep prices due to de-stocking decisions by farmers or an increase in fodder prices as demand for supplementary feed increased. However, the state’s sheep population is now about 13 million head, seasonal conditions have far less impact on fodder and saleyard prices (ABARES, 2022). Accordingly, in our analyses, prices were deemed to be unaffected by the weather-year conditions.

Results

The expected profit generated by the 4-SPR framework is $54,549 (6.8%) per year greater than the profit generated by the DSSE framework (Table 4). The large difference in profit between the models is principally due to the magnitude of additional commercial returns generated by embracing tactical decision-making in the face of weather-year variation. Selection of relevant tactics allows additional profits to be generated in various weather-years, complemented with avoidance of losses in a few other types of weather-years.

The magnitude of additional profits earned, and losses avoided, from embracing tactics is affected by the extent to which the farm strategy involves adopting a crop dominant or livestock dominant enterprise mix. This issue is explored in Appendix 1. In the study region the optimal farm strategy typically involves an expected land allocation such that about 60% of the farm’s area is devoted to crop production. However, if strategically more of the farm’s area is devoted to sheep production, then the difference in expected farm profit generated by each model increases. This reveals that sheep management is particularly sensitive to weather-year variation and tactics. For sheep production the gains in favourable weather-years are not as great as losses in poor years, despite the embrace of various tactical adjustments for the sheep enterprise.

Accompanying these profit differences between the two models are sizable differences in optimal management of the sheep and crop enterprises (Table 4). The strategic 4-SPR farm plans are slightly more crop dominant, especially regarding land allocations to cereal crops, although strategically canola plays a lesser role in the crop mix. Additionally, the 4-SPR modelling results include a 1.5
DSE/ha higher stocking rate accompanied by feeding 76 tonnes more supplements (Table 4). Hence, a more intensive management of the sheep enterprise is revealed in the 4-SPR modelling results.

Further differences in optimal management when weather variation is included are listed below:

(i) More canola is grown in weather-years where there is an early break and more cereals are grown in weather-years with a late break.

(ii) More contract seeding is employed in years with a late break because it is more profitable to pay for additional contracting services to accelerate seeding and mitigate yield losses due to late sowing in these weather-years. Additionally, in weather-years that favour an enlarged cropping program, it is optimal to contract seed in those years (e.g. in weather-years that break early). Additional contract seeding helps ensure crops are established promptly, and any negative impacts of a false break are mitigated when the seeding operation is interrupted due to lack of soil moisture. (Note, a false break has little impact on the yield of early sown crops provided they are established while moisture is available early. However, the impact of a false break on pasture production early in the growing season is severe.)

(iii) In late break years more dry sowing occurs because it is more profitable to get crops established as quickly as possible and pay for additional in-crop herbicides later in the year, (due to foregoing knock down sprays). In short losing crop yield due to later establishment of the crops is a greater expense than the additional cost of herbicides associated with dry sowing.

(iv) In early break years an additional knock down spray is used, which reduces the total crop costs. The additional knock down spray is optimal because it lowers the total herbicide package cost more than the labour and machinery cost incurred with the additional knock down application.

Some of the management tactics listed above (e.g. contract seeding and dry sowing) arise from avoiding crop yield reductions due to untimely sowing of cropping programs. The deterministic steady state expected weather-year framework has only one time of season break and does not represent a false break, so it understates the impacts of certain weather-years on crop production.

Removing the tactical adjustments associated with land use, stocking rate, stock sales and stock liveweight targets from the 4-SPR framework greatly reduces expected farm profit by $144,573 (Table 4 versus Table 5). This 18% reduction in expected farm profit, caused by removing these tactics in the 4-SPR framework, reveals the worth of embracing these management tactics in the face of weather-year variation.
Table 4: Key descriptors of the optimal farm plans generated by the DSSE and 4-SPR frameworks for a typical Great Southern farm.

<table>
<thead>
<tr>
<th></th>
<th>DSSE model</th>
<th>4-SPR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm profit ($/year)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>744,919</td>
<td>799,468</td>
</tr>
<tr>
<td>Max</td>
<td>1,206,763</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>129,063</td>
<td></td>
</tr>
<tr>
<td>Stocking rate (DSE/ha)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>14.6</td>
<td>15.9</td>
</tr>
<tr>
<td>Max</td>
<td>17.2</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>14.0</td>
<td></td>
</tr>
<tr>
<td>Supplement fed (t)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>628</td>
<td>707</td>
</tr>
<tr>
<td>Max</td>
<td>1,470</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>429</td>
<td></td>
</tr>
<tr>
<td>Pasture (% of farm area)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>41</td>
<td>39</td>
</tr>
<tr>
<td>Max</td>
<td>43</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>36</td>
<td></td>
</tr>
<tr>
<td>Cereal (% of farm area)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>30</td>
<td>37</td>
</tr>
<tr>
<td>Max</td>
<td>57</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>28</td>
<td></td>
</tr>
<tr>
<td>Canola (% of farm area)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>29</td>
<td>24</td>
</tr>
<tr>
<td>Max</td>
<td>36</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Flock structure</td>
<td>Ewe dominated flock turning off ~70% of lambs at 6 months of age to the prime lamb market and the remainder at ~12 months of age.</td>
<td>Ewe dominated flock</td>
</tr>
</tbody>
</table>

*‘Expected’ is the weighted average of all weather-years, ‘Max’ is the maximum across the weather-years. ‘Min’ is the minimum across the weather-years.

Table 5: Profit from the 4-SPR model without tactics (all weather-years must have the same management).
Discussion

The comparison between the DSSE and 4-SPR frameworks (Table 4) shows that the inclusion of weather-year uncertainty and relevant management tactics in farm optimisation modelling results in different estimated profits and different strategic farm plans. This is consistent with the results reported by Kingwell et al. (1992), Cacho et al. (1999), Jones et al. (2006) and Crean et al. (2013). Accompanying the strategic farm plans of the 4-SPR model are a suite of associated farm management tactics that bolster farm profit and show how sensitive optimal farm management really is to weather-year variation.

The results from this study contribute to the limited Australian farm management modelling literature on the role and impact of weather-year variation. This current study compares modelling frameworks by applying a newly constructed, full scale, bioeconomic model that accurately represents current farming systems in the Great Southern region of Western Australia. The modelling results reveal important differences between the frameworks regarding key features of farm management such as selection of stocking rate, supplementary feeding and enterprise allocation. The steady state expected weather-year framework overlooks and understates how weather-year variation and associated management tactics impact farm management.

The results from this study support the contention that farm models that explicitly account for weather-year variation and associated tactics are more likely to reveal the nature of optimal farm management regarding the strategic and tactical use of farm resources more accurately. However, an additional gap in our knowledge remains, namely, how similarly or differently will each framework respond to price changes in farm inputs and outputs. For example, if livestock prices increased by 15% would both frameworks respond in the same way? Filling this gap in our knowledge is a subject for further research.

In this study we included detailed options for tactical adjustment in response to the stochastic outcomes. Similar to Kingwell et al. (1992) this study’s results showed that it is optimal to apply short-term tactical management adjustments in response to unfolding weather conditions. The 4-
SPR results showed that without fully representing tactical management in response to the current weather-year conditions, estimates of profit were reduced by $144,573, or 18% of expected profit (Table 4 vs Table 5). This is 6% to 8% more than reported by Pannell et al. (2000), which is likely to be the result of regional differences and the more detailed representation of tactical management in this paper.

The practical implication of these finding is that a farmer with a strategic “set and forget” type management attitude would be substantially worse off by failing to exploit either favourable opportunities or avoid threats associated with weather-year variation. Additionally, the findings suggest that a farm adviser who solely focuses on farm strategy and who does not accurately consider the dynamic nature of farming, and the relevant management tactics applied by farmers, is likely to provide misleading or potentially unhelpful advice.

Furthermore, the importance of accurately representing tactical decision-making also has implications for other types of farming system modelling; for example, when applying dynamic simulation models that represent variation in climate (e.g. CSIRO’s AusFarm). Accurately describing weather-year variation is only a partial aid to improving farm planning or farm management decision-making. A necessary complementary action is to accurately capture tactical management options relevant to each main type of weather-year. Our results show that a farmer’s tactical responses to weather-year variation can unleash opportunities to increase farm profitability. However, identifying optimal choices for tactical management, particularly for livestock, is difficult and time-consuming due to the complexity of interactions and the myriad of options and ramifications. Lack of focus or rigour in this area can generate inaccurate findings, which would result in suboptimal allocation of farm resources and financial losses.

Accurately including uncertainty and tactical management into farm modelling requires data, knowledge and a degree of modelling skill that is rarely available. Additionally, the more realistic representation comes at the modelling cost of increased model size and complexity. The DSSE model in this study currently takes 4 minutes to build and solve whereas the 4-SPR model takes 17 minutes. Interpreting the results and model debugging are also tasks that become more time-consuming as model detail increases. However, in our experience, most time was initially spent on constructing the base DSSE model. The additional time to construct the stochastic component that captured weather-year variation and relevant management tactics was substantial but not excessive and was made more efficient by the flexible nature of modern computer programming. The trade-off between accuracy and complexity, however, raises the question about which framework should be used for different types of analyses. This is an ongoing dilemma faced by many researchers: what is
the appropriate level of detail from which to derive valid and relevant findings? (Kingwell et al., 1992, Cacho et al., 1999, Malcolm, 2000, Pannell, 2006).

Conclusion

In this paper we compare and contrast the profit and optimal farm management generated by two different farm modelling frameworks that examine a mixed enterprise farming system in the Great Southern region of Western Australia. These two frameworks were applied using a whole-farm optimisation model called AFO. The principal findings from applying the two separate frameworks are first, that inclusion of weather variation and associated tactical management generates different results from the more commonly applied steady state expected weather-year modelling; and second, tactical decision-making associated with unfolding conditions of the current weather-years generates substantial opportunities to boost farm profit and/or avoid losses.

Despite exponential computational progress that facilitates application of more complex frameworks, choosing the correct framework for an analysis remains a challenge. The model framework applied needs to be relevant to the problem or opportunity or innovation being analysed. The financial reward of responding to that problem, opportunity or innovation needs to be sufficiently large to justify the costs of model construction and application.
Appendix One

The underlying nature of the farming system, whether crop dominant or livestock dominant, does affect the value of weather-year tactics available to the farm manager. By illustration, the crop enterprise, as represented by a farm with 100% crop, has similar profitability when weather-year variation is included (Table A1). This indicates a symmetric profit response for lower and higher crop yield. In contrast, the livestock enterprise, as represented by a farm with 100% pasture, has a lower profitability when weather-year variation is included (Table A2), which indicates an asymmetric profit response to lower and higher pasture growth. In the DSSE framework the model can optimise the number of stock for the feed budget which is the same each year and equates to the weighted average of all weather-years. However, in the 4-SPR framework, the feed supply changes each year, with the number of stock being less flexible and this is reflected in the larger requirement for supplementary feed in the 4-SPR model (Table 8 & Table A2).

The inflexible nature of livestock feed requirements between years can be mitigated, to some extent, through tactical livestock management. The tactical management includes retaining or selling an extra age group of stock, adjusting the timing of the livestock sales within the year, altering the target liveweight profile and adjusting the grazing management strategy through altering the target feed-on-offer profile during the year. However, even with the inclusion of these tactical management options, the gains in the favourable years are not as great as losses in poor years for the sheep enterprise and there is a change in farm strategy to reduce the number of livestock carried (Table A2). Hence, the outcome of a symmetric profit response for the crop enterprise and an asymmetric profit response for the livestock enterprise, is that the optimum crop area for the 4-SPR model is higher than in the DSSE model. The need to carry sheep across weather-years restricts the tactical options for flexible sheep management and increases the relative attractiveness of cropping enterprises with their associated tactics.

