Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Prime lamb case study

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Executive summary

Importance of climate variability and forecasts

There are many sources of uncertainty in agricultural production systems. Of these, it is agriculture's basic dependence on climatically sensitive biological systems that often exerts the most influence on the sector from one year to the next. Seasonal climate forecasts (SCFs) provide opportunities for farmers to better match farm decisions to pending climatic conditions. Using SCFs, farmers can select crop types, varieties, stocking rates and nutrient inputs that are better suited to expected seasonal climatic conditions. SCFs offer economic value by moving farmers towards a position of greater certainty about the real state of nature at the time decisions are made.

Objective of the project

Insufficient evidence about the value of SCFs has been considered to be a major factor limiting their adoption in Australia and other countries. Hansen (2002) identified that the value of SCFs lies in the intersection of climate predictability, system vulnerability and decision capacity. This project aimed to develop a better understanding of this intersection and assess where, when and how SCFs offer value in agricultural production systems by undertaking a range of case studies. It is important to recognise that case studies provide an example of the potential value of a forecast based on a particular production system, at a specific time of year and at a specific location with its own historical climate variability. While the case studies reflect climate-sensitive management decisions identified by engagement with industries, they were not designed to be statistically representative or assess the potential value of SCFs to a sector as a whole.

Objective of this report

This report focuses on the value of SCFs to the management of prime lamb production systems in southern Australia. The key decision identified by industry was how many lambs to sell in November and how many to carry to target weights to be sold prior to the beginning of March. A total of 11 stocking rate strategies (sell 0%, 10%, …,100% of lambs in November) were analysed. This decision is a trade-off between selling smaller animals now with lower feed costs and selling heavier animals later with potentially higher feed costs. Rainfall over November to February influences the level of pasture production and hence the amount of required supplementary feed to grow lambs to size prior to March. A skilful seasonal climate forecast is potentially valuable if it helps lamb producers to make a different stocking rate decision compared with the decision made based on historical average rainfall amounts.

Methods

A probabilistic climate forecast system was adopted to assess the value of SCFs. Three discrete climate states (dry, average or wet) were identified based on the lower, middle and upper tercile of November–February rainfall received at Holbrook over the period 1889 to 2015. Each year was classified as belonging to one of these climate states. Agricultural production levels (pasture growth, animal weight) for each of these climate states were obtained from outputs of pasture, feed and lamb production data from the biophysical production model *Ausfarm*. These outputs were combined with lamb production costs and built into an economic model to capture the links between climatic conditions, pasture and lamb production. The economic model was used to select the most profitable stocking rate decision under a wide variety of scenarios.

A specific interest of this project was to understand how forecast and other important non-forecast decision variables interplay to influence forecast value. The utilisation of a biophysical model allowed different levels of starting pasture availability in November to be captured and outcomes to be explored in dry, average and wet climate states. Other key decision variables, including the level of lamb and supplementary feed prices, help to represent the decision-making context prior to the consideration of a climate forecast.

A total of 11 skill levels were assessed (0%, 10%, …,100%) with 0% representing climatology and 100% skill reflecting a perfect forecast of the three climate states. Increasing forecast skill results in a higher probability of a particular climate state evolving, providing more certainty about future conditions.

Influence of non-forecast and forecast drivers on the stocking rate decision

Lamb price in November generally had a substantial influence on the optimal stocking rate with and without a climate forecast. Low lamb prices led to a decision to hold all lambs, with skilful forecasts offering little value as selling heavier animals later at higher supplementary feed prices was more profitable than selling lambs at lighter weights. High lamb prices in November tended to lead to a decision of selling lambs to take advantage to high lamb prices and minimising supplementary feed costs.

Although November lamb prices strongly influence the stocking rate decision, pasture availability and supplementary feed prices were also found to be important in determining forecast value. With low pasture availability, skilful forecasts were unable to change the stocking rate decisions from the decision made based on climatology. This illustrates that with poor pasture conditions in November, rainfall differences between the different climate states is insufficient to influence pasture growth sufficiently to change the stocking rate decision.

Value of forecasts

Forecasts of dry, average and wet climate states had different economic values. A climate forecast of average conditions was found to be of limited economic value under all model settings. This is unsurprising as the without-forecast decision is based on climatology, which represents decision-making assuming future conditions follow the long-term average. Dry and wet forecasts were both found to be potentially valuable to lamb producers under high levels of starting pasture availability, with the extent dependent on lamb and supplementary feed prices. The maximum value of a dry forecast occurred under high pasture availability and improved returns by $53.80/ha. The maximum value of a wet forecast also occurred under high pasture availability and improved returns by $43.70/ha. Improved forecast skill was naturally found to be positively related to forecast value, although the extent of value related to incremental improvements was found to be highly variable.

Key findings

A general finding was that forecasts that led to decisions that run contrary to the direction of conditions provided the most value. For example, a dry forecast under high level of starting pasture availability was found valuable as a departure from holding to selling lambs was triggered. This finding has some parallels with observations of Hirshleifer and Riley (1992) that the ‘news-worthiness’ of information is a critical determinant of its value.

It is important to recognise that the decision investigated here represents only part of the risk lamb producers manage. The case study necessarily only represented one site and one production system. Other sites, other systems and other decisions may find different results. It is likely that the general findings around the circumstances for which forecast value was found will provide insights for the use and value of SCFs for southern lamb producers more widely.

Contents

Glossary of terms

Climate state (dry, average, wet): growing seasonal rainfall categorised into terciles of dry, average or wet.

Forecast skill: the improvement in predictability over using climatology. It refers to the improvement in accuracy due to the forecast system alone.

Without-forecast decision: the optimal decision based on climatology where each climate state has an equal chance of occurring (0% skill).

With-forecast decision: the optimal decision based on the shift in probabilities provided by the climate forecast (>0% skill).

Perfect forecast: forecast with 100% skill in predicting a climate state.

Imperfect forecast: forecast with less than 100% skill in predicting a climate state.

Probabilistic forecast system: gives a probability of a climate state occurring with a value between 0 and 1.

1 Introduction

1.1 Background

Variability in inter-annual productivity and profitability in Australian agricultural businesses is the result of tactical and strategic decision-making, within the context of whole-farm planning, largely made in response to economic and environmental conditions. These decisions are sensitive to many factors including economic returns, cash flow, weed and pest control, lifestyle choices and many other influences (Blacket, 1996). Understanding the economic consequences of decisions can be difficult for farmers due to limited predictability of weather, prices and biological responses to different farming practices (Pannell et al., 2000).

Although farmers face many sources of uncertainty, it is agriculture's basic dependence on climatically sensitive biological systems that often exerts the most influence on the sector from one year to the next. With most farm inputs allocated well before yields and product prices are known, farmers allocate resources each season on the basis of their expectations of seasonal and market conditions (Anderson, 2003). Improved seasonal climate forecasts are seen as a key technology to help farmers make better decisions in a risky climate.

In recognising the role and potential value of seasonal climate forecasts (SCFs), it is important to distinguish the costs of climate variability from the value of SCFs. SCFs are a tool that farmers can use to manage production risks associated with climate variability but they cannot remove the impact of a particular climatic event like drought. Even a perfect forecast of drought conditions acts only to remove uncertainty about the timing of its occurrence. Farmers are still left with the problem of drought itself, which will exert some influence over farm incomes however well producers are able to anticipate it (Marshall et al., 1996; Parton and Crean, 2016).

SCFs have been available in Australia since 1989. Early forecast systems of the Bureau of Meteorology (BoM) and the Queensland Government (Stone et al., 1996) were statistical-based systems relating to historical values of the Southern Oscillation Index (SOI). More recently, the BoM developed a dynamic forecasting model known as POAMA (Wang et al., 2004). This is currently being superseded with the ACCESS-S model, which is expected to result in gains in spatial resolution and model skilfulness. Operational SCFs typically provide information about expected climatic conditions over the next three to six months and are often expressed in terms of the probability of receiving above or below median conditions.

Public investment in SCFs is based on the expected value of the information these forecast systems can offer to industries like agriculture. A review report investigated the potential benefit of SCFs to Australian agriculture and estimated a potential value at between $110 million and $1930 million for the cropping and livestock sectors combined (CIE, 2014). This is a large range in benefits and the authors did note many assumptions were required to conduct the analysis due to insufficient research regarding the value of SCFs in Australian agricultural sectors.

Indeed, insufficient evidence about the value of SCFs has also long been considered to be a major factor limiting adoption in Australia and other countries. A detailed review of research investigating the value of SCFs to Australian agriculture confirmed significant gaps (Parton and Crean, 2016). The review highlighted that:

- the majority of previous work has focused on winter grains with fertiliser application in wheat particularly over-represented
- there is much research still to be done to value SCFs in Australian agriculture, particularly relating to livestock industries
- limited research has been directed towards how farmers are actually making decisions using SCFs, highlighting a need for more descriptive studies.

Hansen (2002) provided a concise and application-oriented framework to assist in designing research for using SCFs in agricultural decision-making. In his assessment he identified that the

value of SCFs lies in the intersection of climate predictability, system vulnerability and decision capacity. In considering this intersection, he noted five prerequisites for SCFs to provide value:

1. SCFs need to address a real and apparent need.
2. The benefit of SCFs depends on identification of decision points that are sensitive to SCFs and the SCF is compatible with the decision environment.
3. SCF predictions are relevant to the decision time period, are at an appropriate scale, are sufficiently accurate and are provided with enough lead time to implement the decision.
4. SCF information is provided to the right audiences and is correctly interpreted by those audiences.
5. Ongoing and long-term institutional commitment to providing forecast information specifically for application within farming decision environments is necessary.

These observations have been reiterated by Australian-focused research. There is potential for SCFs to support farm business decisions to strategically allocate resources to manage risks in a variable climate – that is, to minimise losses in poor years and maximise profits in good years (Cobon et al., 2017; Crean et al., 2015; Hayman et al., 2007; McIntosh et al., 2005).

1.2 Project objectives

Given the estimated potential value of SCFs and the identified limitation of previous research in determining this value, a multi-agency project was funded by the Australian Government Department of Agriculture and Water Resources[1] with the aim to bridge the gap between seasonal climate forecasts and farm business decisions to improve productivity and profitability. The project had three aims:

1. Valuing seasonal climate forecasts
2. Using seasonal climate forecasts
3. Improving seasonal climate forecasts.

This report is focused on the first of these aims using a farm-level case study approach.

The case studies aim to provide a better understanding of forecast value by looking at decision-making environments across a range of agricultural industries and locations. This project aims to integrate biophysical models for several industries with economic modelling to assess where, when and how climate forecasts offer value. Undertaking real-time experiments in a simulated environment avoids potentially costly mistakes of trial and error on-farm and allows farmers and advisers to become more confident with forecast use.

1.3 Case study approach

The case study approach was undertaken to provide a more systematic and largely comparable assessment of the value of SCFs. This inter-comparison and common methodological approach applied to several agricultural sectors has not been previously undertaken and lack of information has limited broader understanding of the value of SCFs to Australian agriculture.

A total of nine case studies were conducted covering western grains, southern grains, northern grains, southern beef, northern beef, prime lamb, cotton, rice and sugar.

This report contains findings of the prime lamb case study.

A key aspect of the case studies was the intentional and explicit focus on farm decision environments and the potential value of SCFs within these systems. A common approach was used for each of the nine case studies, consisting of three key steps:

1. Identification of key decision points within the production system sensitive to SCF information.

[1] http://www.agriculture.gov.au/ag-farm-food/innovation/rural-research-development-for-profit/approved-projects

2. Biophysical modelling to represent the production system and the key decision point.
3. Economic modelling to evaluate the value of SCF to the decision point within the described production system.

Industry consultation was undertaken to capture important features of the production system and identify key decision points. A consistent approach was applied to all case studies following Cashen and Darbyshire (2017). A small group of industry experts and practitioners was invited to collaborate on the design of the case study. Invited participants were selected based on industry reputation and experience and differed depending on the case study. The group defined the production system that best reflected local conditions in the area. Subsequently, investigation of decision points within the system were explored. Each major decision point was further scrutinised to:

- identify which decisions were potentially sensitive to SCF information
- identify the key decision drivers including antecedent conditions (e.g. level of starting pasture) and SCF information
- investigate the relative sensitivities of the decision to the identified decision drivers.

The aim of the case studies was to provide some insights into the value of SCFs across a range of production systems and decision environments. They were not designed to be statistically representative and so cannot provide scalable results to indicate total potential value to each industry. Agricultural systems are inherently dynamic and the approach taken here attempts to strike a balance between highly specific farm-level analyses with very limited wider applicability and coarser level, more general analyses which can miss important features of production systems that may influence results.

The decisions evaluated in the case studies do not necessarily represent the highest potential value of an application of a SCF. They were defined through consultation with industry based on their knowledge of the system and understanding of where SCFs could help improve responses to climate variability.

2 Prime lamb production system

2.1 Industry overview

Prime lamb production is a historically important agricultural industry in Australia. National sheep numbers in June 2015 were approximately 70 million (ABS, 2016a) with an associated estimated value of $3.3 billion for sheep and lamb production (ABS, 2016b). Lamb production is generally a dryland system with seasonal climate conditions (rainfall, temperature) driving fluctuations in pasture availability. As such, seasonal climate conditions can directly influence the productivity and profitability of these systems.

Substantial numbers of sheep are grazed in all Australian states territories, except the Northern Territory (Figure 1). New South Wales holds the majority of the national flock, 38% in 2015 (ABS, 2016a). These national flock numbers include sheep bred for wool, for meat and to produce both wool and meat.

National flock number have reduced by 55% between 1991 and 2014 (NSW DPI, 2015). This is a reflection of shifts in sheep production demographics, with the contribution of sheep meat to the gross value of agricultural commodities produced converging to almost parity with the value of wool (1991–2014) (NSW DPI, 2015). In this case study, the focus is prime lamb production in New South Wales.

