Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Southern beef 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 beef production systems in southern Australia. The key decision identified by industry was how many weaners to sell in March and how many to carry through winter to sell as yearlings in November. A total of 11 stocking rate strategies (sell 0%, 10%,..,100% of weaners in March) 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 March to November influences the level of pasture production and hence the amount of required supplementary feed to finish cattle in November under each stocking rate strategy. A skilful seasonal climate forecast is potentially valuable if it helps beef 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 March–May 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 beef production data from the biophysical production model *Ausfarm*. These outputs were combined with beef production costs and built into an economic model to capture the links between climatic conditions, pasture and beef 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 use of a biophysical model allowed different levels of starting pasture availability in March to be captured and outcomes to be explored in dry, average and wet climate states. Other key decision variables, including beef

and supplementary feed prices, help to represent the decision-making context prior to the consideration of a climate forecast.

In order to systematically assess the value of forecast skill, a hypothetical forecast system of dry, average and wet states was used. A total of 11 skill levels were assessed (0%, 10%, …, 100%) with 0% representing climatology (the historical average) 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

The level of pasture availability in March had a substantial influence on the optimal stocking rate decision. Low pasture availability, for example, led to a decision of selling all weaners in March based on prospects of low livestock growth rates and high supplementary feed costs. Even a skilful forecast of future wet conditions offered little value in these circumstances as stock numbers are simply too high for the pasture base to support. In contrast, higher levels of starting pasture (medium and high scenarios) provided conditions for alternative stocking rates to be considered and for climate forecasts to be influential. The optimal stocking rate under high pasture availability in March varied the most with climate forecast state and price settings, indicating that producers have more options to respond to different conditions.

Although the level of pasture availability in March was the major determinant of the stocking rate decision, supplementary feed and cattle price settings were also found to be important. Under low weaner supplementary feed prices, for example, the dominant decision tended towards holding weaners. This was triggered by the prospect of low income from selling weaners now versus higher income from retaining them for sale as yearlings, aided by lower costs of supplementary feeding. Equally, when weaner and supplementary feed prices were both high, there was a tendency to sell weaners in order to take advantage of high income from weaners now and avoid supplementary feeding costs of taking animals to higher weights as yearlings.

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 beef producers under average and high levels of starting pasture availability, with the extent also dependent on beef and supplementary feed prices. The maximum value of a dry forecast occurred under high pasture availability and improved returns by $28.80/ha. The maximum value of a wet forecast also occurred under high pasture availability and improved returns by $22.60/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 tended to be the most valuable as a departure from holding to selling weaners 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 beef 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 producers more widely.

Contents

Glossary of terms

Climate state (dry, average, wet): 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, 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 southern beef 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 Southern beef production system

2.1 Industry overview

Beef production makes an important contribution to the Australian economy with an estimated value of $10.02 billion (ABARES, 2015a) for beef, veal and live feeders in 2014–15. Beef production is typically undertaken on dryland systems with seasonal climate conditions influencing pasture growth and hence potentially impacting productivity and profitability.

Beef production systems in Australia are diverse, encompassing a wide range in climates (tropical, sub-tropical and temperate) and environmental conditions. In recognition of the diversity, Meat and Livestock Australia (MLA) develop their research and development priorities based on three major production zones. Research councils for each of these zones were established (Figure 1): the Southern Australia Meat Research Council (SAMRC), the North Australia Beef Research Council (NABRC) and the Western Australia Livestock Research Council (WALRC). Beef production within the SAMRC was the focus of this case study.