Table A1: The expected profit, and optimal land allocations to cereals and canola for the DSSE model and 4-SPR model when constrained to 100% crop

<table>
<thead>
<tr>
<th></th>
<th>DSSE model</th>
<th>4-SPR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected profit ($)</td>
<td>435,512</td>
<td>438,626</td>
</tr>
<tr>
<td>Cereal (% of farm area)</td>
<td>77</td>
<td>72</td>
</tr>
<tr>
<td>Canola (% of farm area)</td>
<td>23</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>DSSE model</td>
<td>4-SPR model</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Expected profit ($)</td>
<td>571,696</td>
<td>488,270</td>
</tr>
<tr>
<td>Expected stocking rate (DSE/ha)</td>
<td>11.4</td>
<td>10.5</td>
</tr>
<tr>
<td>Expected supplement fed (t)</td>
<td>1,135</td>
<td>1,376</td>
</tr>
</tbody>
</table>
Chapter 5: Representing weather-year variation in whole-farm optimisation models: Four-stage single-sequence vs eight-stage multi-sequence

This chapter has been submitted for publishing in The Australian Journal of Agricultural and Resource Economics and remains in its submitted form with the exception of the removal of the Abstract.

Introduction

Mixed enterprise farm systems often encompass a range of soil types, crop options and livestock options (Young et al., 2020, Mosnier et al., 2022). Farmers’ enterprise choices are often constrained by a range of factors including labour availability, an existing complement of farm machinery and animal production infrastructure (e.g. dams, yards and fences), access to finance, managerial preferences and past decisions that influence current resource status and feasible future actions (Ewing et al., 2004). Given the complexities, farm modelling is often used to aid on-farm decision making (Kopke et al., 2008, e.g. Bathgate et al., 2009, Young et al., 2020).

A further complication for farm management is price and climate variability, which results in significant production variability (Laurie et al., 2019, Feng et al., 2022). For example, Anderson (1979) estimated that climate variability was responsible for just under 40 per cent of the variation in Australia’s gross value of agricultural production and farm income. Malcolm and Wright (2016) note that: ‘Framing and managing uncertainty will continue to be a daunting and often insurmountable challenge for the bulk of Australian farmers.’ (p. 516). To handle these variations, previous research has shown that it is optimal for farmers to adjust both long-term strategic and short-term tactical management (Kingwell et al., 1992, Kingwell et al., 1993, Crean et al., 2013). Accordingly modelling methods that represent uncertainty have been shown to generate more realistic optimal results.

Mathematical programming (MP) is a useful and widely applied modelling framework that can capture a biological and economic interactions of a farming system whilst applying reliable and efficient optimisation techniques (Reidsma et al., 2018, Young et al., 2022). A branch of MP that facilitates the representation of uncertainty is stochastic programming with recourse (Schroeder and Featherstone, 1990, Kingwell et al., 1991, Torkamani and Hardaker, 1996, Flaten and Lien, 2007, Crean et al., 2012, e.g. Britz et al., 2014, Featherstone et al., 2019). Stochastic programming with recourse represents multiple alternative states of nature, each with a given probability, whilst outlining the tactical state-contingent decisions associated with each state or sub-group states of
nature (Rae, 1971, Crean et al., 2013, Kim et al., 2018). Stochastic programs are brought into
equilibrium by making the initial activity levels equal to the probability-weighted average of ending
levels.

Most commonly, in farming system applications of MP, the start and end of the decision framework
(see Figure 2) corresponds to an average or median year (Kingwell et al., 1991, e.g. Cacho et al.,
1999, Crean et al., 2012, Featherstone et al., 2019). A limitation of these MP applications is that they
do not consider the impacts of a sequence of years on farm management and profitability. For
example, there is no consideration of consecutive drought years. Previous MP studies of Australian
farming systems have not considered a multi-year stochastic environment (Kingwell et al., 1992,
Cacho et al., 1999, Crean et al., 2013), so a gap in the literature exists regarding knowing the extent
or implications of the failure to embrace a multi-year framework; even though Featherstone et al.
(2019) have identified that multi-year effects could be important for decision-making concerning
liquidity risk and credit reserve risk.

![Figure 2: The general structure of a two stage, single year sequence stochastic program with recourse. The starting point is the weighted average of the ending points.](image)

A multi-year stochastic program framework is illustrated in Figure 3. Each additional year, however,
exponentially increases the size and complexity of such a model, causing the problem known as the
‘curse of dimensionality’ (Burt, 1982). For example, if a single year stochastic model has 20 terminal
states of nature, a two-year sequence model has 400 possible terminal states and a three-year
model has 8000 terminal states.
In this paper, we apply a single-year and multi-year stochastic program with recourse to a Western Australian farming system to examine the impact of weather-year sequences and associated decision tactics on optimal farm management and profitability. To limit paper size, we only consider weather uncertainty rather than the additional joint complication of input and output price uncertainty as the latter warrant a similar but separate analysis.

Method

Farm system modelled

The model, with 2 sub-frameworks, was calibrated to represent a typical farm in the medium rainfall zone of the Great Southern region of Western Australia. The Great Southern region was selected for two reasons. First, the region has been modelled previously for a variety of analyses (Young, 1995, Poole et al., 2002, Young et al., 2011, Trompf et al., 2014) and thus the farm data required is more readily available. Second, the Great Southern region contains 26% of Western Australia’s sheep flock (ABARES, 2016), so the selection of this region increases the relevance of the study’s findings to farm businesses dependent on sheep production in Western Australia.

The Great Southern region in Western Australia is characterised by a hot dry summer and autumn, with a winter and spring growing season of 400–650 mm rainfall. Farms are typically a mix of cropping and livestock enterprises. Furthermore, as discussed in the weather-years sub section
below, the timing of the start of the growing season, also known as the ‘break of season’, and the quantity of spring rainfall are key management indicators for farmers in the region.

Through discussions with local farm consultants the model was calibrated to represent current farm management technology regarding machinery complement, herbicides and fertilisers used. Tasks contracted and crop and livestock options considered are all consistent with those used currently by farmers in the modelled region (Tim Trezise pers. comm., Ed Rigall pers. comm.).

The model represents a typical 2130 ha farm that includes three land management units to reflect soil heterogeneity in the region. The calibration of crop and pasture inputs was completed through a combination of simulation modelling and expert consultation. The growth rate of the pastures and yield of crops in each rotation were generated using AusFarm simulation modelling (Moore et al., 2007), with the output for each individual year simulated and then allocated to a weather-year category. The simulation model output grouped by weather-year categories was reviewed by a local agronomist who applied broad brush scaling to align the yields with farmer practice. Climate data was sourced from the Kojonup weather station (BOM station 10582) for the period 1970 to 2020. Soil data representing the land management units was sourced from the APSOIL database (Dalgliesh et al., 2012b).

Model overview
Analyses in this study are derived from applying the model Australian Farm Optimisation (AFO). A brief summary of the model is provided below. For a more thorough description see the model’s documentation: https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html. In summary, AFO is a Python-based, whole-farm MP model that supersedes the popular farming system model known as MIDAS (Model of an Integrated Dryland Agricultural system) (Kingwell and Pannell, 1987, Pannell, 1996, Kopke et al., 2008, Bathgate et al., 2009, Kingwell, 2011, Young et al., 2011, Thamo et al., 2013, Young et al., 2020). AFO leverages a powerful algebraic modelling add-on package called Pyomo (Hart et al., 2011) and IBM’s CPLEX solver to efficiently build and solve the farming system model. The model represents the economic and biological detail of a farming system and includes modules for rotations, crops, pastures, sheep, crop residues, supplementary feeding, machinery, labour and finance. Furthermore, it includes land heterogeneity by considering enterprise rotations on a limited range of land management units.

A key aspect of AFO that makes it suitable for this analysis is its flexible stochastic representation. In AFO the user can specify the number of years to include in the weather-year sequence. Variability or uncertainty is represented using the modelling approach of stochastic programming with recourse (Cocks, 1968, Rae, 1971, Crean et al., 2013, Kim et al., 2018). Stochastic programming is a
formulation of a decision tree (e.g. Figure 2, Figure 3 and Figure 1) consistent with state-contingent analysis (Adamson et al., 2007, Chambers and Quiggin, 2000, Mallawaarachchi et al., 2017). It requires the explicit specification of management choices and their possible consequences. The nodes or event forks are usually represented by a relatively small number of discrete outcomes. The inclusion of uncertainty allows the representation of tactical decisions as the year unfolds, which has been noted as an important aspect of farm management (Pannell et al., 2000, McCown et al., 2006). Furthermore, through the use of an expected utility function, AFO has the capacity to represent a farmer’s risk attitude in response to uncertainty or variability. However, in this study we assume a risk neutral attitude and the two different AFO frameworks used are:

(vi) A four-stage single-sequence stochastic programming with recourse framework (e.g. Kingwell et al., 1991). This framework, known as 4-SPR, represents the farm system with multiple discrete states where each state represents a different weather-year that can have separate inputs to reflect different prices and weather conditions. All states begin from a common point determined by the weighted average of the end of all the weather-years. These states separate at various nodes during the production year to unveil the particular nature of that weather-year. Once a weather-year has been identified, the impact of preceding and subsequent decisions can be differentiated based on the known information about that given weather-year. For example, one node is the start of the growing season or ‘break of season’. If that start is what is known colloquially as an ‘early break’, then after that starting point those types of weather-years can be managed differently to weather-years where the break occurs later. For example, in an early break it may be optimal to crop more area and run a higher stocking rate and vice-versa for a late break, although these decisions typically are made after the break of season is known. In reality, at the break of a season the subsequent conditions are uncertain (e.g. 30% chance of a poor spring and a 70% chance of a good spring). Thus, the decisions made at the break of season must factor in future uncertainty about the spring conditions. 4-SPR examines each possible outcome and its probability in determining the optimal decisions. These decisions are a suite of tactical adjustments made at each node that complement or adjust an overarching farm management strategy. The AFO model that canvasses the four-stage single-sequence stochastic programming with recourse (i.e. the 4-SPR version of AFO) includes 476,113 variables and 237,956 constraints.

(vii) An eight-stage multi-sequence stochastic programming with recourse framework (known as 8-SPR) (Xie and Huang, 2018). 8-SPR is similar to 4-SPR with the difference being that the discrete states represent a sequence of weather-years in equilibrium rather than a single
year in equilibrium. Optimisation of management within the sequence of weather-years fully accounts for the temporal effects of management change between years. In AFO, the production data in the 8-SPR is the same as the 4-SPR for the individual weather-years. The difference is that the 8-SPR framework more accurately represents carryover management implications from the previous year. For example, if stock were sold in the previous year the current year would start with a destocked position. This version of the AFO model includes 4,571,881 variables and 2,140,700 constraints.

Figure 4: An example of a decision tree associated with a weather-year classification. The parallelograms are nodes that identify the type of weather-year and the diamonds are subsequent decisions. Note, the nodes reflect the Great Southern version of AFO, however, the decisions are not limited to what is depicted.

The 4-SPR model represents variations between years and tactical management with each year starting with the weighted average end point of all years causing the impacts of consecutive years to
not be captured (e.g. late break following a poor spring). However, the 8-SPR model is more realistic because it is an enlarged sequential version of 4-SPR, meaning that variation in management or production in the previous year is reflected in the starting position of the current year. Note, in order to minimise misrepresentation associated with the starting weighted average, the start of the weather-years is defined as the earliest season break.