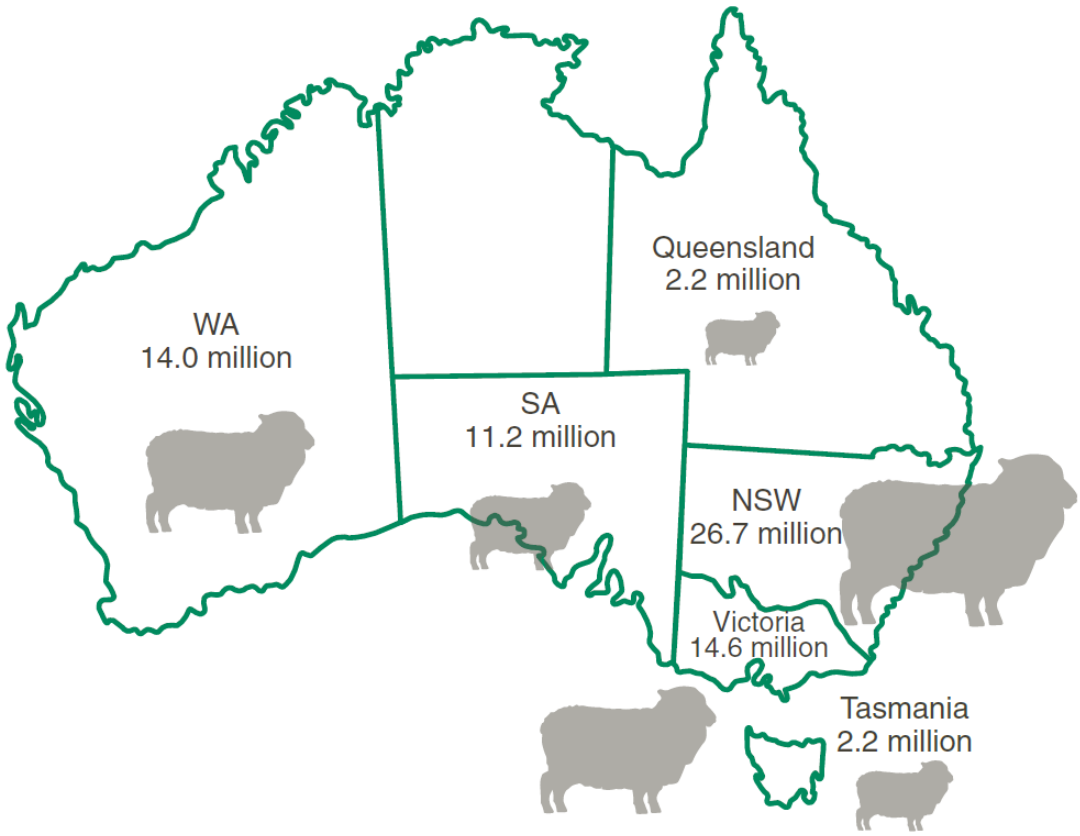


Figure 1 Estimated flock numbers by state for 2015 (MLA, 2016).

2.2 Producing lamb in southern Australia

Good soil fertility and favourable climate conditions in south-eastern Australia allow for a long season of pasture growth through springtime (Campbell et al., 2014). Feed for operations in south-eastern Australia include a mix of annual grasses, perennial ryegrasses, grazing oats, sub clover and supplementary feed (e.g. grains). The conversion of this feed into animal weight is the simplified aim of lamb systems.

In typical lamb operations in southern New South Wales, joining occurs in February and March with lambing through July and August, such that the peak spring growth coincides with lactating ewes (Figure 2). This alignment of flock energy requirements with pasture availability is key to this system as different stock classes have different daily energy requirements, with lactating ewes requiring the most energy. Selling of lambs begins in November after weaning and all lambs are typically sold by March.

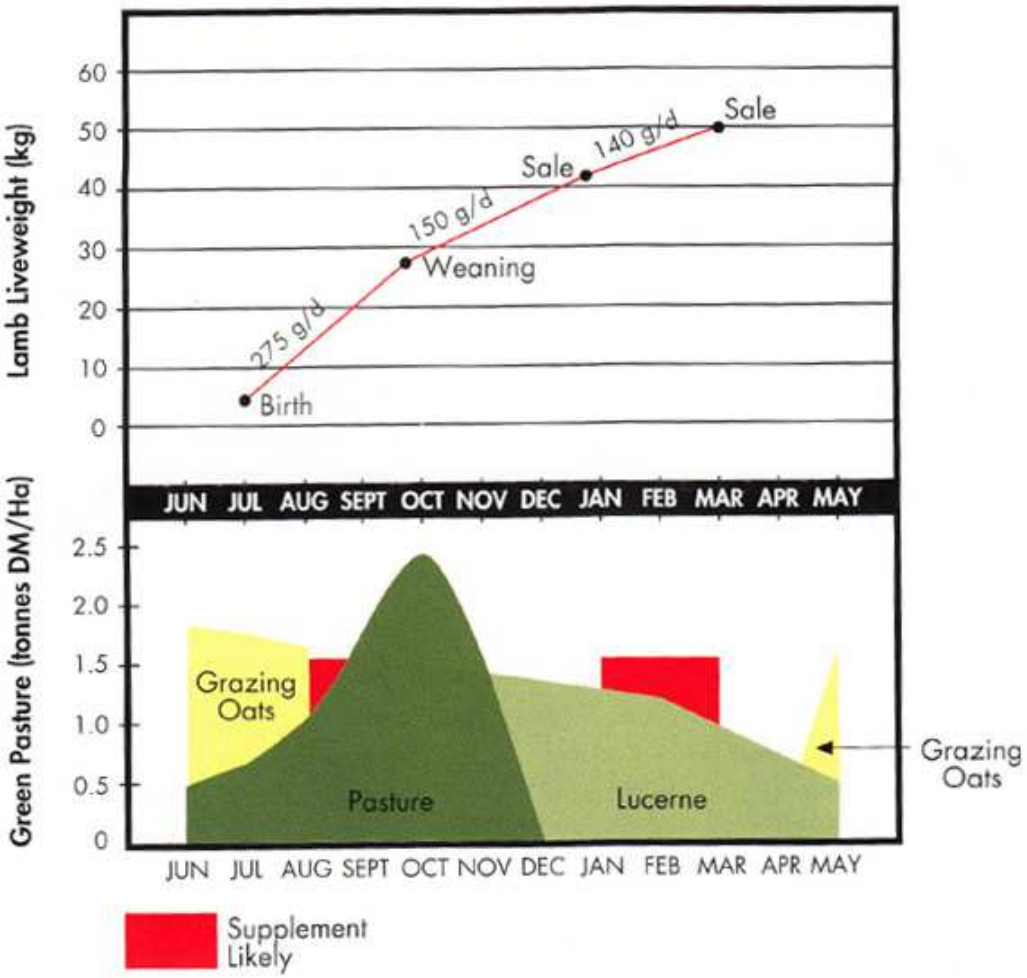


Figure 2 Lamb lifecycle and coincident feed configurations (Ferguson and NSW Agriculture, 1997)

2.3 Description of production system and key decision point

Industry consultation, including with the Southern Australian Meat Research Council (SAMRC), was undertaken to describe the production system and key decision points. Further information on the consultation process is contained in

Appendix 1.

The prime lamb case study was focused on a first-cross ewe flock on a 700 ha farm based in Holbrook, New South Wales (Figure 3). The system is based on 3000 ewes.

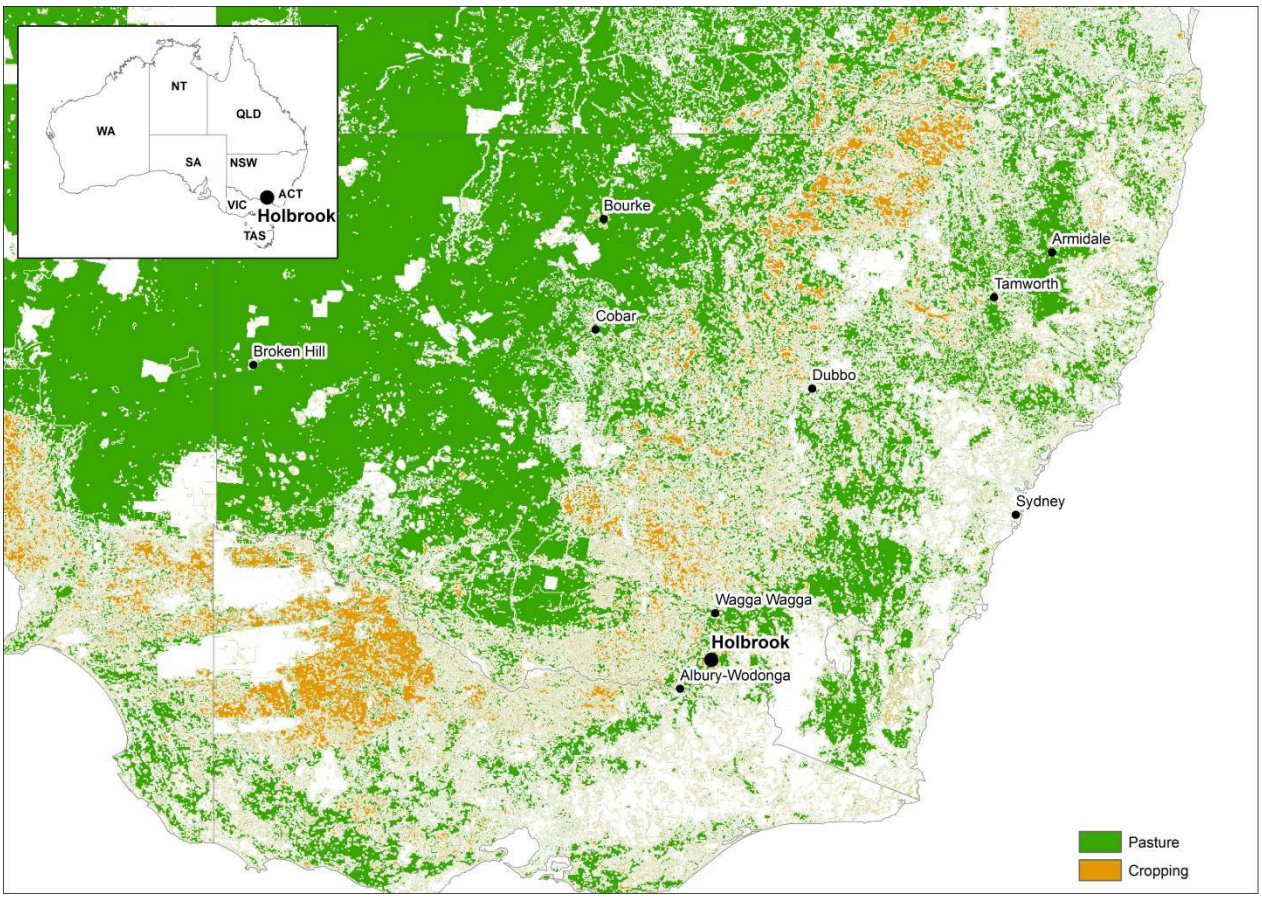
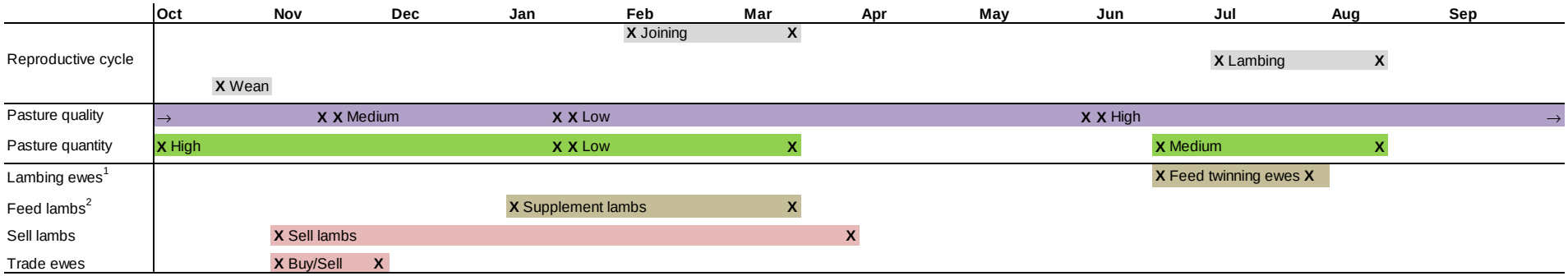


Figure 3 Map showing the location of Holbrook, the case study site

Joining was set to occur through February and into March with lambing through July and early August. Supplementary feeding is common, with twinning ewes supplemented through winter if pasture availability is low. Supplementary feeding of the flock, dependent on feed availability, will occur through summer. Producers aim to begin to sell lambs from November with all lambs sold by the end of March (Figure 4).

Figure 4 Broad system characteristics of prime lamb case study



[1]Highest energy demand is at laming/ lactating. Usually have to feed at least twinning ewes through this time
[2]Supplement feed (e.g. grains) lambs not yet sold, through low pasture growth phase

2.3.1 Decision point

The key decision point investigated for this system was:

How many lambs to sell in November versus selling later?

The time of the first decision to sell lambs was November, with the secondary selling timing in post-November up to March, dependent on when lambs met maximum weights.

Allocating the proportion of lambs to initially sell is not a simple decision. Four key drivers that influence this decision were identified by the group:

1. Price of grain feed: high prices encourage additional selling, low prices discourage selling.
2. Feed availability: low pasture encourages selling, high pasture discourages selling.
3. Price of lamb (in November): high prices encourage additional selling, low prices discourage selling.
4. Rainfall forecast: wet (i.e. good pasture growth) discourages selling, dry (i.e. poor pasture growth) encourages selling.

Figure 5 illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including SCF information against decisions made without SCF information. Further details on the process of defining this decision point and the decision drivers are contained in

Appendix 1.

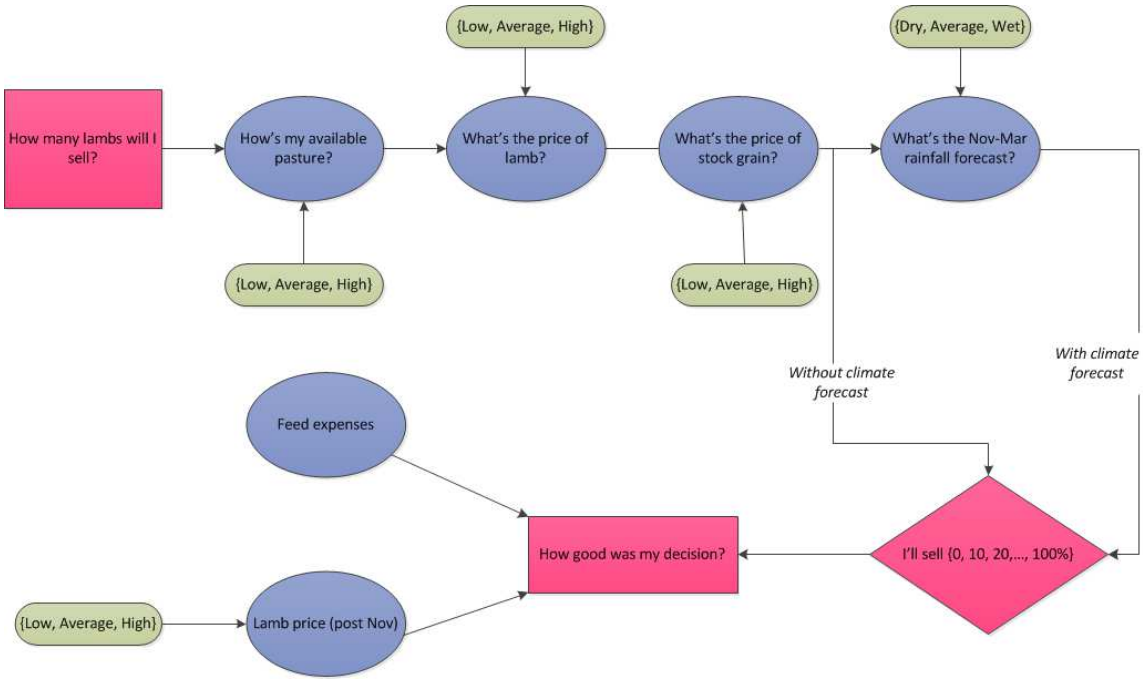


Figure 5 Decision pathway for proportion of lambs sold in November including an evaluation of the decision made.