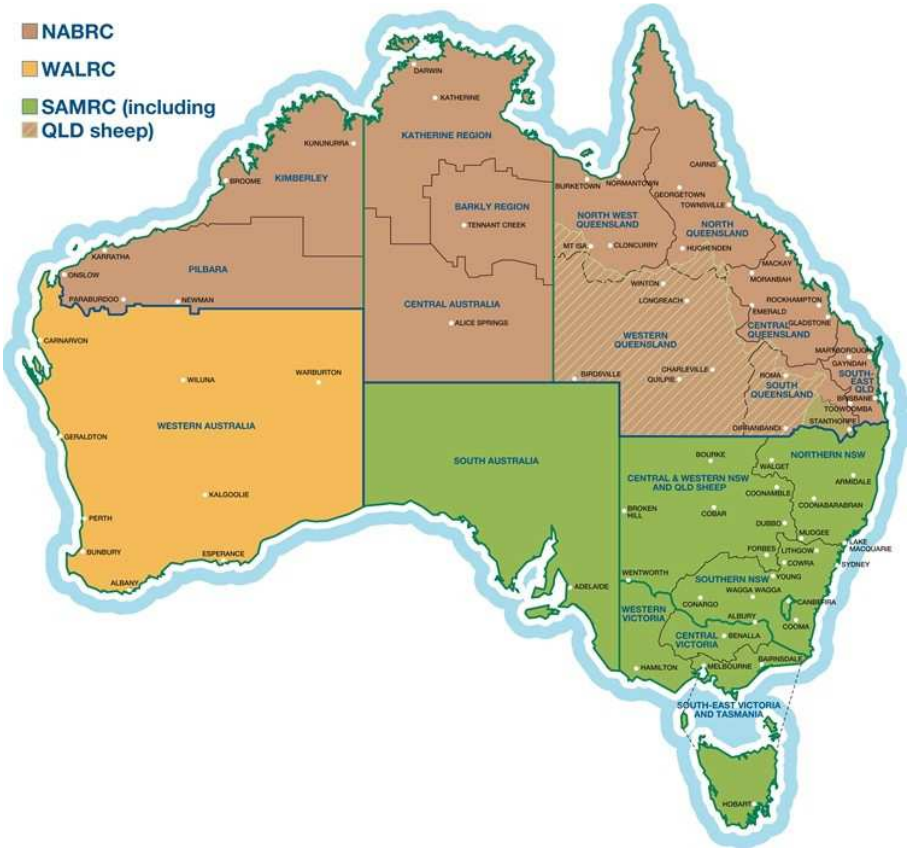


Figure 1 Regionalisation of MLA research councils (SAMRC, 2016)

2.2 Producing beef in southern Australia

Beef production in southern Australia contributes substantially to the value of the Australian red meat industry, accounting for $5.4 billion (approximately 67%) of the value in 2014–15 (SAMRC, 2016).

Good soil fertility and favourable climate conditions allow for a long season of pasture growth, and hence intensive production systems, in southern Australia (Campbell et al., 2014). Industry summaries compiled by Campbell et al. (2014) indicate that an average beef specialist farm in southern Australia has on average 492 cattle on hand, a farm size of 704 ha and operates in high rainfall areas (500–1000 mm annually).

Beef operations in southern Australia are predominately based on improved temperate and/or native pasture systems, where the core goal of production is the conversion of feed into animal weight gain. To optimise beef production, farmers aim to match the feed requirements of the herd to the availability and quality of feed, particularly pasture. The importance of pasture management was highlighted by an evaluation commissioned by MLA (Black and Scott, 2002).

Pasture availability varies throughout of the year, between seasons and differs depending on pasture variety. Typically, pasture growth in southern Australia peaks in early spring, with low levels of pasture growth through summer and winter (Figure 2). To account for low feed availability periods, farmers can store cut hay and/or silage from peak spring pasture growth and/or buy in supplementary feed supplies (e.g. hay).

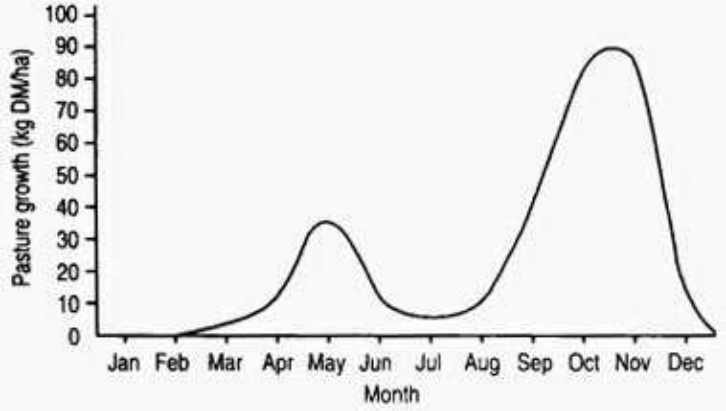


Figure 2 Idealised pasture growth rates in southern Australia (Agriculture Victoria, 2016)

Pasture quality must also be incorporated into feed management strategies as both the quality and volume of feed contribute to animal productivity. The initiation of spring pasture growth coincides with high pasture quality, with quality then declining as the season evolves and the pasture matures (Figure 3).