Tactical decisions in the 4-SPR and 8-SPR frameworks

There are many tactical or adjustment options represented in AFO that reflect a farmer’s reality. The tactics are similar to, but a greater expansion of those represented by Kingwell et al. (1992) and revolve around land use area adjustment, land use inputs, whether a crop is harvested or grazed as a standing crop, intensity of machinery use, labour utilisation, seasonal sheep liveweight patterns, tactical sale of sheep, grazing management of pasture and stubble, and supplementary feeding. The same tactical adjustments are made to all weather-years that are indistinguishable from one another at the time a tactical decision is implemented. Such weather-years are clustered at that decision point, as the node that later differentiates these weather-years remains in the future. By illustration, tactical adjustments selected at the early season break node have to be the same for all weather-years that have an early break, because at the time of making the break of season tactical decision the occurrence of follow-up rain and the spring conditions are unknown. Typical tactical adjustments include:

- **Rotation phase** - the area of each land use can be adjusted depending on the date of season break or other early indicators such as residual soil moisture from summer rainfall. Choice of rotation phase can also be delayed at the break of season, for example waiting to ensure it is not a false break. During this period of delay, pasture will germinate on these paddocks and is able to be grazed (the level of germination is dependent on the rotation history of the paddock).

- **Land use inputs** – in favourable weather-years additional chemicals and fertiliser can be applied to maximise yields and vice-versa in poor weather-years. Note, in this analysis the input level for each land use on each land management unit in each weather-year is optimised by the user externally to the model, reliant on expert agronomist advice for the study region. The optimisation accounted for the clustering of the weather-years.

- **Fodder crops** - in adverse weather-years where either livestock feed is limiting or crops are frosted or are not worth harvesting, saleable crops can be turned into fodder. That is, instead of harvesting a crop it is grazed by livestock as summer feed.
- Bale crops - crops planted with the expectation of being harvested for grain can be baled as hay. This may occur in adverse weather-years where either livestock feed is limiting or crops are frosted or are not worth harvesting.
- Labour supply - permanent and manager labour is fixed (i.e. must be the same for all weather-years). However, casual labour can be optimised for each weather-year as it unfolds.
- Machinery contracting - If the timeliness of an activity is an issue, contract services can be selected to improve the work rate. This could be valuable in a late break weather-year to ensure the crops get the maximum possible growing season. Note, the assumption that contracting services are available can be changed.
- Dry seeding - a useful tactic to improve timeliness of seeding is to sow into dry soil, before the opening rains, to ensure crops experience the maximum possible growing season.
- Confinement feeding - confinement feeding can be a good tactic to allow pasture deferment at the beginning of a growing season or to keep ground cover on paddocks in the late summer and autumn.
- Supplement feeding – in-paddock supplement feeding can be used as a tactic to help finish lambs for sale, ensure ewes reach target conditions for reproduction or to help meet energy requirements during weather-years with poor pasture growth.
- Changing liveweight - altering livestock liveweight targets can be used as a tactic to handle varying feed availability due to seasonal variation.
- Not mating ewes - if the feed supply is sufficiently poor prior to joining then there is the option of not mating ewes.
- Selling scanned dry ewes or other ewes at scanning – sale of dry sheep can be a useful tactic if the year unfolds unfavourably.
- Retain dry ewes - if the usual strategy is to sell dry ewes, and the weather-year is favourable a tactical adjustment can be to retain the dry ewes until shearing, thereby generating wool income and allowing a further decision about retaining them for mating the following year.
- Selling at other times – the ewes and lambs’ sale time can be adjusted, with the value received depending on the liveweight and condition of the animals at sale. In this analysis there were 10 selling opportunities throughout the year for ewes and eight sale opportunities for lambs.

Some aspects of the farm system are represented more realistically in the 8-SPR framework, due to its explicit representation of weather-year sequences rather than assuming each weather-year follows an expected season (as in the 4-SPR framework). These additional aspects include:
Livestock numbers in the year following a destocking event. A valid tactic in a poor production year is to destock. This is represented in the 4-SPR framework as a single occurrence of each weather-year, with the starting stock numbers for the following year being the weighted average of the ending positions of all weather-years. However, if the destocking event involves selling more than one age group of non-reproducing animals or selling reproducing animals prior to them giving birth, then for farmers whose restocking policy is to retain sheep (rather than buy in), the 4-SPR assumptions do not reflect reality. In practice the final numbers will be less than the starting numbers and hence the following year will start understocked. The 8-SPR framework does represent that if destocking occurs in a current year, then the following year begins with lower stock numbers.

Requirement for working capital. In the 8-SPR framework the requirement for working capital varies, based on the closing cashflow position of the previous weather-year. So, years following a poor year may be more constrained by availability of working capital.

Feed carried between years. In the 8-SPR framework the quantity and quality of feed (dry pasture and crop residues or green perennial pasture) carried over will reflect the growing conditions and grazing strategy in the previous spring, summer and autumn.

Land use sequence. For example, if a previous year was a poor production year, and less canola was grown, then there is more scope to increase the area of canola if the current year is seemingly unfolding to be a favourable production year for canola. This is related to the constraint that canola cannot be grown in consecutive years due to increased risk of disease.

Starting liveweight of each animal class. The closing liveweight of animals depends on the growing conditions and grazing strategy in the previous spring, summer and autumn, which affects animal sale values in the following year and in turn may affect subsequent destocking decisions. In the 8-SPR model the impact of the previous year is fully represented in a destocking decision. By illustration, if a poor year follows a good year so that livestock values are higher, compared with a poor year following a poor year in which livestock values will be lower, the incentive to destock changes.

Weather-years

Weather conditions influence crop and pasture growth (e.g. McCown, 1973, Ritchie and Nesmith, 1991). However, modelling the intricacies of weather events leads researchers to experience the “curse of dimensionality” where myriads of sequences of different weather events are possible (Burt, 1982). To lessen dimensionality problems associated with representing weather events and
their effect on pasture and crop growth, discrete weather states were defined in AFO based on their potential to affect farm management. Following a process similar to Kingwell et al. (1991), the classification of weather-years arose, first, from discussions with farmers to identify which features of weather-years most influenced their main farm management decisions; and second, from detailed examinations of the meteorological and farm production characteristics of actual seasons from 1970 to 2020, using a detailed farm simulation model, APSIM (Holzworth et al., 2018). Of main importance to all farmers and advisers were rainfall events. This emphasis placed by farmers on rainfall events, rather than temperature or wind events, was not surprising because in Western Australia’s rain-fed farming systems rainfall is often the main limiting factor for crop and pasture yields (Pratley and Cornish, 1985, Anderson et al., 1992, Stephens et al., 1994). The particular rainfall events that explain the majority of the production variation between years in the simulation modelling are: first, autumn rainfall events that affect pasture germination and crop sowing date; and second, in the case of an early break, whether there are follow up rains or if a false break occurs; and finally, the quantity of spring rainfall. In the 4-SPR and 8-SPR frameworks variance in weather-years was approximated by eight discrete states of nature (see Table 6). The effects of each of these states of nature on major input-output relationships of enterprise options are represented in the model.

Table 6: AFO weather-years

<table>
<thead>
<tr>
<th>Code for weather-year</th>
<th>Definition of each weather-year</th>
<th>Probability of occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>z0</td>
<td>Early break(^1) with follow up rains and a good spring(^2).</td>
<td>24%</td>
</tr>
<tr>
<td>z1</td>
<td>Early break with follow up rains and a poor spring.</td>
<td>20%</td>
</tr>
<tr>
<td>z2</td>
<td>Early break that turns out to be a false break(^2) but is followed up with a good spring.</td>
<td>8%</td>
</tr>
<tr>
<td>z3</td>
<td>Early break that turns out to be a false break and is followed by a poor spring.</td>
<td>4%</td>
</tr>
<tr>
<td>z4</td>
<td>Medium break with follow up rains and a good spring.</td>
<td>14%</td>
</tr>
<tr>
<td>z5</td>
<td>Medium break with follow up rains and a poor spring.</td>
<td>16%</td>
</tr>
<tr>
<td>z6</td>
<td>Late break with follow up rains and a good spring.</td>
<td>4%</td>
</tr>
<tr>
<td>z7</td>
<td>Late break with follow up rains and a poor spring.</td>
<td>10%</td>
</tr>
</tbody>
</table>

\(^1\) Early break (i.e. start of the growing season): before the 5\(^{th}\) May; Medium break: between the 5\(^{th}\) May and 25\(^{th}\) May; Late break: after the 25\(^{th}\) May.

\(^2\) False break: pasture feed on offer reaches 500 kg/ha followed by 3 weeks of no growth.
Good spring: above the median (86mm) rainfall for September and October; Poor spring: below the median rainfall.

Production assumptions

The production inputs were generated using the same process, data and assumptions for each framework. Importantly, we assume that production in any weather-year is not affected by the previous weather-year, therefore 4-SPR and 8-SPR use the same inputs. This assumption is unlikely to be valid in regions where stored soil moisture, especially as affected by summer rain, forms a key ingredient to production outcomes. In the Mediterranean-type climate of the study region the bulk of rainfall occurs from April to October and the hot dry summers limit any carryover of soil moisture and crop pests and diseases. Moreover, unlike the situation in eastern Australia where prolonged dry or wet periods can persist causing production interdependencies across years, repetitious drought or prolonged highly favourable years of production are rare in Western Australia’s agricultural region, making the assumption of independence of weather-years more reasonable.

Weather-year prices

Analysis of commodity prices in different weather-years showed that the prices of agricultural products did not significantly correlate with the weather-years experienced in the study region. This is likely to be due to multiple reasons including the region’s outputs mostly being sold internationally and so the nature of any weather-year experienced in the region will unlikely affect the international prices received for the region’s farm products. In previous decades, such as the 1990s when the state’s sheep population exceeded 30 million head (ABARES, 2010) it was more likely, for example, that a drought year would cause a dramatic lowering of sheep prices due to de-stocking decisions by farmers or an increase in fodder prices as demand for supplementary feed increased. However, the state’s sheep population is now about 13 million head, seasonal conditions have far less impact on fodder and saleyard prices (ABARES, 2022). Accordingly, in our analyses, prices were deemed to be unaffected by the weather-year conditions.

Results

The 4-SPR and 8-SPR models generate similar expected values with the difference in the expected annual profit between the 8-SPR model and the 4-SPR model only being $3,276 (0.4%). This difference is due to small changes in the average land use, stocking rate and supplementary feeding (Table 4). However, the 8-SPR model generates a greater range in profit and other farm management indicators across the weather-years compared to the 4-SPR model (see Table 4 and Table 8).
The range in profit across weather-years in the 8-SPR model is $1,134,524 and in the 4-SPR model the range is less at $1,077,700. Yet in each model the expected profit is similar at $796,191 and $799,468 respectively. This range in profit recorded in the 8-SPR and 4-SPR models reflects the magnitude of variation in crop and pasture production between weather-years and the associated impacts of reliance on short-term tactical management to mitigate or exploit the effects of weather-year variation. In the 8-SPR model, for example, a 5.2 DSE/ha range in stocking rate is observed across the weather-years, along with a 1,108 tonne range in supplements fed, a 15% range in the proportion of the farm area that is allocated to pasture and, a 43% and 41% range in the proportion of the crop area allocated to canola and cereal, respectively (Table 4).

In the 8-SPR framework, removing tactical adjustments associated with changes in land use, stocking rate, stock sale and stock liveweight targets in response to the end-state of the previous year reduces expected farm profit by $110,247, equivalent to a 14% reduction in expected profit. Removing sequential tactics forces the model to optimise decisions for a given weather-year irrespective of the nature of its preceding weather-year.
Table 7: Key descriptors of the optimal farm plans generated by the 4-SPR and 8-SPR frameworks for a typical Great Southern farm.