2.4 Previous studies of SCFs in sheep production systems

Inclusion of SCFs into decision-making processes within Australia's southern lamb production system may provide opportunities for producers to better match decisions with expected seasonal conditions. Economically, this can provide benefit through reducing risk in poor future conditions (e.g. dry seasons with poor pasture growth), by taking advantage of good future conditions (e.g. wetter seasons with good pasture growth) and managing average conditions to maximum production potential.

Some investigations into the use of SCFs within Australian sheep operations have been previously conducted. Most studies focused on management decisions relating to matching pasture availability with animal requirements. The most frequently discussed management options were changing stocking rates (selling and/or buying) and/or supplementary feeding to maintain stocking rates.

For southern Australian operations, three previous papers have considered the use of seasonal climate forecasts in the sheep industry. Bowman et al. (1995) assessed the value of a long-range forecast (12 months) for two wool operations in Victoria over 25 years. Stocking rates were altered using traditional management options and decisions based on a forecast with various levels of skill. It was shown that some increase in gross margin, about 5%, was possible if forecast information was included in decision-making processes. However, the authors commented that the value of forecasts in this system may negatively impact profits for any given year if forecast skill is low.

Hamilton and Clark (2003) evaluated the use of a trigger approach to managing expected drought conditions within wool production systems. They allocated a trigger for management based on winter conditions with low soil moisture and a negative or falling Southern Oscillation Index (SOI) phase. They evaluated options to purchase fodder, destock or a combination. Their results found little economic benefit of this trigger approach to manage drought conditions at the two Victorian locations investigated.

Modification to mixed sheep-wheat farming decisions using the Bureau of Meteorology climate model, POAMA, in Western Australian conditions has been analysed (Asseng et al., 2012). The forecast was incorporated into making decisions for fertiliser application rates to wheat crops and changing the pasture to cropping ratio. They found up to $200 000 extra profit per year could be obtained if the forecast was skilful. Some effort has also been directed into understanding information seeking and use among sheep farmers (Austen et al., 2002; Keogh et al., 2004; Keogh et al., 2006).

Specific studies investigating the value of SCFs within a lamb system in south-eastern Australia were not found.

3 Methods

The potential value of SCFs was evaluated through maximising returns of the system by selecting the optimal percentage of lambs to sell in November under various system conditions. An overview of the methodology is outlined in Figure 6. Four key components are provided to the economic model which then evaluates the potential value of SCFs. Each of these components is described in the following sections.

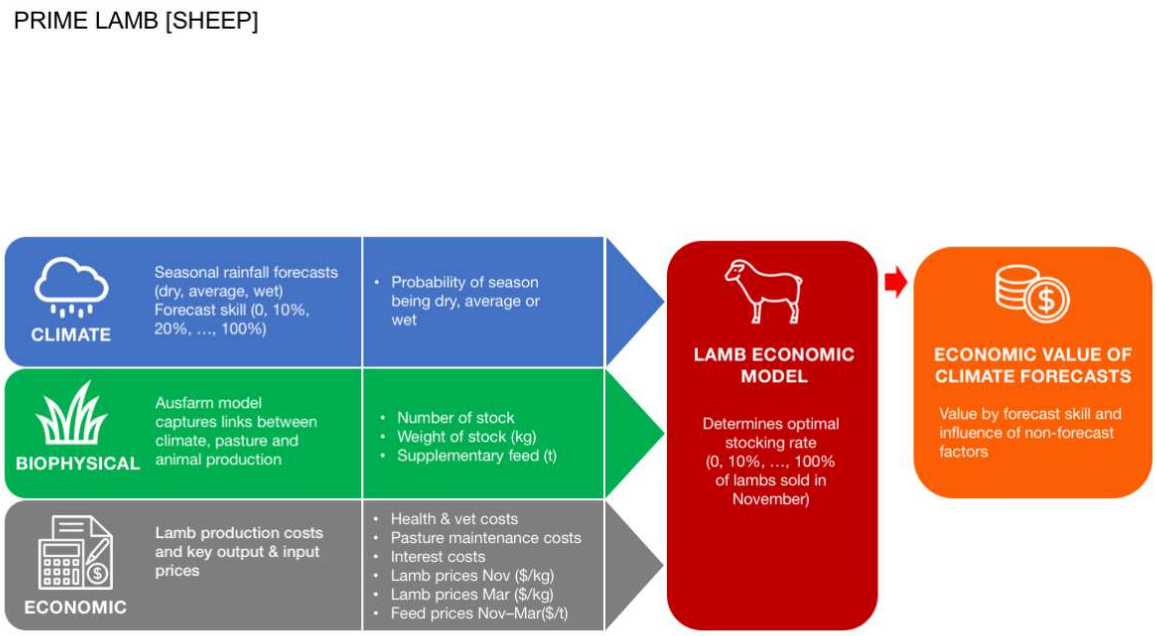


Figure 6 Methodological overview. Generation of biophysical data, lamb production costs, lamb prices and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal percentage of lambs to sell based on maximising returns.

3.1 Prime lamb biophysical simulation model

The link between climatic conditions, pasture and lamb production is captured through detailed biophysical modelling. The biophysical model chosen for this case study was *Ausfarm* (version 1.4.13; Moore et al., 2007). *Ausfarm* operates on a daily time step and consists of dynamic modules including a water balance module, pasture growth module, animal production module and cropping module. *Ausfarm* was chosen due to its flexibility, which allows the user to develop additional modules to represent complex management structures. It should be noted that *Ausfarm*, like other similar livestock production models, does not adequately represent disease (plant or animal), weeds in the pasture base, or the impacts of pest species, and includes set soil fertility with no compaction effect. As such, it tends to overstate biophysical performance.

An *Ausfarm* model was designed to represent the lamb production system using a 700-ha single paddock grazing system on red duplex soils. The pasture species used consisted of phalaris (*Phalaris spp.*), subterranean clover (*Trifolium subterraneum*) and annual ryegrass (*Lolium rigidum*) to represent the pasture mix at Holbrook. The animal production system modelled was a first-cross sheep system (Medium Merino (F) x Dorset (M)).

Two initial pasture compositions (low and high) were tested (Table 1). *GrassGro* (Freer et al., 1997; Moore et al., 1997) was used to validate pasture composition initialisation parameters. Flock structure initialisation parameters were reset annually to consist of 4000 ewes, 4400 lambs and 40 rams. To assess how forecast and non-forecast factors influence forecast value, all initialisation parameters (pasture and flock) were reset on 1 November each year and the model was run with the climate data for each year (1889–2015) until the end of March.

Table 1 Pasture composition attributes used in the *Ausfarm* modelling

Pasture scenario	Total herbage mass (kg/ha)	Total green herbage mass (kg/ha)	Total dry herbage mass (kg/ha)
Low starting pasture	2150		
Phalaris		300	1000
Sub clover		0	10
Annual rye		0	850
High starting pasture	4100		
Phalaris		1500	200
Sub clover		200	500
Annual rye		900	800

The flock was supplementary fed when the condition score of the animals fell below 2.8. Supplementary feed was wheat, fed at a rate of 0.68 kg/head/day.

For each pasture initialisation and each year, 11 different selling options for lambs were evaluated on 10 November. These were 10% steps from 0 to 100% of lambs sold. Lamb sales were proportional across male and female animals. For example, 10% sale was calculated as 10% of males and 10% of females. The second sale opportunity was defined as either when the animals reached their target weight (55 kg for female lambs and 65 kg for male lambs) or the target date was met (5 March). In total, 22 combinations of initial pasture combinations and lamb selling options were evaluated for 126 years of climate data.

3.2 Prime lamb production costs

The production costs of the system, including sheep flock health, selling costs and feeding costs for the model were based the NSW DPI Farm Enterprise Budget Series[2]. Detailed production costs used are included in Appendix 2: Gross margin values.

An annual interest rate of 12% was applied to production costs incurred in the investigation period (November to March).

3.3 Key input and output costs

Sensitivity analyses to November lamb and supplementary feed prices were conducted to consider if the value of SCFs vary under different price settings.

[2] https://www.dpi.nsw.gov.au/__data/assets/pdf_file/0011/175853/1st-Cross-Ewes-Terminal-Rams.pdf

Stock prices were sourced for 2006–2015 for the Wagga Wagga saleyards (MLA, 2017) and adjusted to real prices using (ABARES, 2015). Stock prices used were mixed lamb prices for three carcass weight categories (16.1–18 kg, 18.1–20 kg, 22.1–24 kg) in November, the first selling option and in February, the second selling option. Each category correlates to an approximate dressing percentage for weaned lambs (MLA, 2003). From this, each weight category was assigned a dressing percentage (44, 44 and 45% multiplied by 37 kg for each weight category respectively). This was then used to assign the sale price for lambs to be sold at the two selling time points.

Sensitivity to lamb prices was tested for three possible prices (low, medium and high). These were calculated as the 10th, 50th and 90th percentiles of the prices data (Table 2). Supplementary feed wheat prices (ABARES, 2015) from 2004–2013 were similarly adjusted to real prices and low, medium and high prices determined from the 10th, 50th and 90th percentiles (Table 2).

Lamb prices for post-November sales were fixed. This was implemented as prices after the decision in November are unknown. The 50th percentile of lamb prices in February was used to set the February price (Table 2).

Table 2 November lamb prices and supplementary feed prices evaluated

	November lamb price		
Carcass weight category (kg)	**Low**	**Medium**	**High**
16.1–18	0.64	0.95	1.27
18.1–20	0.73	1.03	1.37
22.1–24	0.95	1.26	1.60
	February lamb price		
16.1–18	1.04		
18.1–20	1.18		
22.1–24	1.51		
	Supplementary feed price		
	Low	**Medium**	**High**
Supplementary feed prices for wheat	292	380	440

3.4 Seasonal climate forecasts

A probabilistic climate forecast system, in line with currently used operational forecast systems, was adopted to assess the value of SCFs. Three discrete climate states (dry, average, wet) were identified based on the lower, middle and upper tercile of November–March rainfall received at Holbrook over the period 1889 to 2015. Each year was then classified as belonging to one of these climate states: drywas categorised by rainfall less than 142 mm, average as rainfall between 142 mm and 222 mm, and wet as rainfall in excess of 222 mm (Figure 7).

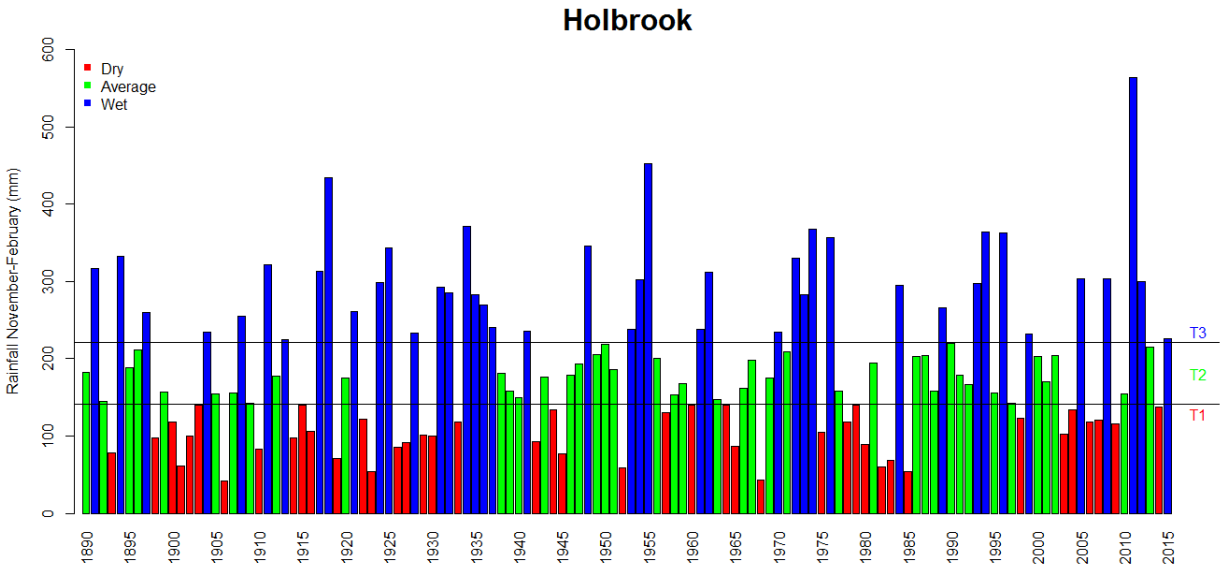


Figure 7 Total rainfall for November to February at Holbrook for 1889–2015. Dry, Average and Wet represent tercile 1, 2 and 3.

Agricultural production levels representing dry, average and wet climate states were obtained by classifying yearly outputs of pasture, feed and lamb production data from the biophysical production model (see section 3.1). Resulting yearly data for each state (42 years) were then averaged to represent each climate state within the economic model. This categorisation is a critical part of the approach because variations in production across climate states provide the necessary, but not sufficient, conditions for forecasts to offer value in decision-making.

The probabilistic climate forecasts evaluated in this case study are based on a hypothetical forecast system. This approach was chosen because there are multiple providers of operational climate forecasts and these systems are regularly updated to reflect improvements in understanding of climate and weather systems and rapid developments in computing and analytical capabilities. The main benefit of introducing a hypothetical forecast rather than relying on operational forecasts, is that key aspects of forecast quality, like skill, can be systematically valued. The results of the analysis are then more readily applicable to decisions around the level of investment in new forecasting systems.

In this study, 11 probabilistic forecasts were created for each of the three climate states (dry, average, wet), each representing a different level of forecast skill (0 to 100%). These probabilistic forecasts are incorporated into the economic model by assigning a probability to the occurrence of each climate state based on forecast skill. The definition for forecast skill with reference to prior (without-forecast) and posterior (with-forecast) probabilities was as defined in Equ 1.

$$\sigma = \frac{\pi_{s|f} - \pi_s}{1.0 - \pi_{sy}} \qquad \text{[Equ 1]}$$

where $\pi_{s|f}$ is the posterior probability of state *s* given forecast *f* and π_s is the prior probability of state *s*. In most forecast value studies, historical climatology is assumed to be the basis of the decision-maker's prior probabilities and the same approach is adopted here. Accordingly, π_s is set at its long-term climatological mean of 0.33 for each tercile.

Forecast skill σ is set at pre-determined levels and is rearranged to provide posterior probabilities (Equ 2).

$$\pi_{s|fy} = \sigma(1.0 - \pi_s) + \pi_{sy} \qquad \text{[Equ 2]}$$

Applying this equation to a forecast of a dry state with an assumed skill of 20% results in a weighting assigned to dry, average and wet states (Equ 3).

Dry = $\pi_{dry|fy} = \sigma(1.00 - \pi_{dry}) + \pi_{dryy} = 0.20(1.00 - 0.33) + 0.33 = 0.47y$

Avg = Wet $= y\frac{(y.00 - \pi_{dry|f})y}{2y} = y\frac{(y.00 - 0.47)}{2} = 0.27y$ [Equ 3]

Using this definition of forecast skill, 0% skill equates to climatology where each state has a 33% chance of occurring. Table 3 provides an example of weighting between the climate states for the 11 skill levels for a dry forecast state.