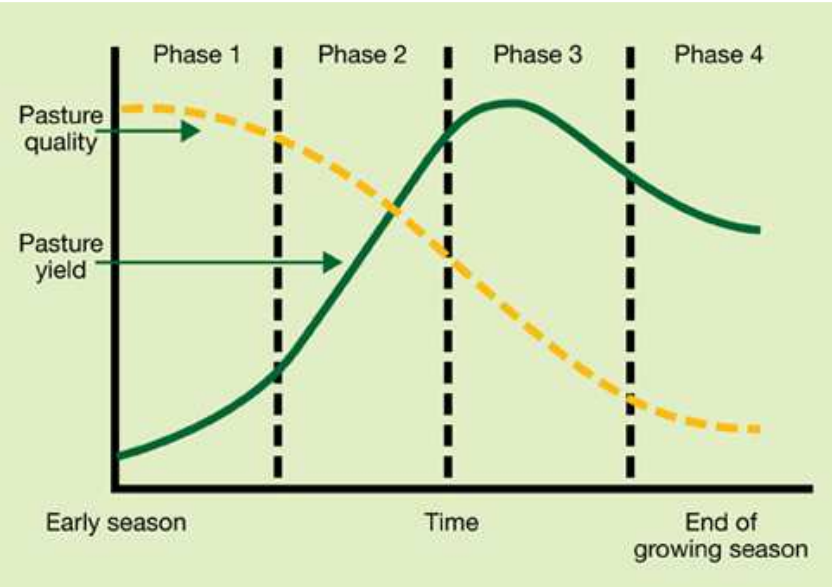


Figure 3 Schematic of pasture quality as pasture ages early season coincides with initial spring growth (MLA, 2016)

Management decisions regarding the utilisation of pasture through time consider the different feed requirements of different classes of stock (lactating cows, weaners, heifers, steers, breeding stock). This is important as the different classes of stock have different energy requirements, with lactating cows demanding the highest energy. The number of animals in the herd in each class changes through time, depending on the life stage of the animal. The timing of calving influences when different classes of the herd coincide with the cycle of pasture growth.

2.3 Description of production system and key decision point

Consultation with industry, including the SAMRC, was undertaken to describe the production system and key decision points. Further information on the consultation process is contained in

Appendix 1.

The southern beef case study was focused on a self-replacing Angus herd on a 700-ha farm in Holbrook, New South Wales (Figure 4). The system is based on 560 cows with winter/spring calving.