<table>
<thead>
<tr>
<th></th>
<th>4-SPR</th>
<th>8-SPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm profit ($/year)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>799,468</td>
<td>796,191</td>
</tr>
<tr>
<td>Max</td>
<td>1,206,763</td>
<td>1,235,051</td>
</tr>
<tr>
<td>Min</td>
<td>129,063</td>
<td>100,527</td>
</tr>
<tr>
<td>Stocking rate (DSE/ha)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>15.9</td>
<td>16.1</td>
</tr>
<tr>
<td>Max</td>
<td>17.2</td>
<td>17.8</td>
</tr>
<tr>
<td>Min</td>
<td>14.0</td>
<td>12.6</td>
</tr>
<tr>
<td>Supplement fed (t)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>707</td>
<td>705</td>
</tr>
<tr>
<td>Max</td>
<td>1,470</td>
<td>1,500</td>
</tr>
<tr>
<td>Min</td>
<td>429</td>
<td>393</td>
</tr>
<tr>
<td>Pasture (% of farm area)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>39</td>
<td>38</td>
</tr>
<tr>
<td>Max</td>
<td>43</td>
<td>48</td>
</tr>
<tr>
<td>Min</td>
<td>36</td>
<td>33</td>
</tr>
<tr>
<td>Cereal (% of farm area)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>37</td>
<td>38</td>
</tr>
<tr>
<td>Max</td>
<td>57</td>
<td>60</td>
</tr>
<tr>
<td>Min</td>
<td>28</td>
<td>20</td>
</tr>
<tr>
<td>Canola (% of farm area)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>24</td>
<td>24</td>
</tr>
<tr>
<td>Max</td>
<td>36</td>
<td>45</td>
</tr>
<tr>
<td>Min</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Flock structure</td>
<td>Ewe dominated flock turning off ~70% of lambs at 6 months of age to the prime lamb market and the remainder at ~12 months of age.</td>
<td>Ewe dominated flock turning off ~70% of lambs at 6 months of age to the prime lamb market and the remainder at ~12 months of age.</td>
</tr>
</tbody>
</table>

*a 'Expected' is the weighted average of all weather-years, b 'Max' is the maximum across the weather-years, c 'Min' is the minimum across the weather-years.
Table 8: Optimal proportion of the crop area sown to canola (%) in the 4-SPR & 8-SPR models. Note, current weather-years that differentiate based on spring condition have the same land use allocation because land use is selected soon after the break of the season before the spring conditions are known. See Table 1 for descriptions of each weather-year code (e.g. z0).

<table>
<thead>
<tr>
<th>Previous weather-year</th>
<th>Current weather-year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>z0 &amp; z1</td>
</tr>
<tr>
<td>Average - 4-SPR</td>
<td>36%</td>
</tr>
<tr>
<td>Average - 8-SPR</td>
<td>34%</td>
</tr>
<tr>
<td>z0</td>
<td>34%</td>
</tr>
<tr>
<td>z1</td>
<td>35%</td>
</tr>
<tr>
<td>z2</td>
<td>31%</td>
</tr>
<tr>
<td>z3</td>
<td>32%</td>
</tr>
<tr>
<td>z4</td>
<td>34%</td>
</tr>
<tr>
<td>z5</td>
<td>35%</td>
</tr>
<tr>
<td>z6</td>
<td>45%</td>
</tr>
<tr>
<td>z7</td>
<td>45%</td>
</tr>
</tbody>
</table>

Table 9: Key descriptors of optimal farm plans for a 8-SPR model without tactical adjustments based on the end-state of the previous year (a given weather-year must be managed the same in all sequences).

<table>
<thead>
<tr>
<th>8-SPR</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm profit ($/year)</td>
<td></td>
</tr>
<tr>
<td>Expected</td>
<td>685,944</td>
</tr>
<tr>
<td>Max</td>
<td>1,135,590</td>
</tr>
<tr>
<td>Min</td>
<td>26,524</td>
</tr>
</tbody>
</table>

Note, the tactics constrained were rotation, stocking rate, liveweight targets and dates of sheep sales. The models still optimised grazing management tactics including use of pasture, supplements and crop residues.

Discussion

The results from this study add to the limited MP farm modelling literature that examines the impact of a sequence of years on optimal farm management. In this study the 8-SPR framework generates an expected profitability and expected management similar to the 4-SPR framework (Table 4). However, importantly, it reveals how the sequence of weather-years generates a larger range in annual profits as well as affecting several other aspects of farm management. A previous year’s weather and farm management directly affect the initial conditions for the current year and thereby affect subsequent farm management decisions. In extreme sequences (e.g. consecutive poor years or consecutive good years) the allocation of the farm’s resources to sheep or crop production shifts...
further from the expected position due to the weather-year effects. For example, if ewes are retained in good years, the second consecutive good year can have an even greater number of ewes resulting in additional wool and meat income. Overall, this does not affect the expected profit because although the extremes differ from the expected, the probability of these extreme sequences is small and their directional impacts on profit are opposite.

The wider range in features of optimal management, especially for the 8-SPR model, is important to note when using modelling results as the basis of advice to farmers about optimal management strategies. For example, the optimal proportion of the crop area to plant to canola in a late break year (z6 & z7) varies from a low of 2%, if following a medium break with a good spring (z4), but up to 11% if following a late break with a failed spring (z7) (Table 8). This illustrates that compared to single-year’s analysis, multi-year stochastic programming generates a similar estimated profit but different optimal management of the mixed enterprise farming system, specifically where livestock make a significant contribution to farm income. In short, the nature of optimal farm management, although delivering similar expected profits, is different between the two frameworks.

The 8-SPR model is the more detailed and realistic framework because it represents variation in production associated with a current weather-year as well as the variation in the starting position of the farm associated with the management in the preceding weather-year. An example of the tactical adjustment of the area of canola planted in response to the previous weather-year is provided in Table 8. Not reported in this paper, in the interests of page limitations, are a myriad of tactical sheep management decisions that allow the profit downside of certain weather-year sequences to be avoided and the profit upside of other weather-year sequences to be exploited. However, accurately including these tactical management options into farm modelling, requires data, knowledge and a degree of modelling skill that is rarely available. Additionally, representing weather-year variation more realistically and the myriad of feasible farm management responses to that variation comes at the modelling cost of increased model size and complexity. With just the standard detail of modelling, the 4-SPR model takes 17 minutes to solve. However, the 8-SPR model with a 2-year sequence takes 6 hours and, not reported here, the solution results for a 3-year sequence takes 15 days.

Interpreting the modelling results, testing and debugging the model for errors are also tasks that become more time-consuming as model detail is enhanced. However, in our experience, most time is spent on the initial construction of the base model. The additional time to construct the model’s stochastic components regarding weather-year variation and relevant management tactics is
substantial but not excessive and is made more efficient by the flexible nature of modern computer programming.

Previous research has shown that tactical management in response to unfolding weather conditions increases profitability (Kingwell et al., 1992, Kingwell et al., 1993, Pannell et al., 2000). However, this previous research is now two to three decades old and was undertaken using a single year sequence stochastic modelling that neglected the effect of the preceding year’s outcome on the implementation of tactics. By contrast, the results from this study quantify the nature and importance of optimal tactical decisions in response to the outcome of the previous year. Tactical decision-making in response to the end-state of the preceding weather-year in this current study increased expected profit by 16% (Table 4 vs Table 5). These results show that tactical management in response to the unfolding conditions of a current year is important but is only part of optimal farm management. Also important is the response to the preceding weather-year conditions.

In practice, optimal farm management is increasingly complex (Kingwell, 2011), although Malcolm (2000) has noted that: ‘A glance through history suggests that in the most important ways, the fundamental elements of managing a farm has altered little.’ (p. 40). Even earlier, Dillon (1980) noted that: ‘Farm management is the process by which resources and situations are manipulated by farm managers in trying, with less than full information, to achieve their goals’ (p. 257). Current success in farming is not only about getting the big strategic decisions right in an uncertain and volatile environment with ever-changing technologies (Kingwell et al., 2020), but as this study shows, it is also about getting the detail right as well.

Previous researchers in this field have identified the constant need to improve farm decision-making (Malcolm, 2000, Schultz, 1939). Schultz (1939) highlighted that two interrelated farm management decisions needed to be made: (i) the amount of needed adjustment, and (ii) the method of adjustment. More recently, other researchers have identified the benefits from farmers undertaking small improvements to their practices; the ‘one percenters’ (Kingwell, 2019, Kirk and Hall, 2015). In attempting to improve farm decision making modellers often face the challenge of determining how much detail and resulting complexity to include in their modelling approach (Pannell, 2006).

Complexity in knowledge discovery is an issue far great than farm modelling and has received significant literature attention (e.g. Domingos, 1999). However, in many farm modelling cases it can be difficult to know the implications of model simplifications without first building a non-simplified model. Thus, in this current study, we explore the impact of excluding weather-year sequence in farm optimisation modelling by applying one modelling framework that includes weather-year sequence and one that excludes weather-year sequence. Our results show that expected
profitability and expected management is similar between frameworks however, if a farmer manages their farm without consideration of the prior years weather conditions profitability reduces by 16%. Thus, in some cases where exact on-farm management is of high importance the added detail of weather-year sequence may be warranted. However, in many cases (e.g. policy evaluation) the assumption that the current year is following an average year will likely be adequate.

Conclusion

In this paper we have compared and contrasted the profit and optimal farm management generated from two different MP frameworks that examine a mixed enterprise farming system in a sub-region of Western Australia. These two frameworks were applied using a whole-farm optimisation model called AFO. The principal findings are: first, that multi-year stochastic programming generates a similar expected profit and expected management as single year stochastic programming. However, optimal farm management in a given year is affected by the outcome of the previous year; and second, tactical decisions associated with the unfolding conditions of a current weather-year are not easily generalisable to a multi-year framework. The implication is that tactical decisions relevant to the unfolding conditions of a current weather-year are rarely reliable and sufficient indicators of what is appropriate in a sequence of weather-years. The end-state of a preceding weather-year significantly alters the nature of subsequently optimal tactical decisions.

Although computational capacity and data availability will likely continue to increase exponentially, in our view the 8-SPR framework is currently too complex for widespread use. By contrast, the 4-SPR framework is quicker and easier to apply, yet its inability to accurately capture important aspects of multi-year effects will constrain its applicability and credibility among potential farmer end users. Overcoming this nexus between ease of applicability and accuracy of impact estimation will be the subject of ongoing research and development.
Chapter 6: Identifying high value tactical livestock decisions on a mixed enterprise farm in a variable environment

Introduction

Australia is renowned for its climate variation including years with drought and years with floods, which result in significant production and profit variability (Trompf et al., 2014, Laurie et al., 2019, Feng et al., 2022). This variation can be very challenging for farmers (Heberger, 2011); particularly for livestock farmers who must adhere to animal welfare standards. In mixed farming systems livestock and associated pasture production complement cropping activities by utilising crop residues, providing disease and pest breaks, providing weed management options and improving labour and machinery use efficiency during the year. As such livestock and pasture production are key components of many farm businesses and farming systems in Australia.

In Western Australia, for example, livestock revenues comprise 21% of average farm total income (Planfarm/BankWest, 2019). Which is likely to be a greater proportion of the total profit as the livestock enterprise typically incurs lower costs than cropping (Planfarm/BankWest, 2019). Farmers can adjust their flock structure to focus on either wool or meat production or both, providing market diversification (Young et al., 2020). Moreover, livestock income is often received at different times to cropping income providing operating cash flow throughout the year. Further benefits of sheep in the farming system included the usage of nitrogen-fixing pastures and salt-affected areas that can reduce costs and environmental damage, while also providing economic opportunities (O’Connell et al., 2006). Year-round employment is possible due to the continuous care required for sheep, which is especially important in rural areas where job opportunities may be limited. Machinery usage can also be improved by utilising it to sow and manipulate pastures during the year. Consumption of crop residues and spilt or split grain occurring during the harvesting process, converting waste into profit. However, although the benefits of mixed livestock and cropping systems are evident sheep flock numbers have been diminishing at a national level.