Table 3 Example calculation of weightings of each climate state for a dry forecast state for skill levels 0% to 100%

		Forecast skill										
	Climate state	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Weighting (%)	Dry	33	40	47	53	60	67	73	80	87	93	100
	Ave	33	30	27	23	20	17	13	10	7	3	0
	Wet	33	30	27	23	20	17	13	10	7	3	0

3.5 Economic model

The economic model used key outputs from the lamb biophysical production model to capture the links between climatic conditions, pasture and lamb production. The economic model evaluated the changes in livestock numbers, livestock weights and feed costs under the different stocking rate strategies (percentage of lambs sold). This was achieved by applying a consistent set of output prices (lamb prices in November and March) and input prices (feed prices) to the biophysical outputs and incorporating baseline information on lamb production costs.

The profitability of each stocking rate strategy was assessed under each forecast state (dry, average, wet). The economic model maximises returns by choosing the percentage of lambs to sell that has the highest return weighted across the three climate states according the prescribed forecast skill. The economic model takes the form of a discrete stochastic programming (DSP) problem which can be solved through adapting a conventional linear programming model and is represented in Equ 4.

$$Max\ E[Y] = \sum_{s=}^{s} \pi_s y_{sy} \qquad \text{[Equ 4]}$$

Where π_s is the probability of state *s* and y_s farm income in state *s*.

The model is also subject to normal constraints on the use of land, labour and capital so that input usage can never exceed availability.

Without a climate forecast, dry, average and wet states all have an equal chance of occurrence so the weighted or expected return (*E[Y]*) is simply the sum of economic returns in each state (Y_{dry}, Y_{avg}, Y_{wet}) multiplied by the probability of each state occurring (π_{dry}, π_{avg}, π_{wet}). The optimal stocking rate without a climate forecast is the one that provides the highest expected return.

The introduction of a climate forecast with skill greater than 0% leads to a revision of the probabilities in line with the extent of forecast skill. A skilful forecast of a dry season results in the

assignment of a higher probability to a dry state so the outcomes of a dry state are given more weight in the objective function of the model (see Table 3 for example). The change in weighting given to a dry state may lead to a change in the stocking rate decision (e.g. sell a greater percentage of lambs in March) and this creates economic value from forecast use.

A more detailed description of the economic model is contained in Appendix 3: Prime lamb economic model.

3.6 Analyses

The potential value of a probabilistic theoretical SCF was evaluated as the marginal benefit of the forecast; specifically, the change in returns using SCF information compared to the return obtained without a forecast. In this analysis, without-forecast is represented by 0% skill which is equivalent to equal weighting in results between dry, average and wet climate state outcomes (33% each). Value was calculated in terms of $/ha.

The value was assessed for several different decision environment settings and for 11 levels of forecast skill for each of the three climate forecasts (dry, average, wet). This produced 594 results representing various decision environment settings, forecasts and forecast skill levels (Table 4).

Table 4 Variables and value levels assessed to evaluate forecast value

Variable	Values tested
November pasture availability	low, high
November lamb price	low, medium, high
Supplementary feed price	low, medium, high
Forecast state	dry, average, wet
Forecast skill (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

Initially, the without-forecast (0% skill) selling decision was reported for all variable values (November pasture availability, lamb price, supplementary feed price). Subsequently, the perfect-forecast (100% skill) selling decision for the three forecast states was similarly reported. The potential value ($/ha) of the perfect forecast was calculated as the difference in returns with and without the forecast. This represents the largest potential value of each climate state. Finally, probabilistic forecast values ($/ha) relative to the without-forecast decision were calculated for each decision environment setting.

4 Results

4.1 Biophysical modelling

Data from the biophysical modelling followed expected patterns given the model and farming system assumptions. Lamb weights (male and female) in March showed a slight increase in weight as pasture availability increased (Figure 8). With higher lamb selling percentages it may be expected that lamb weight would increase, as fewer animals are consuming the same pasture base. Very modest gains in weight were reported for higher lamb selling percentages. Two aspects of the design of the biophysical model contribute to this result. Firstly, the model was designed to feed animals if insufficient pasture was available. Secondly, lambs were prescribed to be sold at particular weights (65 kg and 55 kg for males and females, respectively) for the post-November sale. Hence, the influence of different sale percentages in November is

best seen through the amount of supplementary feed (Figure 8). This decreases with higher lamb selling percentages as well as with higher pasture availability.

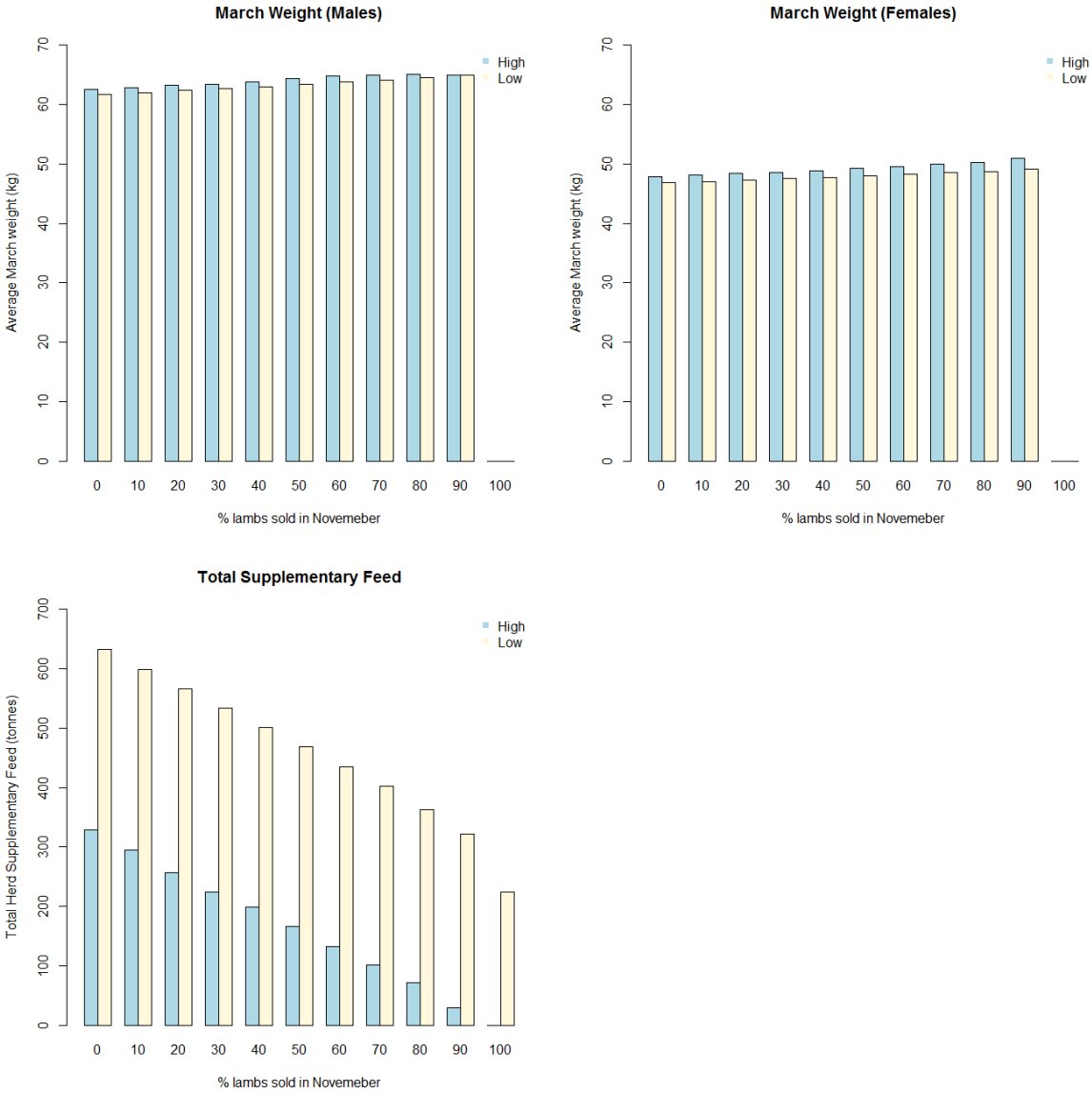


Figure 8 Mean lamb weights (male and female) at post-November sale weights and total supplementary feed (1889–2015) for high and low starting pastures for each of the 11 lamb selling decision points (0, 10, 20, …,100%).

Two parameter combinations were used to investigate the potential impact of different climate states on the amount of supplementary feed consumed: a 'worst-case' (low starting pasture and retaining all lambs, i.e. 0% sell) and a 'best -case' (high starting pasture and selling all lambs, i.e. 100% sell) (Figure 9). These scenarios include all years of data (1889–2015) classified into the dry, average and wet climate states. Comparing the best- and worst-case scenarios illustrates that more supplementary feed was allocated in the worst-case. Within the worst-case scenario, less supplementary feed was required for many, but not all, wet years. More supplementary feed was required in dry and average years as expected (Figure 9). For the best-case scenario, little association between climate state and supplementary feed requirements was found (Figure 9). The influence that climate states have on supplementary feed is strongly affected by the level of starting pasture and this is likely to influence the value of SCFs.

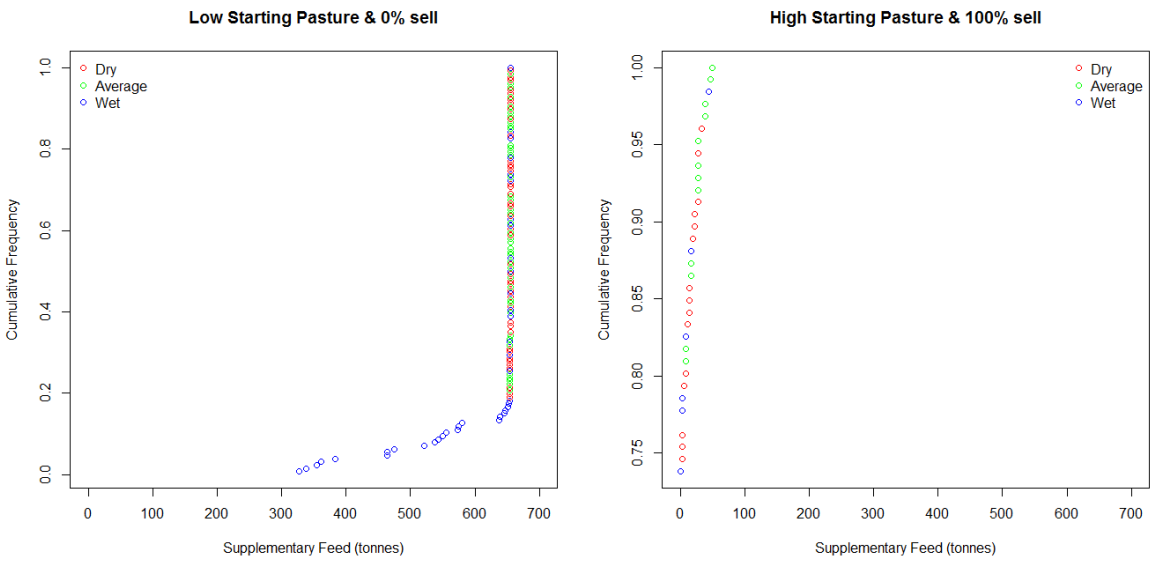


Figure 9 Annual supplementary feed requirements from November to March according to dry, average and wet classifications. Left is a 'worst-case' in relation to supplementary feed requirements with the model fit with low starting pasture and retaining all lambs. Right is a 'best-case' in relation to supplementary feed requirements with high starting pasture and 100% sell of lambs in November.

4.2 Economic modelling

4.2.1 Without-forecast decision

To evaluate the potential value of SCFs, the optimal sell decision made without a forecast must first be assessed. Figure 10 shows the optimal without-forecast sell decision for each combination of the decision drivers (Table 4). For both pasture availability levels (Figure 10), low November lamb prices encourage holding all lambs while high November prices encourage selling of all lambs.

Greater sensitivity to prices can be seen with medium November lamb prices between the pasture availability levels. For low starting pasture, the predominant decision is to sell 100% of lambs, unless supplementary feed prices are low. Conversely, with high starting pasture, lambs are almost all held, unless supplementary feed prices are high in which case10% of lambs are sold in November.

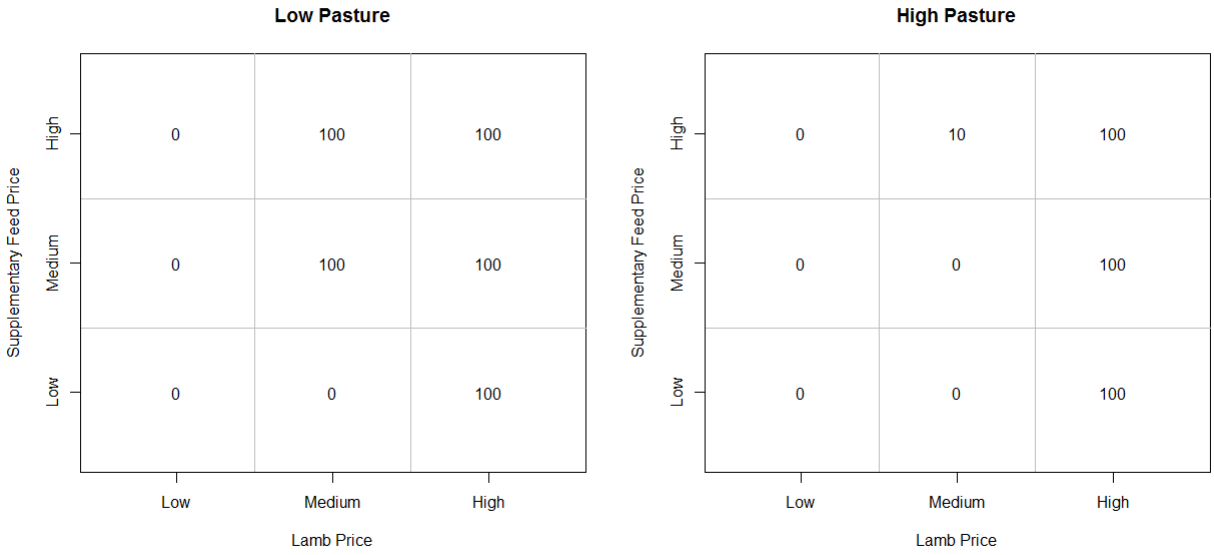


Figure 10 Without-forecast lamb sale decision. Percentage of lambs sold under different levels of current pasture availability (low, high) with supplementary feed prices (low, medium, high) in the internal rows and November lamb price (low, medium, high) in the internal columns.

4.2.2 Perfect-forecast decision

The economic model determined the optimal lamb sell decision for perfect forecasts of dry, average and wet climate states (100% skill) under varying decision drivers (pasture availability, lamb prices and supplementary feed prices) (Figure 11).