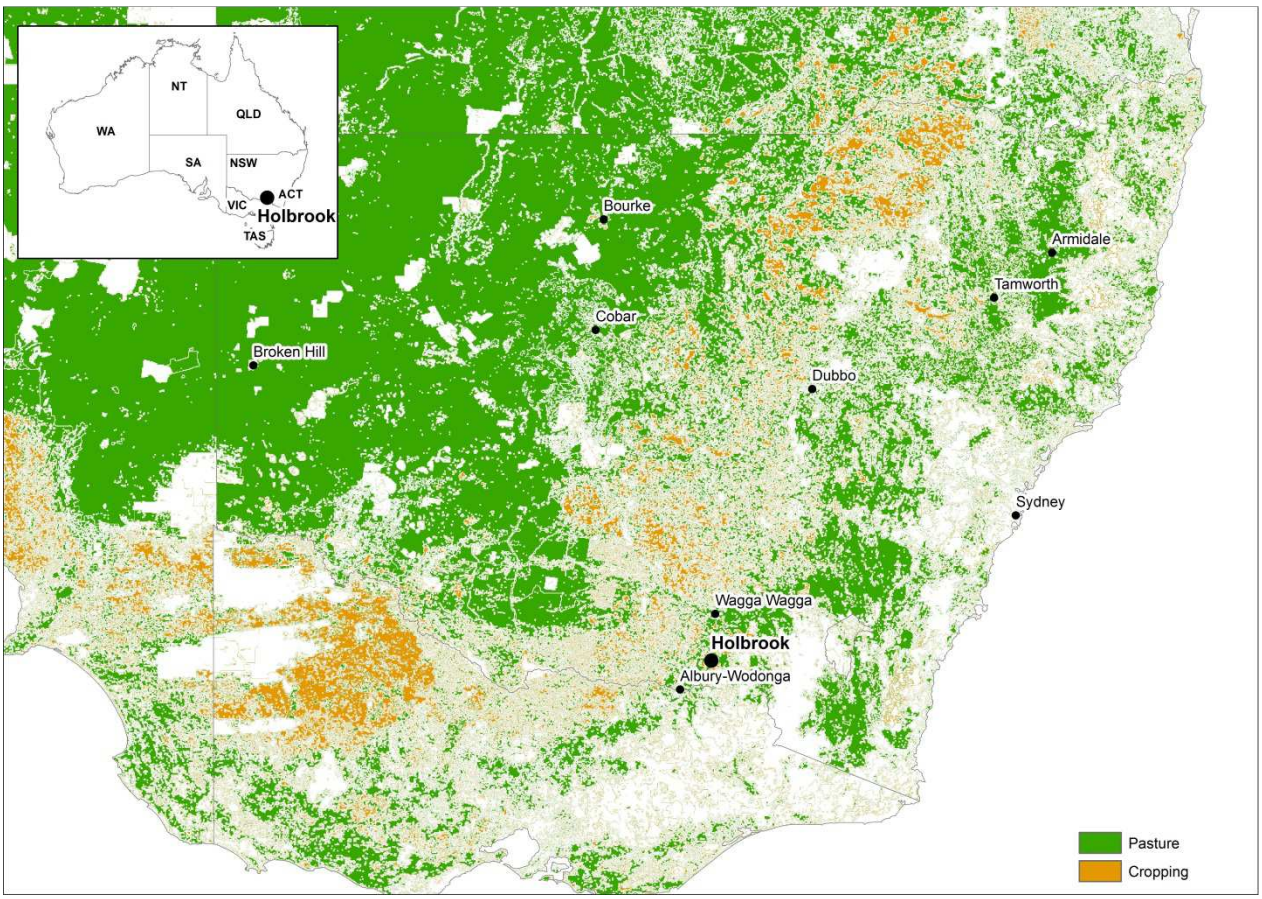
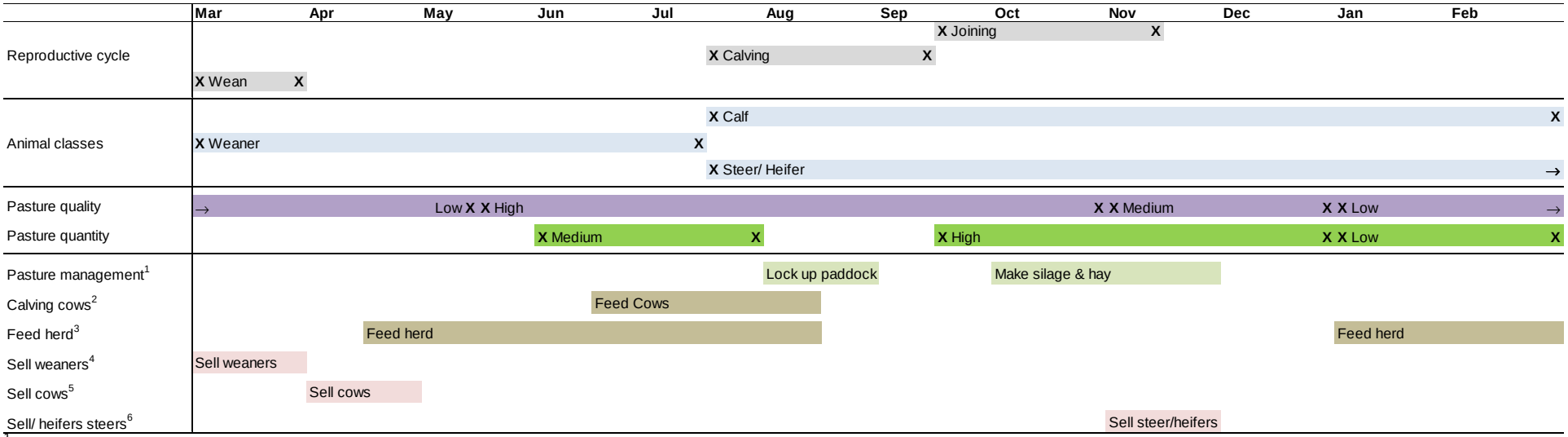


Figure 4 Map showing the location of Holbrook, the case study site

Calving was set to occur from mid-July to mid-September with weaners available for sale from March. Limited hay and silage making was a feature of the system as pasture is largely used by the animals with feed frequently bought in over winter (Figure 5).