The climate variation previously mentioned is a constant challenge to managing mixed enterprise farming systems in Australia; with the incidence of drought especially complicating sheep management when feed and water supplies become increasingly scarce and expensive. To handle climate variation, farmers can alter their “big-picture” strategic management to set up a more versatile and diversified enterprise mix of their farm business (Azam-Ali, 2007, Kandulu et al., 2012). However, Kandulu et al. (2012) suggest that in many locations a sole focus on diversification does not wholly mitigate the financial effects of climate variation. An alternative management method,
applicable by farmers to manage their external variations, is to implement short term tactical adjustments in response to unfolding conditions (Anderson et al., 2020).

Tactical management is most valuable within systems where farmers have a wide portfolio of tactics for use in response to an external change (Cowan et al., 2013). This is the case in mixed farming systems where there are many livestock tactics that can be implemented throughout the year in response to unfolding weather conditions including sale or purchase of stock, adjustment of stock liveweight targets, adjustment of grazing management, adjustment of pasture area and pasture manipulation (Young et al., 2022). In mixed crop and livestock businesses, farmers can adjust enterprise allocation, their interactions and relevant tactics to better suit unfolding climate conditions. The efficacy and value of this suite of adjustment or tactics is commented upon by Pannell et al. (2000) who discuss the inclusion of risk attitudes and production and price risk in farm analyses. They conclude that the most important aspect of risk is a farmer’s short-term tactical responses to variation in weather and prices. Furthermore, as outlined in the previous chapter of this thesis, tactical management generates significant opportunities to boost farm profit and/or avoid losses. Findings in that chapter are that optimal tactical management can increase profitability by at least 14%. However, the large array possible tactics within mixed enterprise farm systems can significantly complicate management, especially when combined with the constantly changing and evolving nature of farming systems. It is challenging for farmers to identify the optimal suite of tactics to apply in different circumstances during a production year or suite of years.

Despite the likely benefit of research that focuses on identifying appropriate tactical livestock management, previous research on mixed enterprise farming systems in Western Australia has mostly focused on tactical management for crops. Topics include the tactics regarding time of sowing, land use and rotation choice and nitrogen application (Kingwell et al., 1993, Abrecht and Robinson, 1996, Chen et al., 2009, Doole and Weetman, 2009). Furthermore, much of this work was conducted over a decade ago and farming systems and technologies have evolved significantly since then. Research on livestock management has either assumed that every year is the same (Kopke et al., 2008, Bathgate et al., 2009, Young et al., 2010, Young et al., 2020, Young et al., 2022) or when year-to-year variation has been included, management has not been optimised and frequently the tactical management options are over simplified (McGrath et al., 2016, Godfrey et al., 2019). For example, supplements are always fed to sheep once they reach a threshold condition score rather than considering the marginal costs and benefits of the supplementary feed. The paucity of Australian studies that examine, in a mixed enterprise whole farm setting, the economic ramifications of tactical management of livestock is a gap in our knowledge.
Given Australia’s variable climate (Feng et al., 2022), the economic importance of livestock in Western Australian farm businesses (Planfarm/BankWest, 2019), the profitability of tactical crop management (Kingwell et al., 1993), and the multitude of tactical livestock options (Young et al., 2022), we hypothesise that the optimal implementation of livestock tactics in modern mixed enterprise farming systems will provide worthwhile increases in farm profit.

Knowing the value of tactics allows farmers to prioritise their management actions. For example, if it is optimal to sell dry ewes in a drought year but the added profit is relatively small then a time-pressed farmer can confidently disregard this tactic without major impacts on their business profitability. However, if the tactic results in large changes in profit then this would indicate that it is highly worthwhile for a farmer to learn and execute this selling tactic.

In this paper, we apply a new whole farm optimisation model that firstly represents year-to-year variation and secondly includes an extensive array of tactical management options tailored to that variation. The model is used to identify and quantify optimal tactical livestock management for different weather-years.

**Methods**

**Model description**

The whole farm model called **Australian Farm Optimisation Model (AFO)** is applied in this study. AFO is a whole farm linear programming model that supersedes the popular MIDAS model (Kingwell and Pannell, 1987, Pannell, 1996, Kopke et al., 2008, Bathgate et al., 2009, Kingwell, 2011, Young et al., 2011, Thamo et al., 2013, Young et al., 2020). A brief summary of the model is provided below. For a more thorough description see the model’s documentation: [https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html](https://australian-farm-optimising-model.readthedocs.io/en/latest/index.html).

*Figure 5: Visual representation of AFO*
The model represents the economic and biological detail of a farming system, including modules for rotations, crops, pastures, sheep, crop residues, supplementary feeding, machinery, labour and finance. Furthermore, it includes land heterogeneity by considering enterprise rotations on a range of soil classes/land management units (LMU). AFO was selected as the appropriate tool to evaluate optimal tactical livestock management in a mixed enterprise, broad acre farming system for several reasons. First, it includes year-to-year climate variation and a large relevant range of tactical management options including; adjusting the number of stock, altering rotations, altering stock liveweights, selling livestock, altering supplementary feeding, manipulating grazing timing and intensity, deferring pastures, and crop grazing. Secondly AFO leverages powerful algorithms to efficiently identify the optimal management for a given farm system. Finally, AFO also has detailed feed budgeting modules that allow the optimum utilisation of feed sources across the whole farm to be identified.

In AFO, the supply side of the feed budget comprises green and dry pasture on arable land areas, green and dry pasture on non-arable land areas, pasture on crop paddocks prior to destocking for seeding, early season crop grazing, standing crop fodder, crop residues remaining after harvest and a range of supplementary feeds.

The biology and logistics of pasture production and utilisation represented in AFO are:

- Pasture growth rate (PGR) is dependent on pasture leaf area, which is quantified by the level of feed on offer (FOO; kg of DM/ha). Additionally, PGR for each pasture type varies with the life cycle phase of the pasture specie, soil moisture, sunlight and level of growth modifier applied. All are quantified by their land management unit (LMU), time of year and weather-year.
- The available FOO depends on grazing intensity.
- The mobilisation of below-ground reserves (germination) of annual pastures at the break of season is dependent on the seed bank. The seed bank is controlled by the rotation in which the pasture is grown and varies with the LMU.
- The mobilisation of below-ground reserves of perennial pastures at the break of season can also be adjusted by rotation. However, perennials usually are not grown in rotation with crops.
- The intake of animals grazing pasture depends on FOO and diet dry matter digestibility (DMD).
- The digestibility of the diet selected by animals grazing green pasture depends on the sward digestibility and the animal’s capacity for selective grazing. Sward digestibility varies
depending on the pasture species, the time of year and the LMU. Selectivity depends on FOO and grazing intensity.

- Dry pasture that is not consumed is deferred to later in the year, with a reduction in both quality and quantity. Livestock can select a higher quality diet when first grazing the dry pasture but quality reduces with extra grazing.
- Livestock trample both green and dry pasture while foraging.
- The risk of resource degradation increases when ground cover is lower so there is a minimum limit to ground cover during both the green and dry phases of the year.

The decision variables optimised in AFO, and that represent the above biology are the:

- rotation phases in which pasture can be grown on each LMU.
- FOO profile during the year that is represented by a discrete range of FOO levels at the start of each feed period.
- grazing intensity and the variation during the year that is represented by a discrete range of the severity of defoliation in each feed period.
- level of growth modifiers (nitrogen or gibberellic acid) applied to the pasture.
- quantity of dry feed consumed from each of two dry feed quality groups in each feed period.

Pasture on non-arable areas is modelled as above with a few additions. First, pasture on non-arable area is represented as a continuous annual pasture. Second, pasture on non-arable areas of cropping paddocks is not available for grazing until after harvest and therefore it goes into the low-quality dry feed pool. Accordingly, pasture on non-arable areas of crop paddocks does not receive any farm inputs.

Pasture on crop paddocks before seeding is represented as a pre-specified quality and maximum quantity available each day on the area that is yet to be seeded, with the additional requirement that pasture must be destocked 10 days prior to seeding to allow time for an effective knockdown spray.

Crop grazing is an option that allows stock to graze green crop from June until August. Green crops have a higher energy content than green pasture and grow more erect allowing for easier grazing, meaning a lower crop FOO is required to meet the livestock needs. However, for every kilogram of crop biomass consumed yield is reduced by 150 grams per hectare, with a corresponding effect on stubble production.

At the end of the growing season AFO has the option of harvesting each crop, which leaves stubble for stock consumption, or crops can be left standing for fodder grazing. Stubble and fodder are
modelled in the same way, as follows: in general, sheep graze crop residues selectively, preferring
the higher quality components. Thus, they tend to eat grain first, followed by leaf and finally stem.
To allow the optimisation of the quantity of the stubble grazed, and to reflect selective grazing, the
total crop residues are divided into ten categories. The higher categories are better quality but
generally lower quantity. Consumption of a higher quality category allows the consumption of a
lower category (e.g. sheep cannot consume any of category B until some of category A has been
consumed).

The total mass of crop residues at first grazing (harvest for stubble and an inputted date for fodder)
is calculated as a product of the biomass, harvest index and proportion harvested. Over time if the
feed is not consumed it deteriorates in quality and quantity due to adverse effects of weather and
the impact of sheep trampling.

Supplementary feeding is the supply of additional feed to livestock, primarily grain and hay (which
are both represented in the model). Supplementary feeding is commonly used to help meet
production targets such as lamb growth rates prior to sale, or to fill the feed gap to allow higher
stocking rates during the summer and autumn months when pastures and crop residues are limiting.
Additionally, feeding supplements can be used as a tactic to allow pastures to be deferred early in
the growing season, which increases subsequent pasture growth rates. Grain and hay as
supplementary feeds can either be grown on farm or purchased from another farmer at a farm-gate
price (i.e. net price of a product after selling costs have been subtracted) plus the transaction and
transport costs.

The demand side of the feed budget comprises livestock nutritional needs. AFO generates
production parameters for livestock under a range of different conditions. These are represented as
different decision variables that allow the optimisation of a wide range of management decisions.
Each animal has an energy requirement and intake capacity that depends on liveweight/nutrition
targets, genetics, gender, physiological state and age.

A powerful and advanced feature of AFO is its ability to optimise livestock liveweight/nutrition
profiles. AFO does this by generating production parameters for animals following a range of
nutrition profiles (up to 2000 profiles for each class of sheep can be concurrently evaluated). The
range of nutrition levels are represented by profiles that are continuous for the entire year. At the
end of the nutrition cycle (year) the range of final liveweights are ‘condensed’ back to a range of
starting weights for the start of the next nutrition cycle. This capacity allows AFO to feed animals
differentially based on reproduction, sale goals and feed supply based on land use selection.
The feed requirement (as measured by metabolisable energy) of each animal is a minimum constraint in the AFO matrix and sufficient feed must be available for each animal that is part of the optimal solution. The feed selected in the optimal solution must also be of sufficient quality that the quantity required to meet the animal’s energy needs is within the intake capacity of that animal – which is represented as a maximum constraint on the volume of feed an animal can consume.

Cross subsidisation of volume is a problem that can occur in the feed budgets of linear programming models. Cross subsidisation occurs if animals with divergent quality requirements are constrained by single energy and volume constraints; the single constraint is termed a feed pool. For example, consider two animals, one losing 100 g/hd/d and one gaining 150 g/hd/d. The first animal can achieve its target on low quality feed whereas the second animal needs high quality feed. However, if both of these animals were constrained using a single feed pool, then the total energy requirement and total intake capacity is combined, such that feeding medium quality feed to both animals meets the constraints. This is likely to be the optimal solution because the cost of feed by quality is a convex function and therefore the cost-minimising solution is to provide an average quality to both classes of stock. However, this is not a technically feasible solution.