Considering low pasture availability (top row; Figure 11), the decision for all climate states is the same as the without-forecast decision. For high pasture availability, the decision to sell lambs does differ with climate state from the without-forecast decision for some price combinations. The decision to hold all animals under low lamb prices highlights the influence of price. Holding and selling animals later at bigger weights, with additional feed costs, generates greater returns independent of climate state. The decision to sell all lambs with high lamb prices does change, with more animals held if the climate state is wet. Less selling of lambs for medium lamb prices occurs for the average and wet climate states if supplementary feed prices are medium or high.

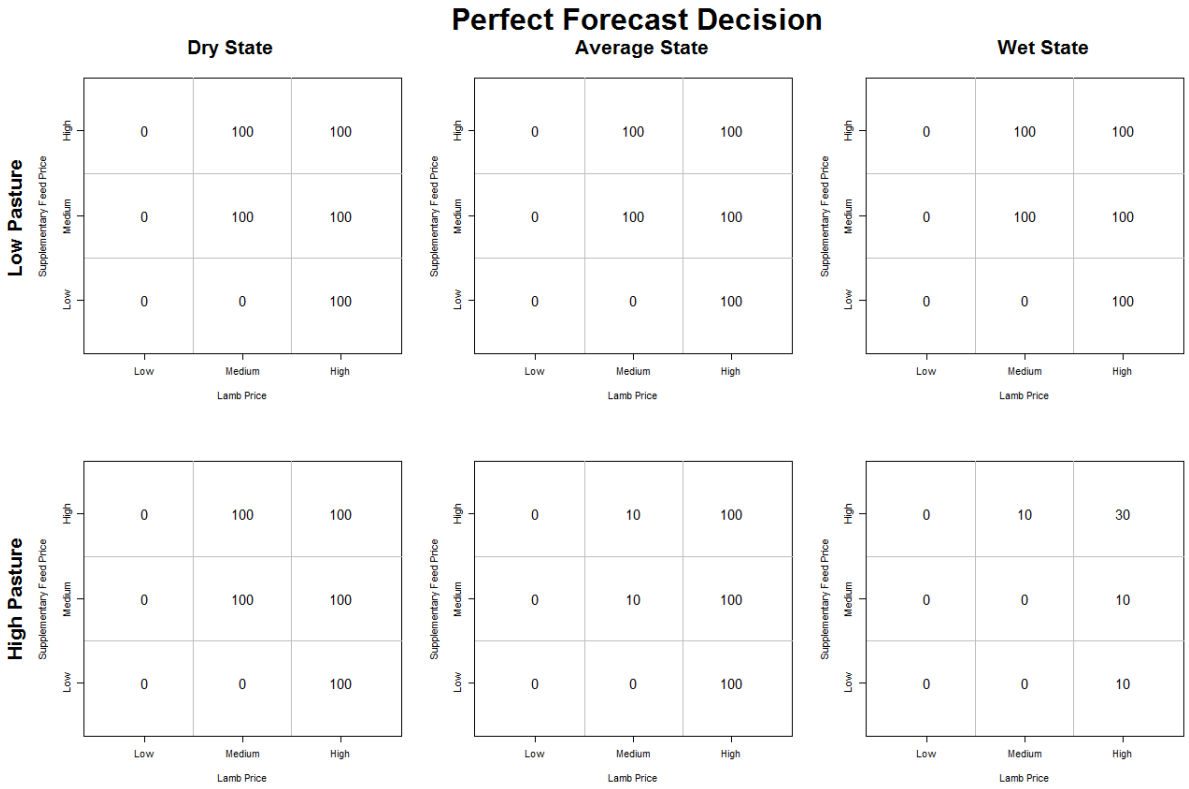


Figure 11 Perfect-forecast lamb sale decisions. Percentage of lambs sold under dry, average and wet states in the three major columns, two levels of current pasture availability (low, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and November lamb price (low, medium, high) in the internal columns.

4.2.3 Perfect-forecast value

Results of the value of a perfect forecast (100% skilful) of the three climate states indicate the importance of the decision drivers. If pasture availability is low in November, even a perfect forecast of any climatic state did not provide any value (zero values in Figure 12). In this case, the farm is overstocked and the dominant decision is to sell rather than retain lambs.

Under high pasture availability, the optimal stocking decision is influenced by price settings as well as climate forecasts in some scenarios (non-zero values in Figure 12). Most value was found for either dry or wet forecasts with limited value found for an average state forecast (middle column; Figure 12).

The greatest value was $53.80/ha for a dry forecast under high pasture availability, medium lamb prices and high supplementary feed prices. Under these circumstances, 100% (Figure 11) of lambs are sold with the forecast, shifting from the without-forecast position of selling 10% (Figure 10). The greatest value for a wet forecast occurred under high pasture availability and high lamb prices. For these settings, the with-forecast decision is to hold more stock (10–30%) compared with 100% sell under the without-forecast scenario. High forecast values are associated with the most substantial shifts in the optimal stocking rate.

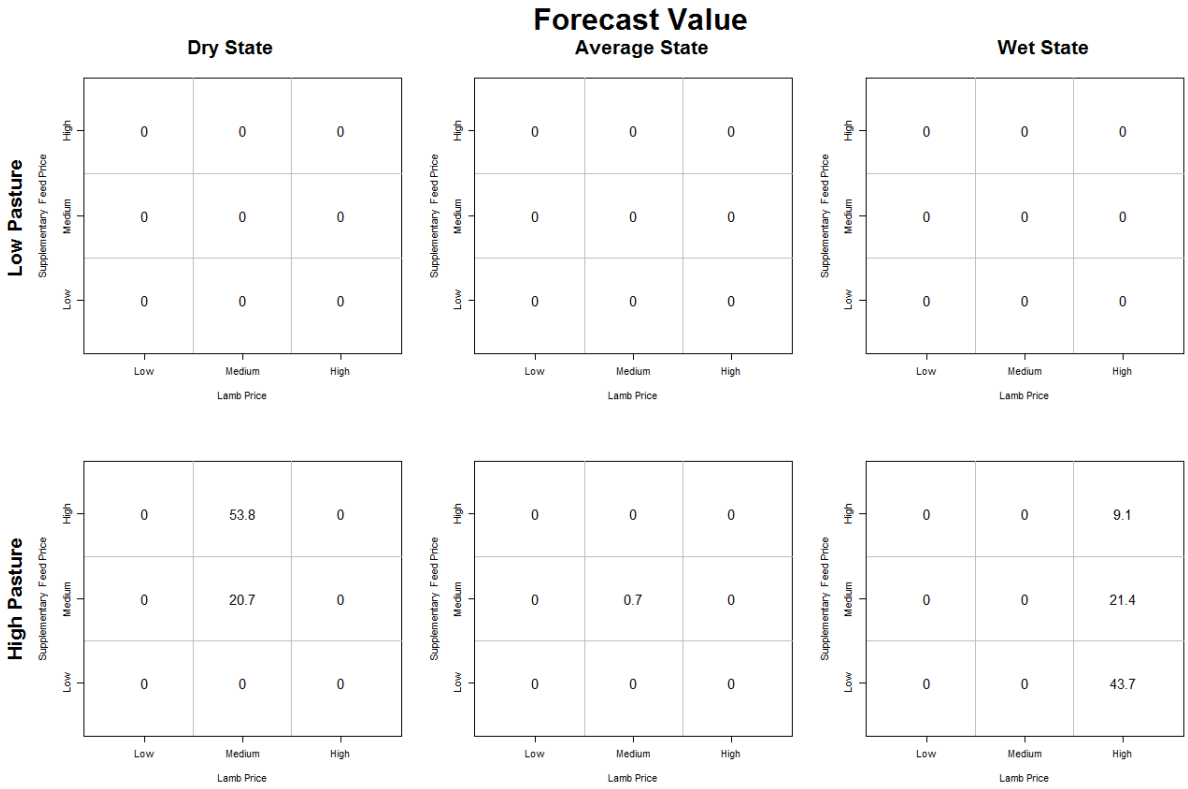


Figure 12 Perfect forecast relative value compared to the without forecast return ($/ha). Dry, average and wet states in the three major columns, two levels of pasture availability (low, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and November lamb price (low, medium, high) in the internal columns.

4.2.4 Probabilistic forecast value

The value forecasts with different levels of skill were assessed for each climate forecast (dry, average, wet), for high pasture availability and different price setting for lamb and supplementary feed prices (Figure 13). Low pasture availability was not plotted as the value is $0/ha for all skill levels.

This plot provides greater detail of the results in Figure 12, illustrating the value of forecasts with various skilfulness levels. Where value was found, value increases as skill increases. Most value was found for wet forecasts or dry forecasts with very little value found for an average forecast (Figure 13). Forecasts with skill above 20% were found to offer value under the settings analysed.

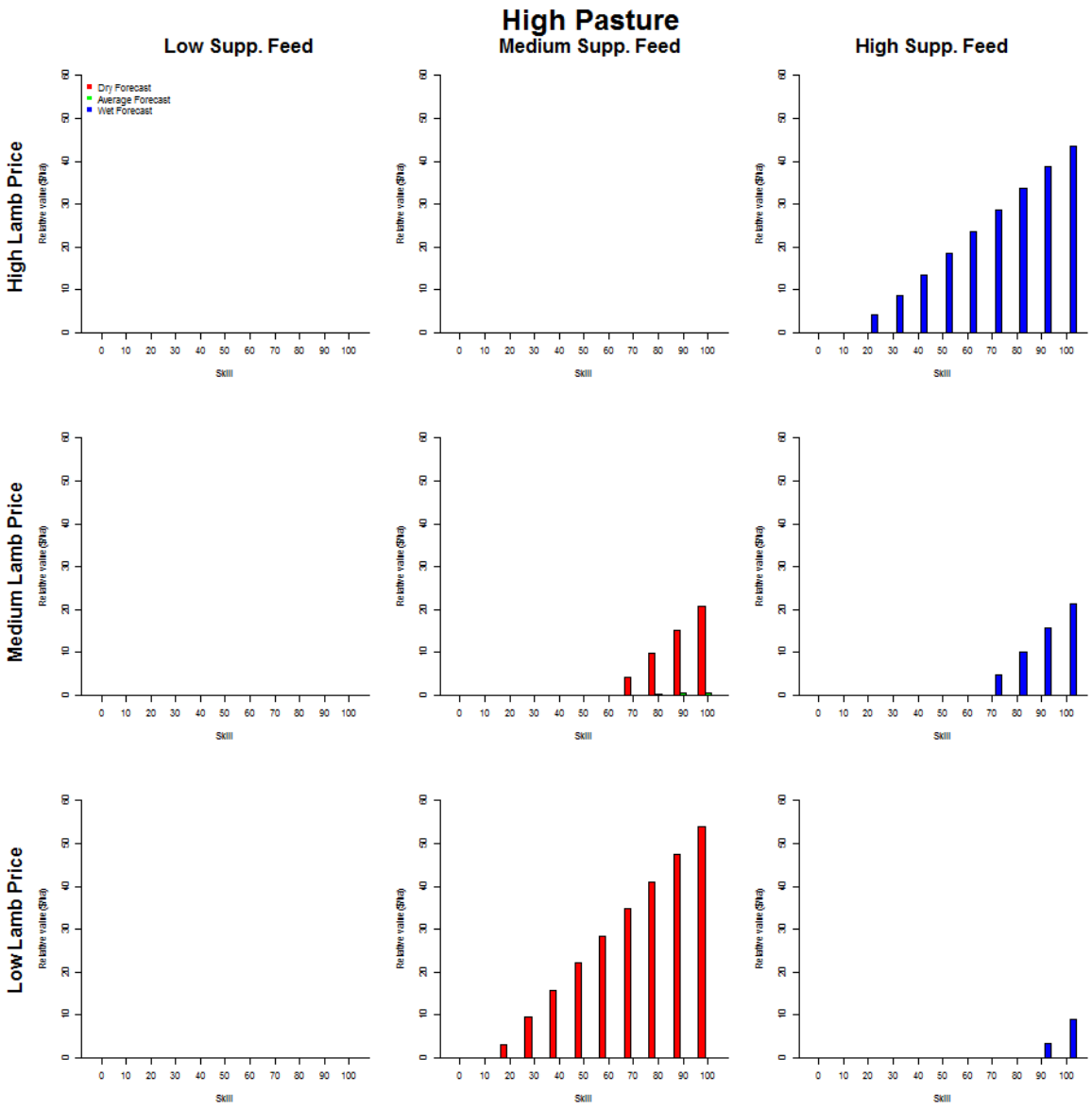


Figure 13 Value of forecast ($/ha) for high pasture availability. Supplementary feed prices (low, medium, high) are the three columns of plots, November lamb price (low, medium, high) in the three rows of plots. Red, green and blue represent dry, average and wet climate forecast. Forecast skill, grouping dry, average and wet forecasts, increases on the x-axis from 0 to 100% with 0% the without forecast and 100% the perfect forecast.

Table 5 provides a summary of the potential value of a forecast with different levels of skill for high pasture availability and for each of the forecast states (dry, average, wet). The range represents variations in lamb and supplementary prices. For all skill levels, nil value is possible depending on the price settings. This illustrates the importance of price setting in determining the value of a forecast. The greater value for wet and dry forecasts is also evident.

Table 5 Range of value of the forecast ($/ha). Range is across different November lamb and supplementary feed prices. Forecast skill is represented by 0%,10%, ⋯,100%.

Pasture	Forecast state	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
High	Dry	NA	0–0	0–3.2	0–9.5	0–15.9	0–22.2	0–28.5	0–34.8	0–41.2	0–47.5	0–53.8
	Average		0–0	0–0	0–0	0–0	0–0	0–0	0–0.1	0–0.3	0–0.5	0–0.7
	Wet		0–0	0–4.1	0–8.7	0–13.5	0–18.6	0–23.6	0–28.6	0–33.6	0–38.6	0–43.7

5 Discussion

The key decision identified by industry was how many lambs to sell in November and how many to carry through to sell by March. This decision is a trade-off between selling smaller animals now with lower feed costs and selling animals later at higher weights with potentially higher feed costs. An important feature of this system is that lambs are sold either once they reach a prescribed target weight or by the beginning of March. As a result, lambs not sold in November may be sold a short time later (e.g. early January) and therefore do not need to be carried through the whole summer, potentially reducing supplementary feed costs.

Pasture availability had a substantial influence on the optimal stocking rate with and without a climate forecast. Low pasture availability led to a dominant decision to sell all lambs in November irrespective of the climate forecast or other non-forecast factors, including lamb and supplementary feed prices. Even a perfect forecast of any of the climate states did not alter the optimal decision. These results indicate that when conditions are poor in November it is difficult to improve the profitability of the system, regardless of seasonal evolution. Under high pasture availability, the optimal stocking decision is influenced by price settings as well as climate forecasts in some scenarios.

Although November pasture availability was an important determinant of SCF value, supplementary feed and lamb price settings and the particular climate state (dry, average or wet) were also found to be key drivers.

Lamb price in November strongly influenced the selling decision. When November lamb prices were low, the decision was to hold all lambs, regardless of pasture availability or climate state (Figure 11). This indicates that the cost of supplementary feed did not outweigh the benefit of selling lambs later at higher weights. An important additional aspect to appreciate in this result is the differential prices in lamb across the calendar year. Historically, lamb prices are higher in February than in November (analysis not shown). As such, weight-for-weight, greater income is obtained for lambs sold in February. Due to this market setting, holding lambs has additional benefit in addition to greater weights.