Figure 5 Broad system characteristics of southern beef case study



[1]Only make silage and hay if sufficient pasture available.
[2]Highest energy demand is at calving/lactating. Usually have to feed cows for a part of this period if pasture does not meet energy requirements. Cows often fed before calving to ensure good animal condition.
[3]Of kept animals, feed if available pasture is insufficient.
[4]Sell if pasture supply does not meet energy requirements.
[5]Sell empty cows and cows surplus to breeding requirements.
[6]Only sell heifers not kept as part of replacement herd.

2.3.1 Decision point

The key decision point for this system was:

How many weaners will I sell versus how many will I carryover winter?

The time of the decision to sell weaners was March. Secondary selling occurs in November with the animals sold as steers or heifers.

Allocating the proportion of weaners to sell in March is not a simple decision. Four key decision drivers were identified:

1. Cash flow: low cash flow encourages selling, good cash flow discourages as much selling.
2. Relative price of weaners: good prices encourage additional selling, low prices discourage selling.
3. Feed availability: low pasture encourages selling, high pasture discourages selling.
4. Rainfall forecast for March, April and May: wet (i.e. good pasture growth) discourages selling, dry (i.e. poor pasture growth) encourages selling.

Figure 6 illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including SCFs 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.

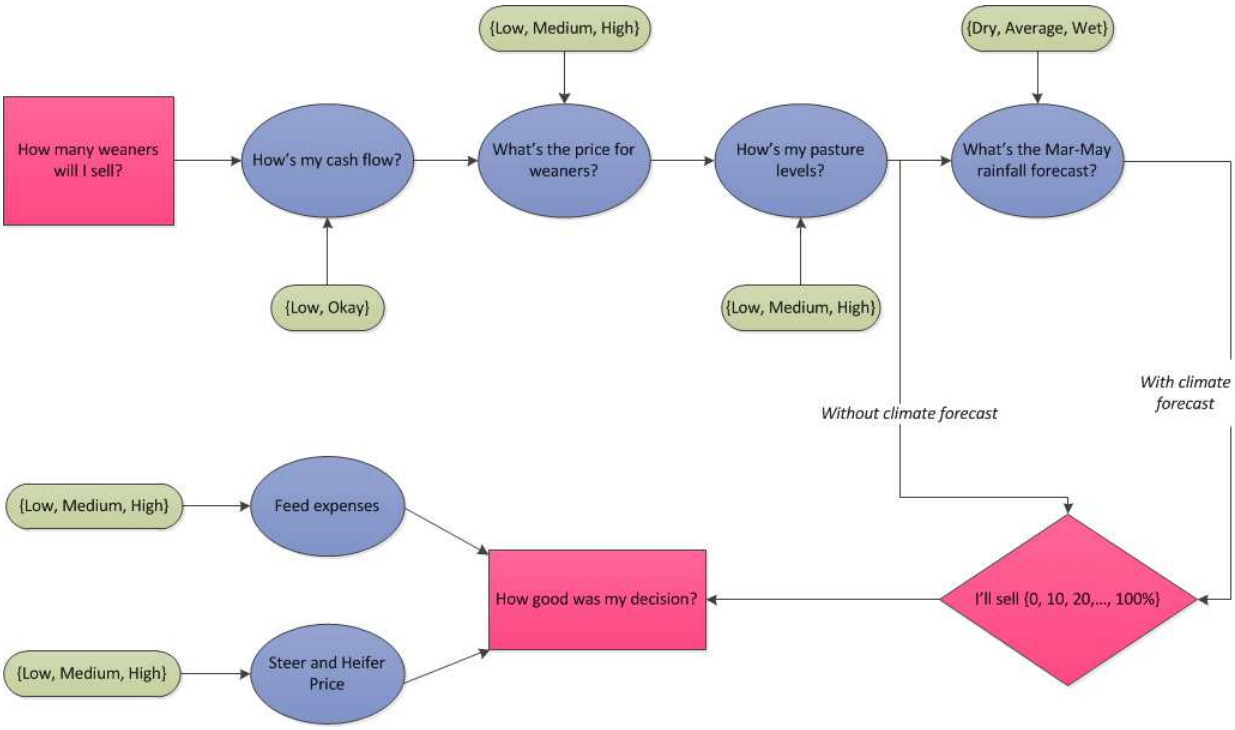


Figure 6 Decision pathway for proportion of weaners sold in southern beef systems including an evaluation of the decision made

2.4 Previous studies of SCFs in southern beef production systems

Inclusion of SCFs into decision-making processes within Australia's southern beef system may provide opportunities for producers to 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.