To reduce the possibility of cross-subsidisation of volume, while still limiting model size, the energy requirement and maximum volume constraints are applied in multiple nutritive value pools, each spanning a small range of nutritive value (where nutritive value = ME requirement / volume capacity). This is more efficient in reducing model size and complexity than having a feed pool for each animal class.

Importantly, based on the findings of in the previous chapter we are able to adopt the four-stage single-sequence stochastic program with recourse (4-SPR) model housed within AFO to examine the role and value of tactical livestock decisions on a mixed enterprise farm in a variable environment. As discussed in the previous chapter “4-SPR represents the farm system with multiple discrete states where each state represents a different weather-year that can have separate inputs to reflect different prices and weather conditions. All states begin from a common point that is determined by the weighted average of the end of all the weather-years, but then these weather-years separate at multiple nodes during the production year to unveil the particular nature of that weather-year. Once a weather-year has been identified, subsequent decisions can be differentiated based on the known information about that given weather-year.” The eight-stage multi-sequence stochastic program with recourse (8-SPR) also available in AFO was shown to yield similar expected results to the 4-SPR model but significantly increased execution and interpretation time (chapter 5). Thus, for this analysis, the 4-SPR model was selected as the optimal trade-off between time and accuracy.
However, it should be noted that the 4-SPR model does not accurately reflect how the outcome of the previous year affects tactical management in the current year. As such, optimal implementation of tactics on-farm may differ slightly from that reported in this paper, as a response to the outcome of the previous year. Refer to the previous chapter or to the AFO documentation for more information about the handling of weather variation in AFO.

Overview of the farm system
AFO was calibrated to represent a typical farm in the medium rainfall zone of the Great Southern region of Western Australia. The Great Southern region was selected for two reasons. First, the region has been modelled previously for a variety of analyses (Young, 1995, Poole et al., 2002, Young et al., 2011, Trompf et al., 2014) and thus the farm data required are more readily available. Second, the Great Southern region contains the largest breeding ewe population (5.6 million head) in Australia (Meat and Livestock Australia, 2022), so the selection of this main sheep production region helps ensure the study’s findings are likely to be relevant to many sheep producers.

Through formal discussions (human ethics approved ET000181) with local farm consultants the model was calibrated to represent current farm management technology including machinery complements, herbicides and fertilisers used and rates applied. Tasks contracted and crop and livestock options considered are all consistent with those used by farmers in the modelled region (Tim Trezise pers. comm., Ed Rigall pers. comm.).

The Great Southern region in Western Australia is characterised by winter-dominant rainfall (400–650 mm) and a 6-month growing season that supports a mix of cropping and livestock enterprises. Weather variance in the region was approximated by eight discrete states of nature (see Table 10). The model represents a typical 2130 ha farm that includes three land management units (LMU) (Table 11). The calibration of crop and pasture inputs was completed through a combination of simulation modelling and consultation with experts. The growth rate of the pastures and yield of crops in each rotation were generated using AusFarm, a simulation model (Moore et al., 2007) with the output for each individual year being simulated and then allocated to a relevant weather-year (Table 10). The simulation model outputs, grouped by weather-year categories, were reviewed by a local agronomist who applied broad brush scaling to align the yields with farmer practice. Climate data was sourced from the Kojonup weather station (BOM station 10582) over the period from 1970 to 2020. Soil data representing the land management units defined in Table 11 was sourced from existing data in the APSOIL database (Dalgliesh et al., 2012a). Other key features of the modelled farm are shown in Table 12, Table 13 and Table 14.

Table 10: Summary information for each weather-year represented in the Kojonup version of the AFO model.
<table>
<thead>
<tr>
<th>Code for weather-year</th>
<th>Definition of each weather-year</th>
<th>Probability of occurrence</th>
<th>Growing season rainfall</th>
<th>Crop yield scalar&lt;sup&gt;4&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>z1</td>
<td>Early break&lt;sup&gt;1&lt;/sup&gt; with follow up rains and a good spring&lt;sup&gt;3&lt;/sup&gt;.</td>
<td>24%</td>
<td>447</td>
<td>1.2</td>
</tr>
<tr>
<td>z2</td>
<td>Early break with follow up rains and a poor spring.</td>
<td>20%</td>
<td>346</td>
<td>1.0</td>
</tr>
<tr>
<td>z3</td>
<td>Early break that turns out to be a false break&lt;sup&gt;2&lt;/sup&gt; but is followed by a good spring.</td>
<td>8%</td>
<td>416</td>
<td>1.22</td>
</tr>
<tr>
<td>z4</td>
<td>Early break that turns out to be a false break and is followed by a poor spring.</td>
<td>4%</td>
<td>294</td>
<td>0.87</td>
</tr>
<tr>
<td>z5</td>
<td>Medium break with follow up rains and a good spring.</td>
<td>14%</td>
<td>448</td>
<td>1.05</td>
</tr>
<tr>
<td>z6</td>
<td>Medium break with follow up rains and a poor spring.</td>
<td>16%</td>
<td>392</td>
<td>0.83</td>
</tr>
<tr>
<td>z7</td>
<td>Late break with follow up rains and a good spring.</td>
<td>4%</td>
<td>477</td>
<td>0.95</td>
</tr>
<tr>
<td>z8</td>
<td>Late break with follow up rains and a poor spring.</td>
<td>10%</td>
<td>337</td>
<td>0.65</td>
</tr>
</tbody>
</table>

<sup>1</sup> Early break (i.e. start of the growing season): before the 5<sup>th</sup> May; Medium break: between the 5<sup>th</sup> May and 25<sup>th</sup> May; Late break: after the 25<sup>th</sup> May.

<sup>2</sup> False break: pasture feed on offer reaches 500 kg/ha followed by 3 weeks of no growth.

<sup>3</sup> Good spring: above the median (86 mm) rainfall for September and October; Poor spring: below the median rainfall.

<sup>4</sup> Yield scalar is the relationship between yield in the given weather-year and the average yield. This was calculated using the output of APSIM modelling using Kojonup climate and soil data from 1970 - 2019.

Table 11: LMU definitions for a typical farm in the Great Southern region of Western Australia.

<table>
<thead>
<tr>
<th>Soil class</th>
<th>Description</th>
<th>Arable %</th>
<th>Grazing area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep sands</td>
<td>Deep sands but not waterlogged.</td>
<td>100</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>Over mottled clay.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sandy gravels</td>
<td>Gravels and sandy gravels to 50 cm over clay or gravelly clay.</td>
<td>80</td>
<td>1230</td>
</tr>
<tr>
<td>Sandy loams</td>
<td>Sandy loam, loamy sand over clay rock outcropping in landscape.</td>
<td>80</td>
<td>750</td>
</tr>
</tbody>
</table>

Table 12: Key features of the modelled farm.
**Farm size (ha)** 2130
**Time of lambing** Spring lambing
**Pregnancy scanning management** Scanning for pregnancy status only
**Sheep liveweight** Nutrition profile is optimised by AFO
**Sheep genetics** Medium frame merino
  - Standard reference weight (kg) 55
  - Fibre diameter (µ) 20
**Canola yield (t/ha)**
  - Roundup-ready 2.6
  - Standard (non-GM) 2.2
**Wheat yield (t/ha)** 4.5
**Barley yield (t/ha)** 5.0
**Oat yield (t/ha)** 4.5
**Hay yield (t/ha)** 8.0
**Lupin yield (t/ha)** 2.5
**Fababean yield (t/ha)** 3.0

1 Reported yield is on LMU 4 (best-performing areas of the farm) in a canola–cereal or pulse-cereal rotation weighted across all weather-years.

**Table 13: Meat and wool prices in the analysis (before fees).**

<table>
<thead>
<tr>
<th></th>
<th>Prime Lamb</th>
<th>Store lamb</th>
<th>Export wether</th>
<th>Breeding ewe</th>
<th>Mutton ($/kg)</th>
<th>Wool ($/c/kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>($) /kg</td>
<td>6.98</td>
<td>6.24</td>
<td>112</td>
<td>127</td>
<td>4.87</td>
<td>1432</td>
</tr>
</tbody>
</table>

1 18 kg carcass weight Merino prime lamb, maximum age is 15 months with a 10% discount after 12 months of age.

2 Lambs younger than 15 months sold to other graziers.

3 Wethers sold to the export market. No sales between May and July inclusive.

4 5.5 yo Breeding ewes in condition score 3. There is a 10% premium for ewes sold at 19 mo or younger.

5 Fleece price ($/kg) for clean 20 micron wool

**Table 14: Grain prices in the analysis (before fees).**

<table>
<thead>
<tr>
<th></th>
<th>Canola ($/t)</th>
<th>Wheat ($/t)</th>
<th>Barley ($/t)</th>
<th>Oats ($/t)</th>
<th>Lupins ($/t)</th>
<th>Fababean ($/t)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>566</td>
<td>301</td>
<td>283</td>
<td>235</td>
<td>305</td>
<td>350</td>
</tr>
</tbody>
</table>

**Tactics comparison**

Farmers have a large array of tactics they can apply as the year unfolds and many of these are represented in AFO. However, to economise on word count, in this study we only examine some of the more common livestock tactics and so focus on the following tactics:
i) Sale quantity and timing – additional classes of sheep can be sold or retained in response to the unfolding years condition.

ii) Pasture area and rotation – the area of pasture can be adjusted based on the time of break and pasture can be established in paddocks with different land use histories that impact germination (e.g. continuous pasture has a higher germination than pasture following multiple years of crop).

iii) Grazing management – depending on the unfolding year stock can follow different grazing management (e.g. pasture can be deferred for longer in weather-years in which pasture growth is limiting).

iv) Crop grazing – crops can be grazed early in the growing season when pasture is limiting or to allow pasture to be deferred.

v) Stock nutrition profile – animals can gain more weight in a good year and lose more weight in a poor year.

To understand the value of each tactic we compare the profitability of the farm with the tactic versus a farm with a “minimal” level of the tactic. A minimal level of each tactic is used as the comparison because it is impossible for a farmer not to change some part of their management in response to changing conditions between years. For example, in a poor year even a farmer with a largely ‘set and forget’ style of management will be forced to accommodate some management mix of feeding more supplements, allowing animals to lose weight or selling some animals as a response to the lower pasture production. The “minimal” scenario is defined below.

i) Sale quantity and timing – in the “minimal” scenario, sale quantity and timing is forced to be the same in each weather-year.

ii) Pasture area and rotation – in the “minimal” scenario, rotation selection is forced to be the same in each weather-year.

iii) Grazing management – in the “minimal” scenario, sheep are forced to graze at a similar intensity on all the paddocks of each LMU. This represents a simple set stocking management practice. Both sheep liveweight and the quantity of supplement fed can vary between years. The grazing intensity level selected is calculated as the weighted average of the grazing intensities selected in the full model for a given level of FOO, at a given time of the year, on a given LMU, in a given weather-year. It should be noted that in the “minimal” grazing management scenario, pastures can still be deferred because it was too challenging, in a realistic way, to prevent AFO optimising all short-term grazing management decisions. This may result in an underestimate of the importance of grazing management tactics.
iv) Crop grazing – in the “minimal” scenario crop grazing is not included.

v) Stock nutrition profile – for farmers both actively and not actively implementing tactical management, the nutrition profiles of livestock are likely to change between weather-years. Therefore, to remove any arbitrary impact of setting the livestock nutrition profile in the “minimal” scenario, stock nutrition is optimised by AFO.