With high November lamb prices, the without-forecast decision was to sell all lambs regardless of pasture availability (Figure 10). This is due to higher relative prices compared with February prices and lowered supplementary feed prices for selling lambs early in the season. Incorporating SCFs, the decision at high November lamb prices only differed for a wet forecast (Figure 11 and Figure 12). With a perfect wet forecast, 10% or 30% of lambs were sold, compared with 100% sold in the without-forecast scenario, as supplementary feed costs were reduced. A perfect forecast of a wet state resulted in an improvement in returns from $9.10–$43.70/ha, depending on supplementary feed prices.

For the price and pasture settings where forecasts influenced decisions, forecasts of dry, average and wet climate states had different economic values. A climate forecast of average conditions was found to be of limited economic value under all model settings. The maximum value of a forecast of average conditions was $0.70/ha. This low value of an average forecast state reflects the limited change that occurs in decision-making with and without the forecast. As climatology is simply the average climate conditions, only small changes to the selling decision with an average forecast state (middle tercile of climate data) is unsurprising.

For high pasture availability, greater value of dry or wet forecast states was found (Figure 13 and Table 5). Two examples will be used to explore the different circumstances for which dry and wet forecasts have value. With medium November lamb prices and high supplementary prices, the without-forecast decision was to sell 10% of lambs. With a perfect **dry** forecast, the optimal decision changes to selling 0% of lambs, driven by savings in feeding costs when a dry season evolved, which was particularly important as supplementary feed prices were high. A perfect forecast of a dry state resulted in an improvement in returns of $53.80/ha under this scenario.

A scenario with high November lamb prices and low supplementary feed prices provides an example of the benefit of a **wet** forecast. The without-forecast decision in this scenario was to sell 100% of lambs, largely due to cost of supplementary feed. With a perfect wet forecast the optimal decision changed to selling just 10% of lambs. In this example, a wet forecast provided greater surety about the occurrence of additional pasture growth that occurs in a wet state, reducing supplementary feed costs and making holding stock more profitable. A perfect forecast of a wet state resulted in an improvement in returns of $43.70/ha under this scenario.

These examples highlight the maximum possible value of SCF under different scenarios through assuming the forecast was perfect or 100% skilful. However, in reality SCFs are imperfect and different levels of skill were analysed to assess the value of improvements. Positive value of SCFs was obtained, for certain decision driver settings, at about 20% or 70% skill (Figure 13). This suggests that the value of SCFs can be unlocked each year given market pricing and, to some extent, the configuration of farm risk management strategies.

The case study design used particular parameter settings both within the *Ausfarm* production model and for the economic modelling. For the *Ausfarm* settings, the farm characteristics were developed in consultation with industry to provide a representative farm. These characteristics will likely be different for individual farms, for instance, with different stocking rates used. Furthermore, the timing of the sell decision will differ for different systems and for different production areas with different climate profiles (e.g. earlier/later lambing).

The timing of joining and hence when lambs can begin to be sold is an important strategic farm decision to consider further. If a farm operates with a different joining time, the SCF of interest will change to match the weaning time. Here, industry advice was taken regarding likely joining times which resulted in a rainfall SCF from November–February being investigated. At Holbrook, rainfall at this time of year is not historically highly variable (Figure 7) and the difference in rainfall between dry and average states was only 80 mm. Other case studies at different locations with greater seasonal variability or for a system with different joining times which moves the SCF window may lead to value of SCFs under a greater number of system settings (pasture availability and prices).

The design of the analysis includes two categories of information which were used in the economic assessment: information that can be known at the decision time (pasture availability, lamb price, supplementary price) and future information that is unknown at the decision time (climate state, price of lambs post-November). Sensitivity analyses were included to evaluate the impact of different settings of the known information and a probabilistic forecast system was explicitly used to assess the value of SCFs. Prices for post-November lamb sales were fixed to the median of historical values. This approach was undertaken as a rational assumption of uncertain future prices. However, producers may have additional information in November to the likely price of lambs later in the season (e.g. greater market access leading to higher demand for lamb). Additional information that changes the price of lamb post-November would likely change the with- and without-forecast selling decision. This was investigated through a sensitivity analysis to post-November lamb prices using historically low (10th percentile) and high (90th percentile) prices (Appendix 5: Perfect forecasts with low/high February prices). These additional analyses show that changes to the information available can change the selling decision and hence the value of the forecast. In general, for a selling decision made in November, if it is known that lamb prices in February will be relatively higher due to historical values, fewer lambs will be sold. Conversely, if prices are expected to be low in February, more lambs are sold.

Lamb and supplementary feed prices in the analysis were treated as being independent of the climate state. In other words, the same lamb and feed prices existed in each state (non-state contingent). There is an argument, however, that lamb prices could be lower and feed prices higher in a dry state and potentially the converse in a wet state. This, in effect, would create bigger differences in economic returns between dry and wet states and would makes forecasts

more valuable, keeping all other factors constant. The modelling approach is particularly well suited to including prices as state-dependent variables. However, a review of historical lamb and supplementary feed prices did not find any correlation between price levels and rainfall states. There are a range of possible reasons relating to the length of the forecast window (December–March), historically low sheep numbers, the timing of grain production relative to the forecast window, and the coarseness of the climate states used based on terciles (a dry state is not drought).Under different assumptions, there may well be a link between prices and states but treating prices as independent seems to be a reasonable assumption in this case study.

Finally, it should be acknowledged that this analysis was conducted using a theoretical tercile SCF. Operational forecasts, such as the SOI phase system (Stone and Auliciems, 1992) or Bureau of Meteorology POAMA model (Wang et al., 2004) were intentionally not used. The use of theoretical rather than actual forecasts was preferred given the focus here on potential value rather than actual value. The methodology outlined here does provide a robust framework for further analyses of operational forecast systems.

Like operational forecasts, the theoretical forecasts used in this analysis provided an indication of the likely climate state (dry, average or wet) not the precise evolution of weather conditions. The value of a higher resolution forecast, such as a decile forecast, may be greater. This sets a challenge to the forecasting community. For instance, the Bureau of Meteorology currently operates on a two-state climate forecast (above or below median). The current percent consistent score for the Holbrook region for rainfall November to January is approximately 60%, equating to a skill score used here of 20%.

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Appendix 1: Industry engagement

Engagement for the development of a case study for lamb was conducted in consultation with members of the southern NSW SAMRC, following advice from MLA representatives (Tom Davidson and Irene Sobotta; 13 April 2016).

A workshop was held in Wagga Wagga (29 July 2016) to explore the lamb system to identify climate-sensitive decision points at a seasonal scale (months). Those present were: Angus Hobson, Michael Campbell, Phil Graham, Steve Exton and two project members, Rebecca Darbyshire and Michael Cashen.

1 Identifying climate-sensitive decision points

Discussions were focused on a representative farm system. The group selected Holbrook and a second-cross (non-self-replacing) operation as representative for southern Australian lamb producers. A farm size of 700 ha was used carrying 3000 ewes. It was highlighted that variable seasonal conditions tend to be managed via buying in feed, such as grain, rather than adjusting stocking rates.

Joining was set to occur through February and into March with lambing through July and early August. Supplementary feeding is common, with twinning ewes supplemented through winter if pasture availability is low. Additional supplementary feeding of the flock, dependent on feed availability, will occur through summer.

Producers aim to begin to sell lambs from November with all lambs sold by the end of March.

2 Decision point

The group identified that the decision of how many lambs to sell in the early season (November) is sensitive to seasonal climate forecast information. This decision was classified as the critical climate-sensitive decision as this sets the number of animals carried through to later selling opportunities. In evaluating this decision economically, a comparison between profit gained from selling lambs early will be compared with the alternative potential profit of holding stock to sell later at higher weights.

A seasonal rainfall forecast close to the first sale time, November, can provide an indication of summer pasture availability and hence assist with decisions around selling rates.

This decision of how many lambs to sell in November is made in November and the relevant rainfall forecast is for November, December, January, and February.

Allocating the proportion of lambs to initially sell is not a simple decision. Three key drivers were identified by the group which influence this decision:

1. Feed availability: low pasture encourages selling, high pasture discourages selling.
2. Relative price of grain feed: high prices encourage additional selling, low prices discourage selling.
3. Rainfall forecast: wet (i.e. good pasture growth) discourages selling, dry (i.e. poor pasture growth) encourages selling.

Figure **14** illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including seasonal climate forecast information against decisions made without this information.

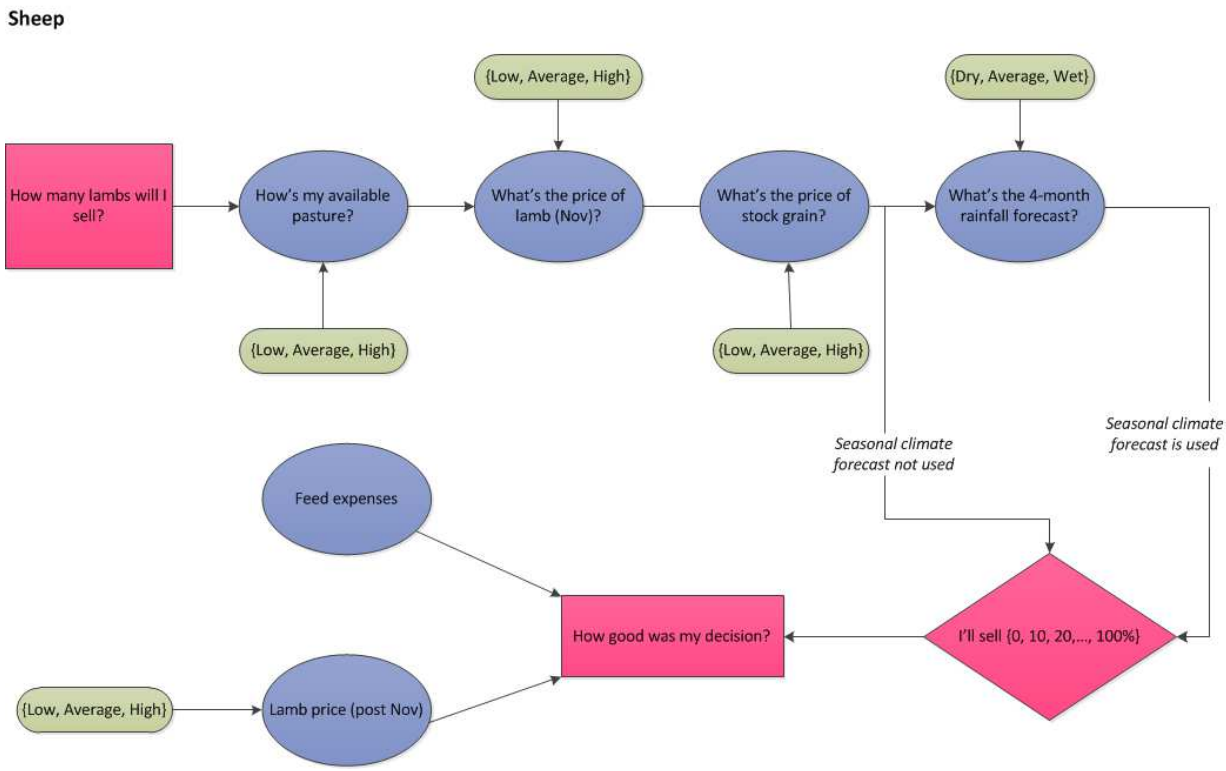


Figure 14 Decision pathway for proportion of lambs sold in southern lamb system including an evaluation of the decision made.

3 Selling decision

The workshop participants allocated selling decisions based on different values of the three drivers (Table 6). Under 'average' circumstances for all drivers, 30% sale of lambs was allocated. This represents the business-as-usual decision.

Table 6 Lamb sell decisions in November with different options for the key drivers as determined in consultation with industry. Seasonal rain forecast is for November, December, January and February. *Industry values determined through the workshop. The remaining values were determined subsequently and confirmed by the participants at a later date.

Feed available	Grain price	Climate outlook (Dec, Jan, Feb)	% sell
*Average	Average	Equal chance	30
Low	Low	Dry	50
Low	Low	Equal chance	40
Low	Low	Wet	30
*Low	High	Dry	100
Low	High	Equal chance	60
*Low	High	Wet	30-40
*High	Low	Dry	30
High	Low	Equal chance	20
*High	Low	Wet	10
High	High	Dry	80
High	High	Equal chance	50
*High	High	Wet	20

In allocating these selling decisions, maintaining consistency between the different values of the drivers and across the different combinations was difficult. Modelling provides a method to optimise such decisions across multiple drivers which can take several values. Furthermore, using modelling approaches, the benefit or otherwise of including seasonal climate forecast information in the decision-making process can be isolated.

Appendix 2: Gross margin values

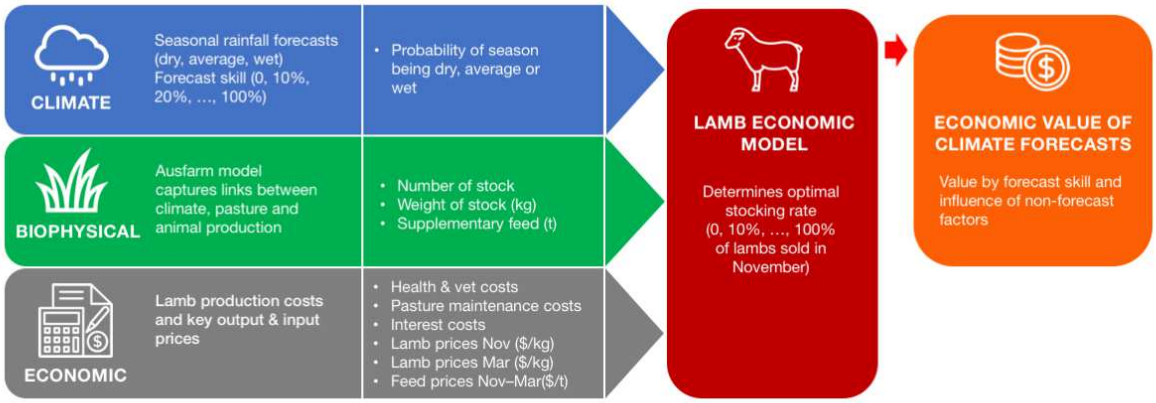
Table 7 Production costs used in the economic analyses

Variable costs	Cost (A$) Ewe/ram	Cost (A$) Lamb to Nov	Cost (A$) Lamb post-Nov
Replacement costs			
Replacement ewes	37.98		
Replacement rams	5.60		
Cartage ewes	0.35		
Cartage rams	0.20		
Wool harvesting and selling costs			
Shearing ewes	6.86		
Shearing rams	0.20		
Crutching ewes	1.25		
Crutching rams	0.05		
Crutching lambs			1.30
Wool tax	0.44		0.01
Commission, warehouse, testing charges (per bale)	0.99		0.05
Wool-cartage	0.21		0.01
Wool packs	0.26		0.01
Sheep herd health costs			
Broad spectrum adults (ewes+rams) x2 repeats	1.90		
Broad spectrum lambs no of repeats		0.88	1.32
Narrow spectrum adults (ewes+rams)	0.35		
Narrow spectrum lambs		0.16	0.16
Fly control long acting for adults	1.76		
Fly control short acting lambs			0.46
Lice control for adults	1.14		
Vaccination - 6-1 adults 1x	0.24		
Vaccination - 6-1 lambs no of repeats		0.24	0.48
Marking lambs		1.68	1.68
Scanning ewes	0.80		
Livestock selling costs			
Freight costs to saleyard	0.29	1.60	1.60
Livestock Selling Costs (Yard dues, MLA levy, LLS rates) - Commission percent - 4.95%	1.07	Calculated in the model depending on no sold per strategy	Calculated in the model depending on no sold per strategy
Feeding costs			
Pasture Maintenance per ha	11.81		
Miscellaneous supplementary feed	6.72		
Total costs	**80.47**	**4.56**	**7.09**

Appendix 3: Prime lamb economic model

1 Overview of the modelling approach

PRIME LAMB [SHEEP]



2 Economic model description

The economic model used key outputs from the lamb biophysical production model to capture the links between climatic conditions, pasture and lamb production. The model evaluated the changes in livestock numbers, livestock weights and feed costs under the different stocking rate strategies (percentage of weaner lambs sold). This was achieved by applying a consistent set of output (lamb prices in November and March) and input prices (feed prices) to the biophysical outputs and incorporating baseline information on lamb production costs.