The potential incorporation of SCFs into beef systems in western New South Wales was explored in a guide produced by NSW Department of Primary Industries (Hacker et al., 2006). They noted that decisions that are potentially influenced by SCF information need to be tactical decisions which are commensurate with the length of the forecast. For instance, livestock sales and purchase decisions may be influenced by SCFs but strategic decisions, such as joining time, were not changeable in relation to the timeframe of SCFs (months). The guide provided information regarding risk management decisions for livestock with a focus on the SOI phase approach as rainfall and, importantly, pasture growth was shown to be correlated to the SOI phases. In particular, use of forecasts for June–September was suggested, as this is the time of year when there is a stronger association between pasture growth and SOI phase. No assessment of economic implications of use of SCFs was considered.

A search of the scientific literature for studies that evaluated the economic benefit of SCFs for southern Australian beef enterprises did not find any previous work.

3 Methods

The potential value of SCFs was evaluated through maximising returns of the system by selecting the optimal percentage of weaners to sell under various system conditions. An overview of the methodology is outlined in Figure 7. 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.

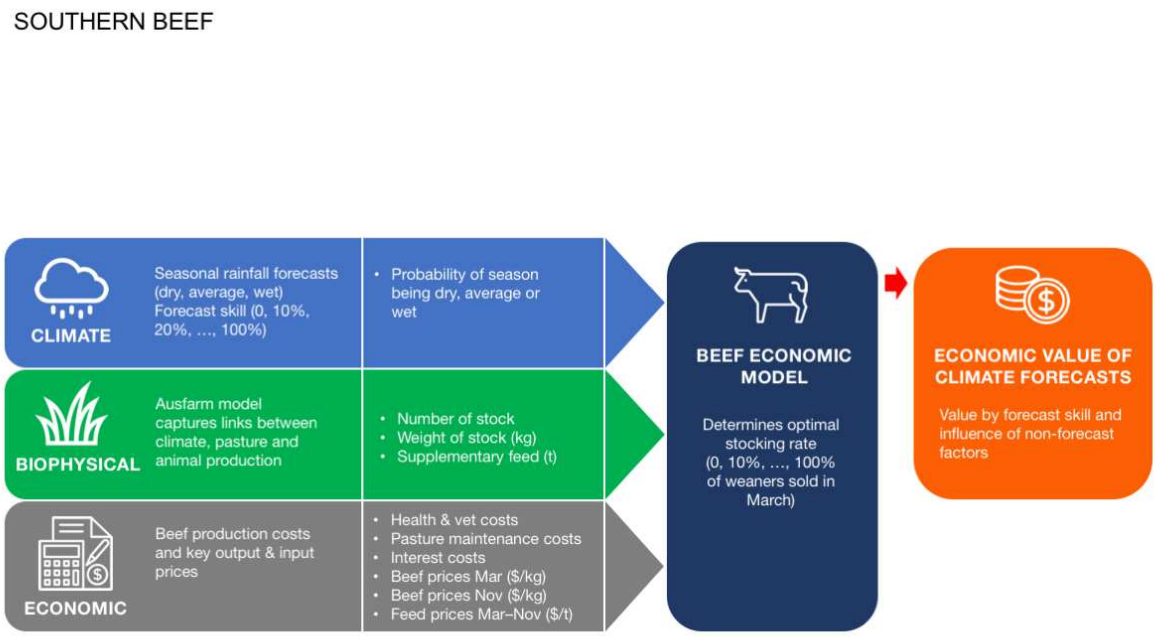


Figure 7 Methodological overview. Generation of biophysical data, beef production costs, beef prices and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal percentage of weaners to sell based on maximising returns.

3.1 Beef biophysical simulation model

The link between climatic conditions, pasture and beef 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) or the impacts of pest species and as such tends to optimise biophysical performance.