AFO is an optimisation model. Therefore, even with the constraints applied to the “minimal” scenario the model will optimise the management within the restricted remaining options that are available. Therefore, the results provided are representative of a highly skilled operator implementing a less than optimal system. As such, the value of adopting tactical management is likely to be underestimated in our analysis. For example, the livestock nutrition profile is being optimised in the “minimal” scenario and will maximise any opportunities to alter the temporal allocation of feed between classes of stock while meeting the constraint that the pasture must be grazed at the same intensity in each paddock. Accordingly, the estimates of the role and value of key sheep management tactics should be seen as conservative estimates.

Results

Value of tactics and strategic impact

Dynamically managing farming systems in response to unfolding weather conditions increases expected profit by $127806 (16%) (Table 15). Tactical management has a large impact in early break years that have no follow up rain (z2 and z3) (Table 15). This is largely because in the Great Southern region of Western Australia false breaks do not affect crop production (Table 3). However, pasture production during the false break period is significantly reduced. Thus, tactical adjustments have the potential to significantly boost profit in those years.

A farm managed with a full complement of tactics has a different overall strategy to a farm managed with minimal tactics. For example, with tactics, the optimal overall stocking rate is increased by 30% (Table 16). Thus, the change in profit reported in Table 15 is not necessarily a reflection of the importance of including tactics in a given weather-year. For example, other results (not included here) show that the value of tactics in z7 is $90,402 (105%). Utilising tactics in z7 (a poor weather-year) allows the profit to remain similar whilst the strategic stocking rate is increased.

All tactics have a significant impact on farm profit (Table 17). However, due to interactions between the different tactics, the exact value depends on the complement of tactics being applied.

Table 15: Weather-year profit with full tactics versus minimal tactics.
## Table 16: Summary of farm strategy with full tactics and minimal tactics.

<table>
<thead>
<tr>
<th>Weather-year</th>
<th>Full tactics</th>
<th>Minimal tactics</th>
<th>Change $ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected</td>
<td>903511</td>
<td>775705</td>
<td>127806 (16%)</td>
</tr>
<tr>
<td>z0</td>
<td>1344834</td>
<td>1164089</td>
<td>180745 (16%)</td>
</tr>
<tr>
<td>z1</td>
<td>990190</td>
<td>871961</td>
<td>118229 (14%)</td>
</tr>
<tr>
<td>z2</td>
<td>1068357</td>
<td>767379</td>
<td>300978 (39%)</td>
</tr>
<tr>
<td>z3</td>
<td>369734</td>
<td>105682</td>
<td>264052 (250%)</td>
</tr>
<tr>
<td>z4</td>
<td>931467</td>
<td>875724</td>
<td>55743 (6%)</td>
</tr>
<tr>
<td>z5</td>
<td>624457</td>
<td>526782</td>
<td>97675 (19%)</td>
</tr>
<tr>
<td>z6</td>
<td>836309</td>
<td>777798</td>
<td>58511 (8%)</td>
</tr>
<tr>
<td>z7</td>
<td>186841</td>
<td>183151</td>
<td>3690 (2%)</td>
</tr>
</tbody>
</table>

*1 Weighted average of weather-years

## Table 17: The expected change in profit of including and excluding each tactic individually.

<table>
<thead>
<tr>
<th></th>
<th>Full tactics</th>
<th>Minimal tactics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit ($'000)</td>
<td>903.5</td>
<td>775.7</td>
</tr>
<tr>
<td>Stocking rate</td>
<td>18.6</td>
<td>14.3</td>
</tr>
<tr>
<td>(DSE/Wgha)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supplement fed (t)</td>
<td>937.3</td>
<td>829.8</td>
</tr>
<tr>
<td>Pasture area (%)</td>
<td>35.6</td>
<td>39.2</td>
</tr>
<tr>
<td>Cereal area (%)</td>
<td>39.4</td>
<td>38.7</td>
</tr>
<tr>
<td>Canola area (%)</td>
<td>25.0</td>
<td>22.1</td>
</tr>
</tbody>
</table>
Key tactical decisions

In early break years it is optimal to increase the canola area by up to 55% and in late break years it is optimal to decrease canola area by 55% (Table 18). All of the tactical rotation adjustments occur on the productive soils (LMU 3 and LMU 4). Sandy soils (LMU 2) are never tactically adjusted and always remain in continuous pasture (Table 18). The difference in rotation selection based on the presence or absence of follow up rains in early breaks shows that in years with an early break it is optimal to delay the rotation decision on a proportion of the area until follow-up rains are received. The results in this paper only report the changes in land use area on each soil type. However, the adjustments are fine-tuned based on the rotation history. This is accounted for in AFO, but for simplicity we have not reported the full rotation changes.

Under minimal tactics, all pasture is grazed at a similar intensity and all paddocks have a similar level of FOO. Optimal management employs rotational grazing, grazing low FOO paddock lightly to maximise growth (Figure 6). In early break weather-years it is optimal to graze pastures heavily early and then defer them by grazing crops.

The optimal level of crop grazing correlates with the break of season timing, where early break seasons have the highest level of crop grazing (Table 19). After an establishment period, crops can be grazed. However, it is optimal to further delay grazing to increase relative availability of the feed. At low FOO levels the relative availability of pasture is low, which reduces intake and nutritive feed values for sheep. At low nutritive value the yield penalty outweighs the value of grazing. Hence, in late break and false break years, some of the crop available for consumption is not grazed (Table 19). Crop grazing is economical even in favourable weather-years because the stocking rate is increased, which outweighs the negative impact of yield loss.

The majority of sales that differ based on weather-year conditions are related to stock less than 18 months of age. Additionally, there are some smaller tactical sales of sheep that include the oldest age group of ewes. Adjusting only the youngest and oldest age group of animals allows the breeding strategy to remain constant, suggesting that destocking of ewes in a poor year is not profitable due
to the opportunity cost caused by being understocked in the subsequent years. The farm strategy (minimal tactics) is to sell the heavy proportion of wethers at 8 months of age and the remainders after the second shearing at 18 months of age (Figure 7). With tactical management included the general strategy is similar however, in years with a false break or a poor spring, a large proportion of the wethers are sold after shearing at 5.5 months of age. Additionally, in years with a false break, a greater proportion of wethers are sold at 8 months of age.

Implementation of these short-term tactical management increases the optimal winter stocking rate (Table 20), whilst reducing supplement fed per DSE in five out of eight weather-years (Table 21).

Table 18: Optimal land use choice on each LMU for each weather-year.

<table>
<thead>
<tr>
<th>Weather-year</th>
<th>Pasture (ha)</th>
<th>Cereal (ha)</th>
<th>Canola (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LMU2</td>
<td>LMU3</td>
<td>LMU4</td>
</tr>
<tr>
<td>z0</td>
<td>150</td>
<td>95</td>
<td>424</td>
</tr>
<tr>
<td>z1</td>
<td>150</td>
<td>95</td>
<td>424</td>
</tr>
<tr>
<td>z2</td>
<td>150</td>
<td>107</td>
<td>475</td>
</tr>
<tr>
<td>z3</td>
<td>150</td>
<td>107</td>
<td>475</td>
</tr>
<tr>
<td>z4</td>
<td>150</td>
<td>132</td>
<td>620</td>
</tr>
<tr>
<td>z5</td>
<td>150</td>
<td>132</td>
<td>620</td>
</tr>
<tr>
<td>z6</td>
<td>150</td>
<td>99</td>
<td>506</td>
</tr>
<tr>
<td>z7</td>
<td>150</td>
<td>99</td>
<td>506</td>
</tr>
<tr>
<td>Minimal tactics¹</td>
<td>64</td>
<td>498</td>
<td>271</td>
</tr>
</tbody>
</table>

¹ All weather-years are the same without tactics
Figure 6: Full tactics green pasture grazing summary for LMU4 and z4. The columns indicate both the total FOO and FOO per hectare at the specified date. The data labels indicate the FOO per hectare of each FOO level. The shaded segments indicate the grazing intensity where Graz100 means grazing all the available feed (including the growth).

Table 19: Tonnes of crop grazing in each weather-year.

<table>
<thead>
<tr>
<th>Weather-year</th>
<th>Crop consumed (t)</th>
<th>Available proportion consumed (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>z0</td>
<td>543</td>
<td>100%</td>
</tr>
<tr>
<td>z1</td>
<td>543</td>
<td>100%</td>
</tr>
<tr>
<td>z2</td>
<td>395</td>
<td>89%</td>
</tr>
<tr>
<td>z3</td>
<td>395</td>
<td>89%</td>
</tr>
<tr>
<td>z4</td>
<td>329</td>
<td>100%</td>
</tr>
<tr>
<td>z5</td>
<td>329</td>
<td>100%</td>
</tr>
<tr>
<td>z6</td>
<td>4</td>
<td>4%</td>
</tr>
<tr>
<td>z7</td>
<td>4</td>
<td>4%</td>
</tr>
<tr>
<td>Minimal tactics¹</td>
<td>0</td>
<td>-</td>
</tr>
</tbody>
</table>

¹ All weather-years are the same without tactics
Figure 7: Sheep numbers by age group in each weather-year.

Table 20: Winter stocking rate in each weather-year

<table>
<thead>
<tr>
<th>Weather-year</th>
<th>Stocking rate (DSE/WgHa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$z_0$</td>
<td>21.1</td>
</tr>
<tr>
<td>$z_1$</td>
<td>21.1</td>
</tr>
<tr>
<td>$z_2$</td>
<td>18.3</td>
</tr>
<tr>
<td>$z_3$</td>
<td>18.3</td>
</tr>
<tr>
<td>$z_4$</td>
<td>15.3</td>
</tr>
<tr>
<td>$z_5$</td>
<td>15.3</td>
</tr>
<tr>
<td>$z_6$</td>
<td>18.0</td>
</tr>
<tr>
<td>$z_7$</td>
<td>18.0</td>
</tr>
<tr>
<td>Minimal tactics $^1$</td>
<td>14.3</td>
</tr>
</tbody>
</table>

$^1$ All weather-years are the same without tactics
Table 21: Supplement fed in each weather-year with full tactics vs minimal tactics.

<table>
<thead>
<tr>
<th>Weather-year</th>
<th>Full tactics</th>
<th>Minimal tactics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total (t)</td>
<td>Kg/dse</td>
</tr>
<tr>
<td>z0</td>
<td>1173</td>
<td>87</td>
</tr>
<tr>
<td>z1</td>
<td>889</td>
<td>69</td>
</tr>
<tr>
<td>z2</td>
<td>1010</td>
<td>78</td>
</tr>
<tr>
<td>z3</td>
<td>1614</td>
<td>122</td>
</tr>
<tr>
<td>z4</td>
<td>898</td>
<td>68</td>
</tr>
<tr>
<td>z5</td>
<td>1011</td>
<td>77</td>
</tr>
<tr>
<td>z6</td>
<td>1095</td>
<td>84</td>
</tr>
<tr>
<td>z7</td>
<td>1173</td>
<td>87</td>
</tr>
</tbody>
</table>

Discussion

Australia’s variable climate results in the need to manage its dryland farming systems dynamically to maximise profitability. This paper goes beyond past work, utilising a more comprehensive, current up-to-date farm optimisation model with a full array of tactical options, to identify the optimal complement of tactical adjustments to apply and their associated profitability. The findings indicate that managing farming systems dynamically in response to unfolding weather conditions is highly profitable, increasing the expected profit by 16% (Table 15). This concurs with the few previous studies that have examined the mixed enterprise farming system of Western Australia. For example, in the previous chapter we showed that including tactical decision-making increases expected farm profit by at least 14%. Kingwell et al. (1993) also showed that implementation of rotation tactics in the wheatbelt region increased expected profit by 22% and Trompf et al. (2014) showed that stocking rate adjustments due to stock sale adjustments, increased profit by up to $112,000 depending on the strategic stocking rate. These results illustrate that deterministic models and even stochastic models that do not include tactical adjustments miss a key feature of the management of the farming system and may incorrectly identify optimal activities. Furthermore, from a farmer’s point of view, the key message from all these studies is that a ‘set and forget’ management approach is far from optimal.