A two-stage discrete stochastic programming (DSP) model was developed for the prime lamb case study where time was divided into the 'present' and the 'future'. A standard linear programming model was developed into a DSP model by introducing a second period decision. The $x \rightarrow s$ format of static linear programming changes to $x_1 \rightarrow s \rightarrow x_2$ (s, x_1) in the DSP case. Here x_1 represents Stage 1 decisions (11 stocking rate strategies – sell 0%, 10%, ...,100% of weaner lambs in November), s is the state of nature (tercile rainfall – dry, avg and wet) and x_2 (s, x_1) represents Stage 2 decisions (supplementary feed, number and weight of stock sold, level of debt, labour related to feeding days). These Stage 2 decisions are contingent upon earlier Stage 1 decisions and the state of nature that occurs. The farm-planning problem is to choose the optimal stocking rate in November to maximise the expected level of net farm income across climatic states. In algebraic terms, the main elements of the model are:

$$Max\ E[Y] = \sum_{s=}^{s} \pi_s y_{sy} \qquad \text{[Equ 1]}$$

$$y_s = \sum_{j=}^{Jy} y\ cy_j\ xy_j + \sum_{n=}^{N} c_{2nsy} x_{2nsy} \qquad \text{[Equ 2]}$$

Where:

π_s probability of state *s*

y_s net return in state *s*

Model parameters

c_{1j} the net return from the sale of weaner lambs under stocking rate *j* in Stage 1 ($/hd) – November

c_{2js} the net return from activity *n* chosen in state *s* in Stage 2 (lamb price, feed price, labour cost, interest) – March

Model variables

x_{1j} the number of male and female lamb weaners *j* sold in Stage 1 – November

x_{2ns} the level of activity *n* chosen in state *s* in Stage 2 (lamb – sales, feed – tonnes, labour – hours, debt – interest) – March

The objective function (Equ 1) maximises the expected net return from activities across three climatic states. The expected return takes into account the level of return in each state and the probability of each state occurring. The expected net return is maximised subject to constraints on the overall size of the flock and the number of weaner lambs and older lambs available for sale. The DSP model was solved using the What's Best!® 8.0 add-in to Microsoft Excel®.

The two-stage decision process is reflected in returns for each state (Equ 2). In Stage 1, the term $c_{1j}\, x_{1j}$ represents returns from a particular stocking rate strategy. The return c_{1j} is simply price of weaner lambs in November ($/kg) multiplied by their live weight and x_{1j} is the number of male and female weaner lambs sold. In Stage 2, the term $c_{2ns}\, x_{2ns}$ represents state-contingent revenue and costs related to decisions about the sale of older lambs, purchase of supplementary feed, labour use and debt levels. These are state-contingent because climatic conditions influence the live weight of lambs retained and the level of supplementary feed needed, with flow on effects in terms of labour and debt.

A key part of the analysis is that decisions taken in Stage 1 are the same in every state of nature, whereas the decisions taken in Stage 2 are specific to each state. While production is state-contingent, as per the outputs from the biophysical model, the prices of inputs (e.g. supplementary feed) and outputs (e.g. lamb prices) were assumed to be independent of climatic conditions. A review of available lamb price and supplementary feed price data did not establish a correlation with November–March rainfall.

The modelling approach has a number of strengths in the context of valuing seasonal climate forecasts. First, because production in each state of nature is explicitly recognised, it is straightforward to assess the consequences of different stocking rate decisions in each state. This is an important feature when considering the value of imperfect forecasts. Second, the modelling reflects the ability of farmers to consider state-contingent responses, something readily observed in practice. Third, with operational forecasts being probabilistic in nature, rational farmers will interpret probabilistic forecasts as a shift in the odds. This can be readily reflected in a DSP model through the assignment of posterior probabilities to each state based on forecast skill.

2.1 Valuing the forecast system

Without a climate forecast, dry, average and wet states all have an equal chance of occurrence so the weighted or expected return ($E[Y]$) is simply the sum of economic returns in each state (Y_{dry}, Y_{avg}, Y_{wet}) multiplied by the probability of each state occurring (π_{dry}, π_{avg}, π_{wet}). The optimal stocking rate without a climate forecast is the one that provides the highest expected return.

The introduction of a climate forecast with skill greater than 0% leads to a revision of the probabilities in line with the extent of forecast skill. For example, a skilful forecast of a dry

season results in the assignment of a higher probability to a dry state, so the outcomes of a dry state are given more weight in the objective function of the model. For a forecast to have economic value, the change in weighting must lead to a change in the stocking rate decision (e.g. sell a greater percentage of weaner lambs in November) relative to the without-forecast scenario. Model restrictions ensure that the overall probability of the occurrence of each climatic state is the same as its historical probability of occurrence (i.e. the prior probability π_s). This restriction ensures that the model is valuing improved knowledge about the occurrence of each state.

The value of the forecast system is derived from optimal decisions taken with and without the forecast. Expected farm income in the DSP model (*Y*) is a consequence of non-stochastic returns in Stage 1 (prior to uncertainty being resolved) and stochastic returns in Stage 2 (after the state of nature is revealed). With a risk-neutral objective function of the DSP model (Equ 1) and the hypothetical forecast system described elsewhere, the value of a specific forecast *f* within this system was defined as:

$$V_f = \sum_{s=1}^{3} \pi_{s|f} y^*_{sf} - \sum_{s=1}^{3} \pi_s y^*_{so} \qquad \text{[Equ 3]}$$

where:

y^*_{sf} denotes the net return in state *s* resulting from implementing the optimal stocking rate strategy x^*_{sf} based on forecast *f*; and

y^*_{so} denotes net return in state *s* resulting from implementing the optimum optimal stocking rate strategy x^*_{so} based on the prior probabilities (assumed to be historical climatology).

This is simply a statement that the value of forecast f is equal to the difference in expected net return with and without the forecast. The forecast will have no value in the event that $x^*_{sf} = x^*_{so}$ (i.e. where the with-forecast and the without-forecast decision is the same). The estimated value of a particular forecast accounts for both the decisions made in Stage 1 (November) and the state-contingent tactical adjustments made in Stage 2 (March).

The value of a forecast system is obtained by weighting the value of each forecast within the system by the frequency with which each forecast occurs. If *F* denotes a forecast system and q_f is the frequency with which each forecast occurs, then the value of a forecast system with three possible forecasts can be defined as:

$$V_F = \sum_{f=1}^{3} q_f V_f \qquad \text{[Equ 4]}$$

The value of the forecast system is influenced by attributes of the forecast system and attributes of the decision setting. The main attribute of the hypothetical forecast system assessed is forecast skill. An increasingly skilful forecast allows the DSP model to divert more resources towards production in the forecasted state. With a forecast of three rainfall states ($f = f_{dry}$, f_{avg}, f_{wet}) and 11 skill levels (σ = 0, 10%, 20%, …, 100%), the DSP model is solved 33 times in order to value the hypothetical forecast system for a given set of conditions (levels of pasture availability, stock and feed prices).

Appendix 4: Probabilistic forecast sell decision

Change in % of lambs sell decision from without-forecast decision

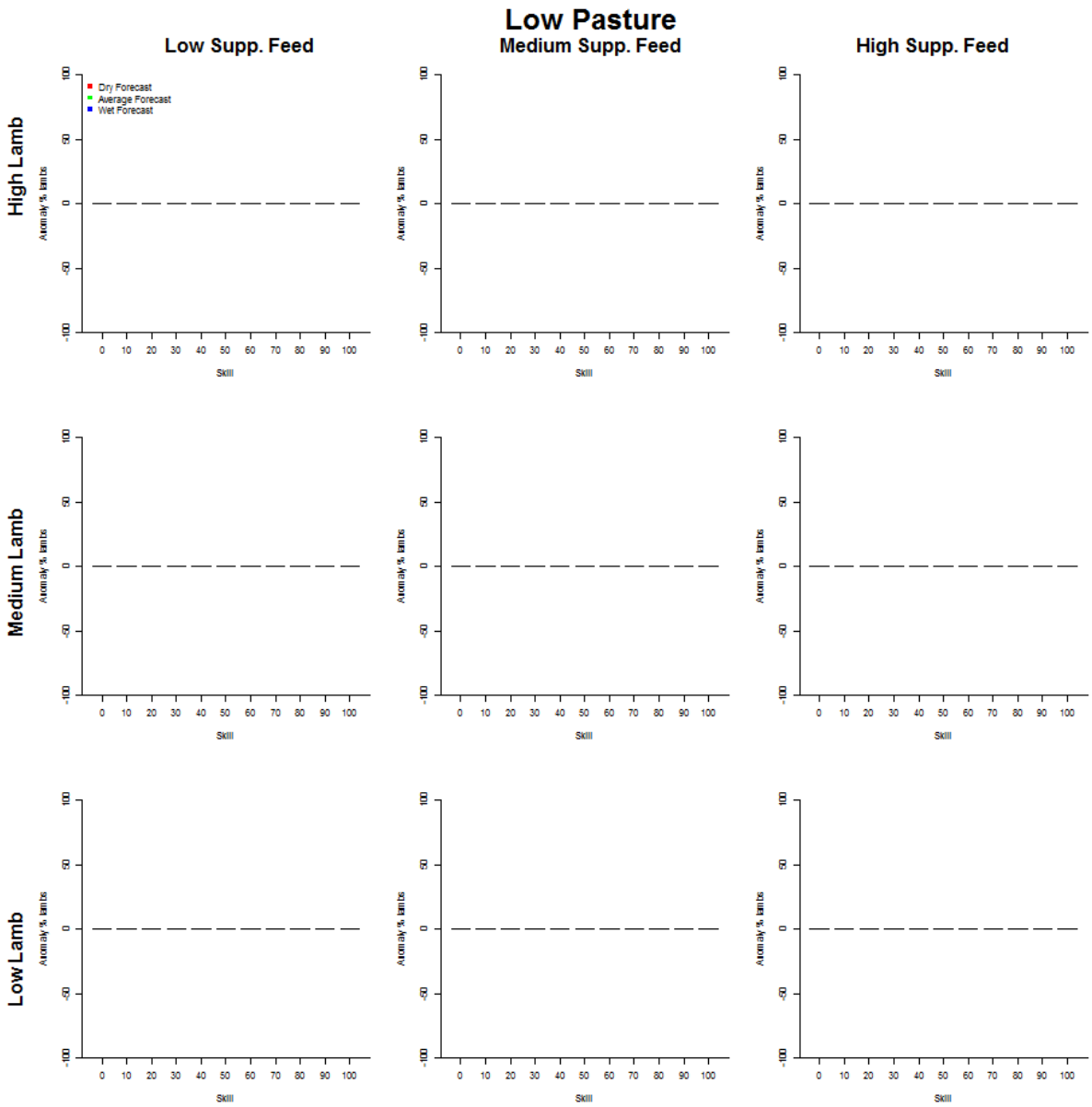


Figure 15 The change in the percentage of lambs sold based on increasing skill of probabilistic forecasts, relative to the without-forecast sell decision (i.e. 0% skill) for low pasture availability. Red, green and blue indicate dry, average and wet forecasts.

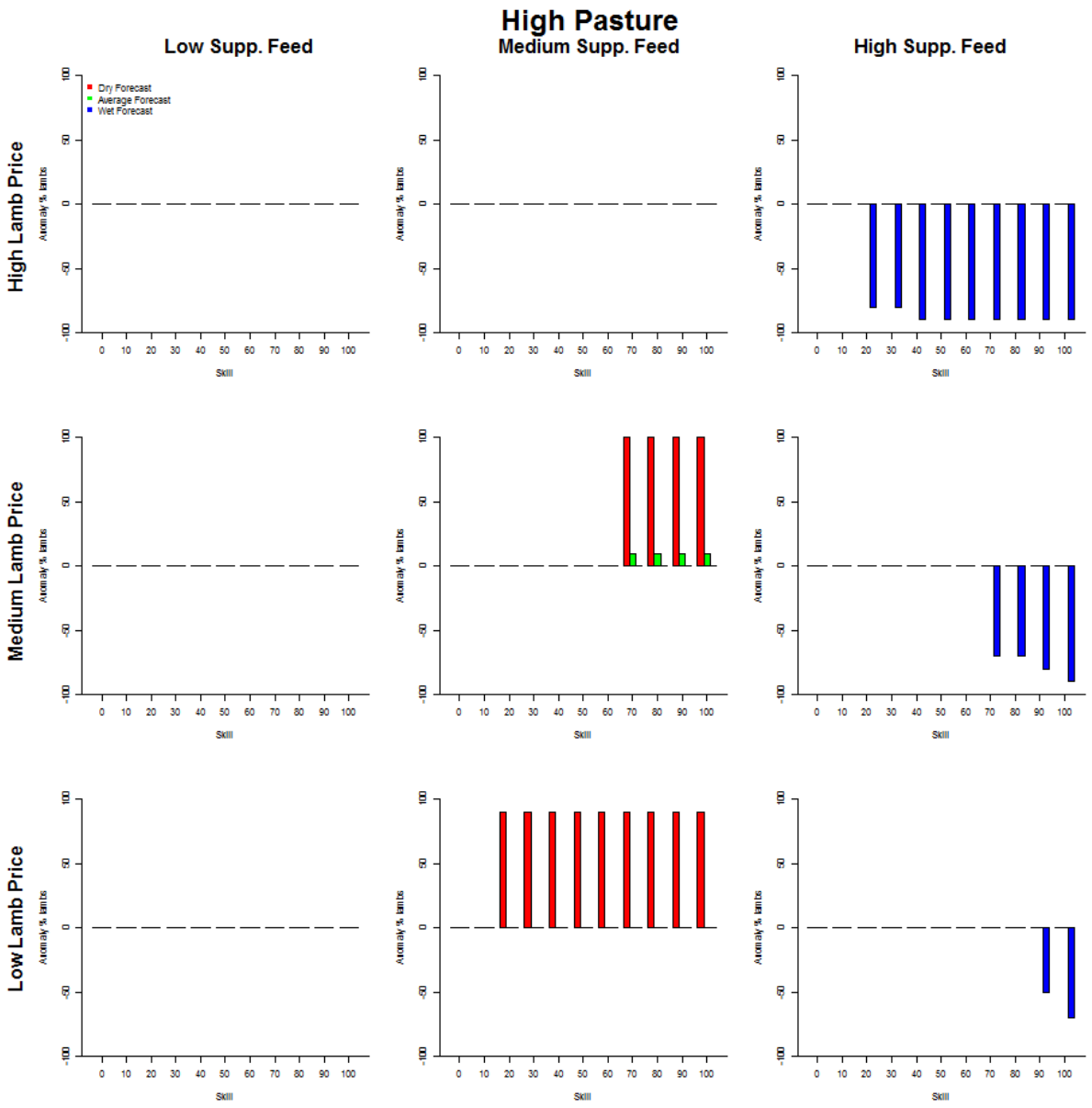


Figure 16 The change in the percentage of lambs sold based on increasing skill of probabilistic forecasts, relative to the without-forecast sell decision (i.e. 0% skill) for high pasture availability. Red, green and blue indicate dry, average and wet forecasts.