For this case study, an *Ausfarm* model was designed 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*), representative of the pasture mix at Holbrook. The animal production system modelled was a self-replacing Angus cattle system.

Three initial pasture compositions (low, medium and high) were tested (Table 1). The *GrassGro* model (Freer et al., 1997; Moore et al., 1997) was used to validate pasture composition initialisation parameters. Herd structure initialisation parameters were reset on 1 March to consist of 560 cows, 560 weaners and 11 bulls. Weaner males were reset to 302 kg and weaner heifers were reset to 246 kg. 13% heifers were retained as part of a self-replacing herd. All initialisation parameters were reset on the 27 February each year.

SILO patched point daily weather data (Jeffrey et al., 2001) were sourced from station 72022 (Holbrook (RSL)) from 1889–2015 and used for all analyses. Using these climate data, the model was run each year (1889–2015) until the end of November.

Table 1 Pasture composition attributes used in the *Ausfarm* modelling. Note: the fertility scalar for all pasture species was set to 0.8.

Pasture scenario	Total herbage mass (kg/ha)	Total green herbage mass (kg/ha)	Total dry herbage mass (kg/ha)
Low starting pasture	1140		
Phalaris		0	780
Sub clover		0	60
Annual rye		0	300
Medium starting pasture	2220		
Phalaris		300	900
Sub clover		50	70
Annual rye		100	500
High starting pasture	2740		
Phalaris		900	600
Sub clover		140	0
Annual rye		600	500

Supplementary feed was provided when condition scores of the herd fell below set thresholds. From 1 March to 31 August, feed was provided when the condition score fell below 2.0. From 1 September to 30 November, feed was supplied when the condition score fell below 1.5. Supplementary feed consisted of oaten hay and lucerne pellets, both fed at a rate of 3.0 kg/animal/day.

For each pasture initialisation and each year, 11 different selling options for weaners were evaluated on 10 March. These were 10% steps from 0 to 100% of weaners sold. Weaner sales were proportional across male and female animals. For example, the 10% sale decision was calculated as 10% of males and 10% of available females, with fewer females available as some were retained as is common practice in self-replacing herds. The second selling point of the remaining weaners, now steers and heifers, was set to 20 November. In total, 33 combinations of initial pasture and weaner selling options were evaluated for 126 years of climate data.

3.2 Beef production costs

The production costs of the system, including beef herd 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.

Farm debt was used to investigate the impact of cash flow on the decision to sell weaners. Sensitivity to farm debt was evaluated for analyses with and without farm debt representing low and moderate cash flow. Farm survey results for beef specialists in New South Wales from 2010–2015 indicted that average farm debt was $225 000 (Department of Agriculture and Water Resources, 2017). This was used to represent farm debt. An annual interest rate of 10% was used and was applied to production costs and farm debt, for scenarios with debt.

[2] http://www.dpi.nsw.gov.au/__data/assets/pdf_file/0007/175534/14-Inland-weaners.pdf

3.3 Key input and output costs

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

Stock prices were sourced for 2006–2015 for the Wagga Wagga saleyards (MLA, 2017) and adjusted to real prices using (ABARES, 2015b). Stock prices used were weaner prices in March (the first selling option) and steer and heifer prices in November (the second selling option). Sensitivity to weaner 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 prices were sourced from *The Land* newspaper from 2004–2013, and similarly adjusted to real prices, with low, medium and high prices determined from the 10th, 50th and 90th percentiles (Table 2). For the sensitivity analyses, weaner male and female prices were linked (i.e. low male and female prices represented low weaner prices). Supplementary feed prices were similarly linked (i.e. low oaten hay and lucerne prices represented low supplementary prices).

Steer and heifer prices in November were fixed, because prices in November are unknown when the selling decision in March is made. The 50th percentile of steer and heifer prices in November was used to set the November price (204 c/kg and 194 c/kg live weight, respectively).

Table 2 Stock and supplementary feed prices evaluated in this case study

	Low	Medium	High
Male weaner (c/kg live weight)	196	224	258
Female weaner (c/kg live weight)	183	217	247
Supplementary feed – oats ($/t)	159	203	267
Supplementary feed – lucerne ($/t)	210	259	386

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 March–May rainfall received at Holbrook over the period 1889 to 2015. Each year was then classified as belonging to one of these climate states: dry was categorised by rainfall less than 100 mm, average as rainfall between 100 mm and 175 mm, and wet as rainfall in excess of 175 mm (Figure 8).