However, the implementation of tactics can potentially be complex. Farmers must consider that, as they implement tactics into their system, their underlying strategy must also be adjusted (Table 16). For example, stocking rate is significantly increased as tactical management is implemented. Additionally, each category of tactics defined in this paper is made up of many sub options. For
example, rotation tactics are defined by LMU and rotation history. The added complexity means that the farm manager must be suitably skilled to identify the type of unfolding season and implement the correct tactics in a timely manner (in the future monitoring tools such as Pastures from Space may have an important role in assisting farmer to identify the weather-year being experienced). Given farmers are time-pressed (Kingwell, 2011) they may want to implement only a subset of the available tactical options. The economic value of implementing an additional tactic varies depending on the complement of tactics being applied (Table 17). There is scope to further examine the interactions between tactics, however, in the eight scenarios tested in this paper an additional tactic was worth between $7,704 and $53,171. This indicates that a time poor farmer can improve farm profitability and robustness in a variable climate by implementing only a subset of the available tactics.

Furthermore, there are several technologies that may warrant further investigation as tools to aid the management process. First, improved seasonal forecast is likely to be valuable as it ensures the tactics being considered are more likely to be appropriate and most profitable when that forecast season eventuates. Second, low cost instrumentation or data sources that provide accurate indicators of *in situ* impacts of an unfolding season (e.g. pasture growth rates, FOO, animal weight gain or loss) will facilitate tactical decision-making; and likely increase the returns (or losses avoided) from such decision-making.

Our results are based on expected long-term prices and market conditions. However, short term price fluctuations, if they can be predicted, may mean farmers could implement extra tactical adjustments to those reported in this paper to increase returns. This would be a valuable direction for future research.

**Conclusion**

Short-term adjustments to the overall farm strategy in response to unfolding weather condition can result in substantial improvements in expected profit on dryland mixed enterprise farms in the Great Southern region of Western Australia (by approximately 16%). Benefits stem firstly from capitalizing on knowledge about the profitability of different decision tactics tailored to the unfolding weather conditions. Secondly, the benefits accrue from more optimally selecting the underlying farm management strategy of the farm business. Deterministic models and even stochastic models which do not include activities for tactical adjustments miss this key feature of the system and may incorrectly identify optimal activities.
Caveats

In the previous chapter we showed that the more realistic 8-SPR framework in AFO behaved very similar to the 4-SPR framework, however tactical management did change based on the end-state of the preceding year. Thus, it is expected that the value of the tactics identified in this paper are likely to be correct but, in practice, the execution of the tactics will vary based on the preceding year.

A limitation with all modelling frameworks such as detailed in this paper is the exclusion of any transition cost from a farmer’s current business structure to the optimal structure. There are two factors that need considering; first, does the initial farm structure impact the future optimal farm structure?, and second, how should farmers most efficiently transition from their current state to the optimal state? Answering these questions requires a multiperiod model. AFO has the capacity to handle this, but it adds layers of complexity.
Chapter 7: General discussion

Farm systems operate within a constantly changing environment. Market and climate conditions are rarely static (Feng et al., 2022, Laurie et al., 2019) and technology is continually advancing, resulting in efficiency changes and greater access to farm and market information (Neethirajan and Kemp, 2021). As such, continuous appraisal of management practices within mixed farming systems is essential for farmers wishing to maximise profitability. However, after reviewing literature on the critical decision of stocking rate (chapter 2), it was confirmed that mixed farm systems that incorporate both livestock and cropping enterprises are highly complex and can be challenging to accurately evaluate. Accurate analysis of livestock decisions often requires consideration of the quantity and quality of feed available throughout a year, the optimal live weight profile throughout a year, the impact of seasonal variation, the impact of labour availability, the risk preferences of the farmer, the array of crop and pasture options available to the farmer, the tactical management options farmers can embrace, the accuracy of seasonal forecasts they can draw upon to facilitate their decision-making, relative prices of inputs and outputs and greenhouse gas abatement policy settings that in combination will alter the costs of running livestock (Young et al., 2022).

The findings in chapter 2 show that, to address this complexity in farm analysis, computer programs are frequently utilised. However, many of these models contain significant simplifications of reality. For example, MIDAS, a prevalent whole farm optimisation model used throughout Australia (Bathgate et al., 2009, Kingwell, 2011, Kingwell and Pannell, 1987, Kopke et al., 2008, Pannell, 1996, Thamo et al., 2013, Young et al., 2011, Young et al., 2020), was built on the assumption that every year is the same (i.e. steady state). As is the case with MIDAS, year-to-year variation is often excluded in whole farm optimisation models as its inclusion exponentially increases the size of these model. This issue is commonly known as the “curse of dimensionality” (Burt, 1982). However, without representing year-to-year variation and the resulting uncertainty, models are less realistic and their results can lack credibility (Young et al., 2022). Although, commonly used steady state models are less realistic, little research to-date has formally quantified the importance of these limitations, leaving a gap in our knowledge regarding the implications of using steady-state optimisation models to address on-farm decision making.

To help fill this gap in our knowledge, this thesis aims to, firstly, quantify the impact of the steady state assumption when applied in mixed enterprise, livestock-focused research. Secondly, an improved methodology is developed that encompasses optimal strategical and tactical management of livestock within a mixed enterprise farm business. A hypothesis tested in this thesis is that the steady state assumption embedded in many whole farm optimisation models leads to inaccurate
estimations of profitability and a potential non-optimal allocation of farm resources. The hypothesis was tested and accepted in chapter 4 via applying the model described in chapter 3.

Chapter 4 illustrates that stochastic modelling with the inclusion of weather-year variation and associated tactical management generates substantially different results than the more common steady-state deterministic modelling. In chapter 5 the farm modelling literature is further expanded by examining the impact of weather-year sequence on farm business management. The outcomes of the model-testing in chapters four and five are that for many farm systems economic analyses, where accuracy is of importance, more detailed modelling methodologies are required than has traditionally occurred.

A significant component of the improved accuracy, resulting from representing year-to-year variation, is the identification of useful short-term tactical management adjustments that farmers can implement in response to their unfolding weather-year conditions. In a variable climate, short-term tactical management generates significant opportunities to boost farm profit and/or avoid losses (by at least 14%) (chapters 4 and 5). The benefits are due to capitalizing on knowledge about the profitability of different aspects of the farm system under varying weather-year scenarios.

Farmers have hundreds of potential tactical opportunities, but due to previous data and computational restrictions, little research has identified what and when these tactics should be applied. In chapter 6 we describe and apply a newly constructed farm optimisation model (AFO) that encompasses short term tactical livestock management on a mixed enterprise farm in a variable environment. Our results include practical detail regarding the on-farm implications of the different tactics.

Overall, this thesis significantly contributes to the agricultural science knowledge base concerning the optimal management of mixed enterprise farming systems in Western Australia. Specifically, this thesis evaluates the impact of including and excluding weather-year variation and the corresponding tactics on farm profitability and optimal farm management. Secondly, this thesis quantifies the importance of short-term tactical management and identifies the optimal implementation of these tactics under different weather-year scenarios.

The novelty of this thesis lies largely in the extension of AFO which extends previous farm modelling research boundaries. Recent advances in computer technologies are leveraged to develop and document a farm model called AFO. AFO is a large applied application of the widely used stochastic programming methodology (e.g. Kingwell et al., 1991, Moore, 1990, Moore and Noble, 1993). functionally flexible model containing three sub frameworks that vary in detail and represent
different aspects of the farm management decision environment. AFO overcomes many of the
limitations identified with prior whole-farm optimisation models and the construction and
application of the AFO is itself a main contribution of this PhD thesis.

The model comprises of over 32,000 lines of code and over 120 pages of documentation. AFO is the
first whole farm optimisation model in Western Australia constructed using Python (a popular
programming language). Using Python, AFO has been developed in a modular style, separating the
model into components that represent different aspects of the farm system and splitting out its
inputs and outputs. This results in a more flexible model than previous Excel®-based models, which
can be more easily applied to a range of different farm systems and topics. For example, since its
conception, AFO has been used to facilitate analysis into the profitability of pregnancy scanning of
ewes, the value of mating ewe lambs and the benefits of establishing salt land pasture. AFO also
utilises other modern programming concepts such as multiprocessing, cloud-based solutions and
automated documentation to provide improved capability and transparency over previous modelling
methods. Furthermore, the complete and flexible design of the model allows it to facilitate future
development such that it can be used to address future research questions and issues.

AFO is a highly complex model that requires a significant level of user skill. Hence, its application is
likely to be limited to dedicated researchers who have the recourses to learn and apply the model.
However, the design of AFO means it could encompass a user-friendly front end. This is a potential
future development that would extend AFO’s usability.

AFO’s complexity comes with a lot of analytical capabilities and a range of potential uses such as: (i)
policy evaluation, (ii) research prioritisation and (iii) aid on-farm decision making (as in chapter 6 of
this thesis. Furthermore, although in this thesis, AFO has been solely applied to farming systems in
the Great Southern region of Western Australia, AFO is not limited to this region. The built in
flexibility will allow AFO to be adapted to other regions within Western Australia and Australia. For
example, AFO has been successfully applied to the Hamilton region of Victoria (John Young pers.
comm.).

Of course, there is further work as an outcome of this thesis. This thesis has focused on weather-
year variation. However, another significant source of uncertainty within the farming system is input
and commodity price variation. Thus, some similar analysis could be completed focusing on price
variation and the tactical adjustments farmers could implement in response to price changes. In
developing AFO, price variation was included to ensure relevant analyses would be possible without
major methodology updates.
The focus of this dissertation is primarily on Western Australia with AFO being calibrated for the Great Southern region. Thus, the results and findings are specific for the Great Southern region. However, much of the methodology and modelling contributions have potential wider benefits. For example, the AFO modelling method applied throughout this PhD could be replicated for other regions or properties.
References


DALGLIESH, N., COCKS, B. & HORAN, H. 2012b. APSOil-providing soils information to consultants, farmers and researchers. 16th Australian Agronomy Conference, Armidale, NSW.


KINGWELL, R. & PANNELL, D. 1987. MIDAS, a Bioeconomic Model of a Dryland Farming System, PUDOC.


MALCOLM, B. 2000. Farm management economic analysis: a few disciplines, a few perspectives, a few figurations, a few futures. *Annual Conference of Australian Agricultural and Resource Economics Society*.


MCKINNEY, W. 2012. Python for data analysis: Data wrangling with Pandas, NumPy, and IPython, "O'Reilly Media, Inc.".


MCLENNAN, S. R., MCLEAN, I. & PATON, C. 2020. Re-defining the animal unit equivalence (AE) for grazing ruminants and its application for determining forage intake, with particular relevance to the northern Australian grazing industries, Meat and Livestock Australia.


ROSE, I. J. 2011. A study of labour use and efficiency for mixed sheep and crop agricultural systems of the Central Wheat Belt of Western Australia. University of Western Australia.


THOMPSON, A., FERGUSON, M., GORDON, D., KEARN EY, G., OLDHAM, C. & PAGANONI, B. 2011. Improving the nutrition of Merino ewes during pregnancy increases the fleece weight and reduces the fibre diameter of their progeny’s wool during their lifetime and these effects can be predicted from the ewe’s liveweight profile. Animal Production Science, 51, 794-804.


YOUNG, J. 1995. MIDAS: Model and Documentation for the Great Southern Model (version GSM92-3), University of Western Australia, Nedlands, Western Australia.


YOUNG, J., TROMPF, J. & THOMPSON, A. 2014. The critical control points for increasing reproductive performance can be used to inform research priorities. Animal Production Science, 54, 645-655.