Appendix 5: Perfect forecasts with low/high February prices

The perfect-forecast decision (Figure 17) and value of a perfect forecast (Figure 18) for low February prices. The perfect-forecast decision (Figure 19) and value of a perfect forecast (Figure 20) for high February prices. Low and high prices evaluated are in Table 8.

Table 8 Low and high February prices ($/kg) tested for sensitivity to this value

	Low	High
Carcass weight category (kg)		
16.1–18	0.83	1.33
18.1–20	0.95	1.47
22.1–24	1.17	1.75

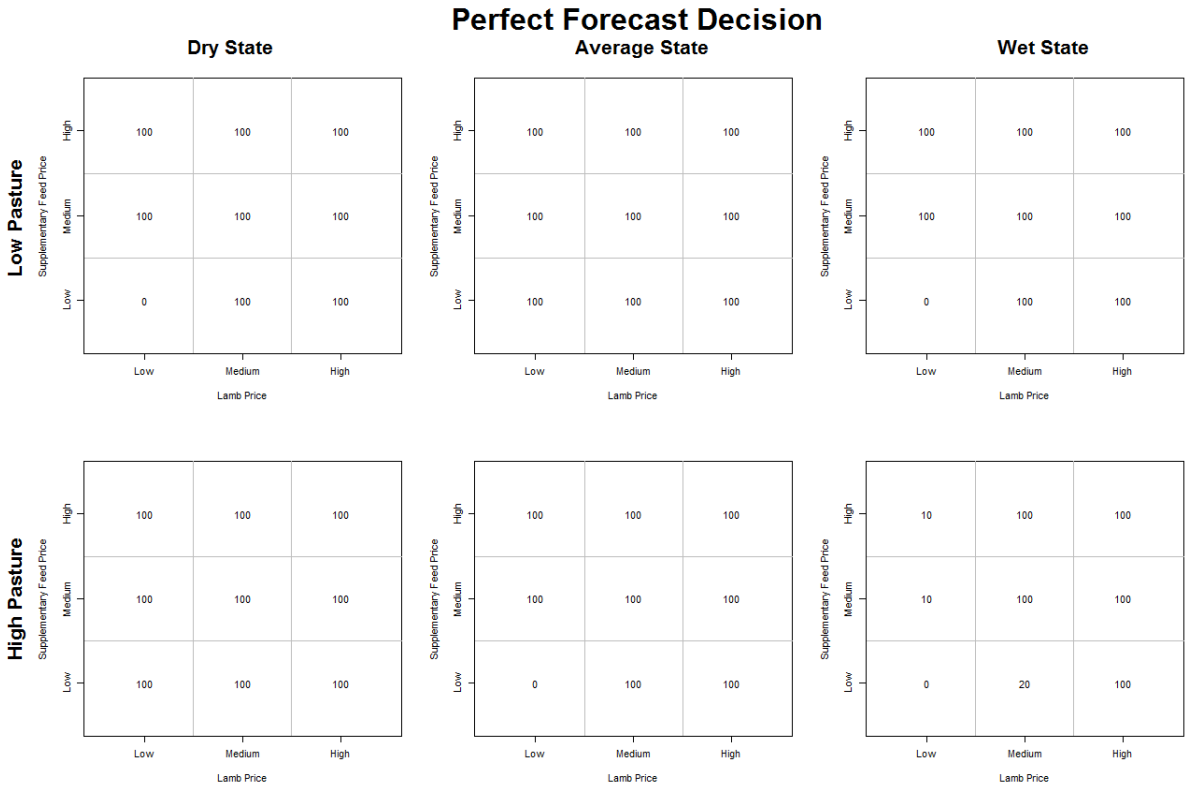


Figure 17 Perfect forecast percentage lambs sold decision for low February prices. Dry, average and wet states in the three major columns, two levels of current pasture availability (low, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and lamb price (low, medium, high) in the internal columns.

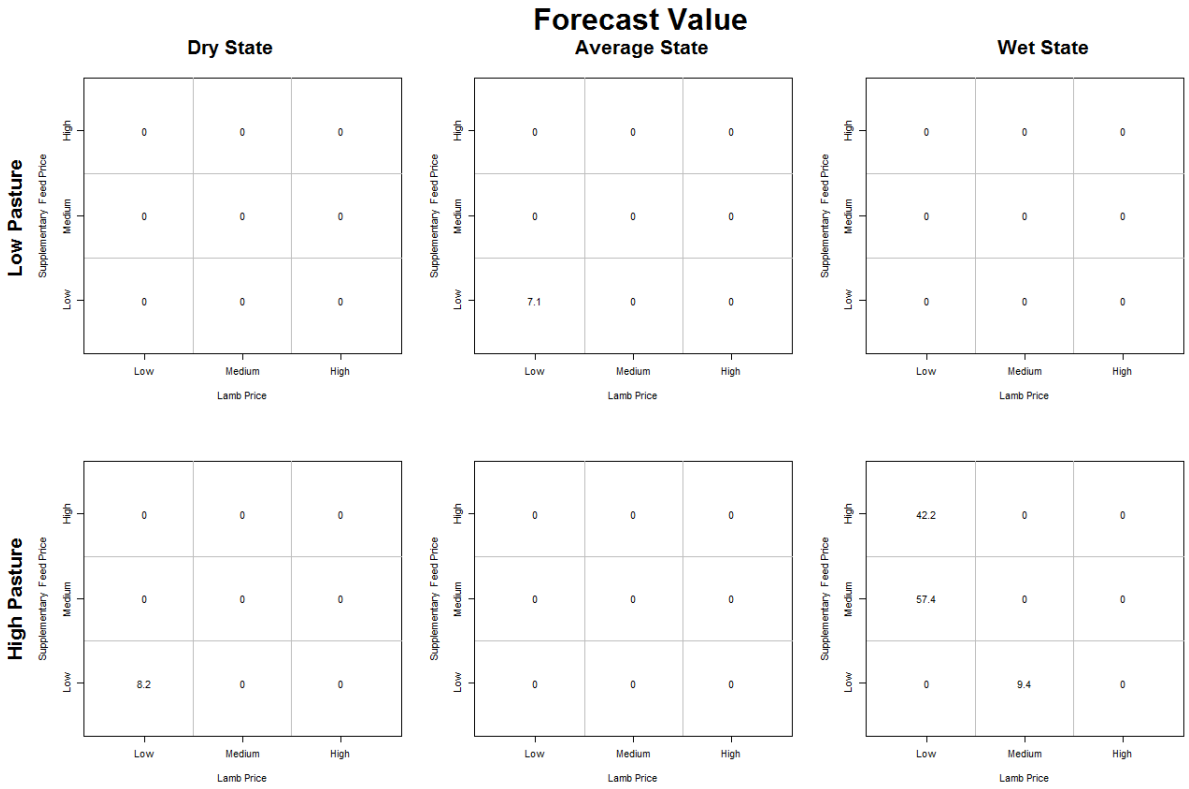


Figure 18 Perfect forecast relative value compared to the without forecast return ($/ha) for low February prices. Dry, average and wet states in the three major columns, two levels of current pasture availability (low, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and lamb price (low, medium, high) in the internal columns.

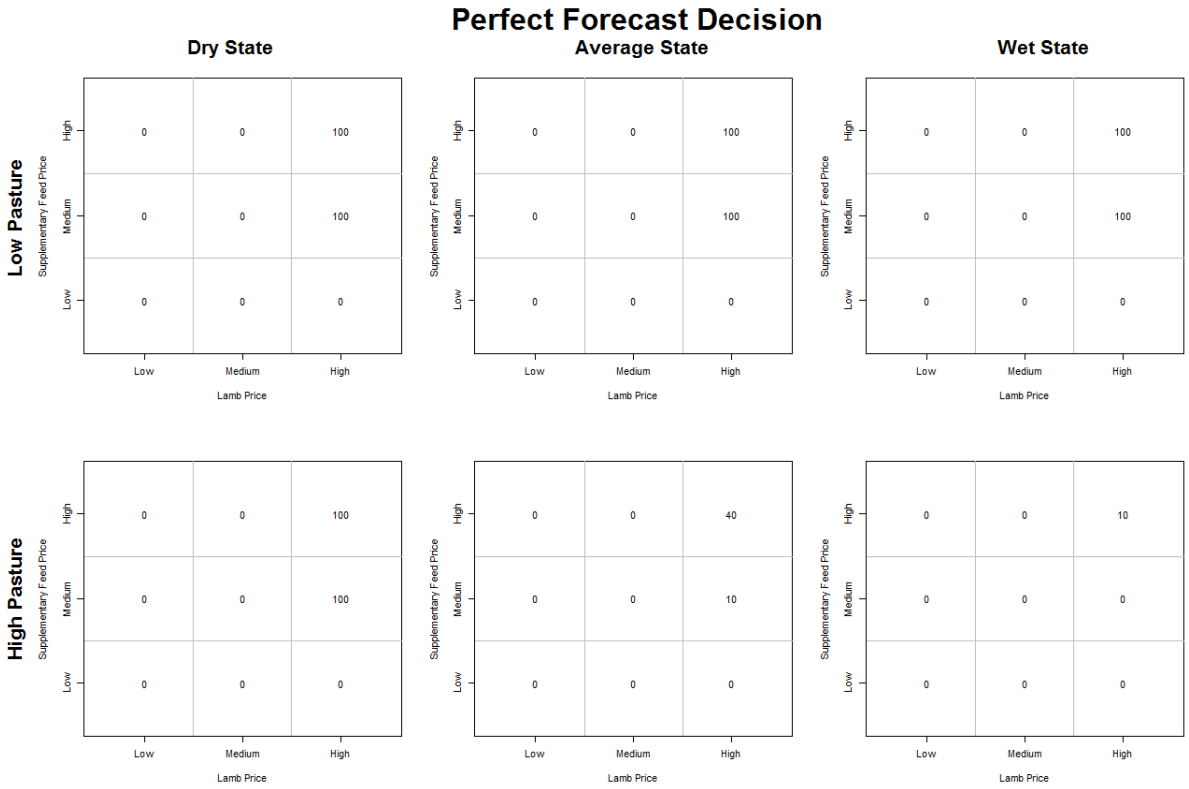


Figure 19 Perfect forecast percentage lambs sold decision for high February prices. Dry, average and wet states in the three major columns, two levels of current pasture availability (low, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and lamb price (low, medium, high) in the internal columns.

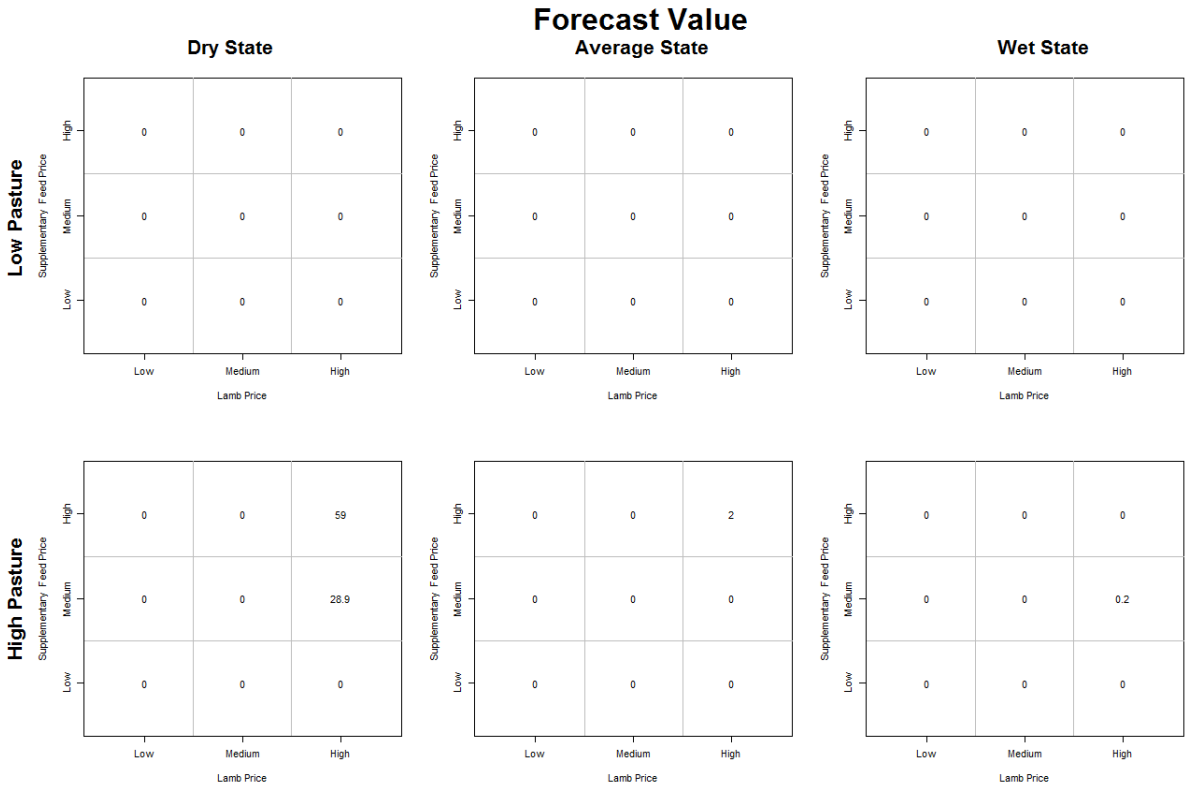


Figure 20 Perfect forecast relative value compared to the without forecast return ($/ha) for high February prices. Dry, average and wet states in the three major columns, two levels of current pasture availability (low, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and lamb price (low, medium, high) in the internal columns.