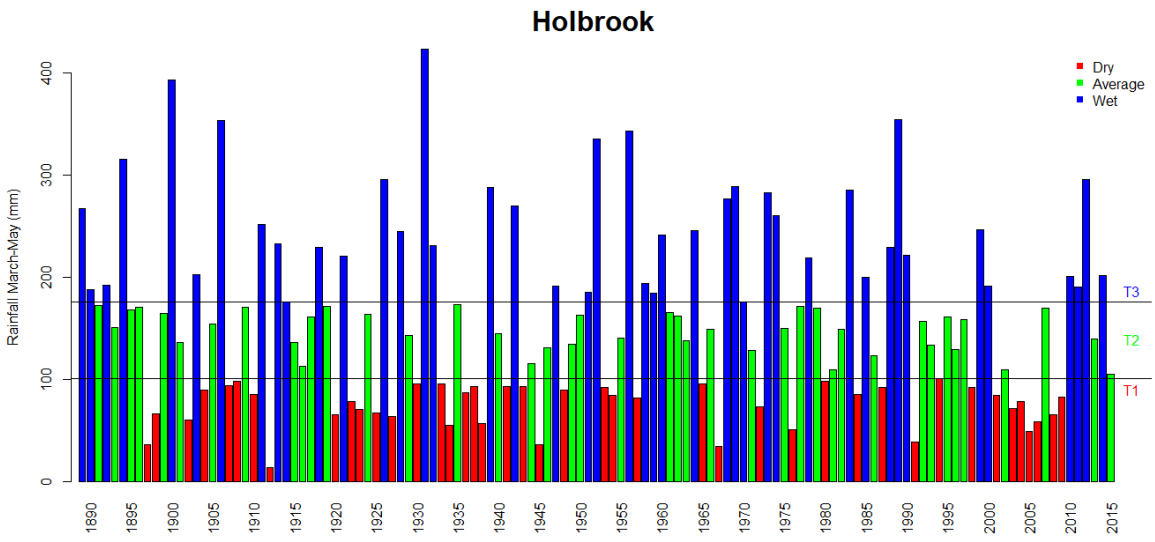


Figure 8 Total rainfall for March, April and May at Holbrook for 1889–2015. Dry, Average and Wet represent tercile 1, 2 and 3.

Agricultural production levels representing dry, average and wet climate states were obtained by classifying yearly outputs of pasture, feed and beef 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.

$$\sigma = y\frac{\pi_{s|f} - \pi_s}{.0 - \pi_{sy}} \qquad \text{[Equ 1]}$$

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

Avg = Wet $= y\frac{\left(y.00 - \pi_{dry|f}\right)y}{2y} = y\frac{(y.00 - 0.47)}{2} = 0.27y$ [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 beef biophysical production model to capture the links between climatic conditions, pasture and beef production. The economic model evaluated the changes in livestock numbers, livestock weights and feed costs under the different stocking rate strategies (percentage of weaners sold). This was achieved by applying a consistent set of output prices (beef prices in March and November) and input prices (feed prices) to the biophysical outputs and incorporating baseline information on beef 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 weaners 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 weaners in March) and this creates economic value from forecast use.

A more detailed description of the economic model is contained in Appendix 3: 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 1782 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

Farm debt	no debt, debt
March pasture availability	low, medium, high
Weaner 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 (farm debt, March pasture availability, weaner price, supplementary feed price). Subsequently, the perfect-forecast (100% skill) selling decision for the three forecast states was similarly reported. This potential value ($/ha) of the perfect forecast was calculated as the difference in returns with and without the forecast. This represents largest potential value of climate forecasts for each climate state. Finally, probabilistic forecast value ($/ha) relative to the without-forecast decision were calculated for each different decision environment setting.

4 Results

4.1 Biophysical modelling

Data from the biophysical modelling followed expected patterns given the model parameterisations. November steer and heifer weights progressively increased as pasture availability increased (Figure 9). With higher weaner selling percentages it may be expected that steer and heifer weight would increase as fewer animals are consuming the same pasture base. Only modest gains in weight were reported for higher weaner selling percentages as the model was designed to feed animals if insufficient pasture was available. As a result, the amount of supplementary feed decreases with higher weaner selling percentages as well as with higher starting pasture (Figure 9).

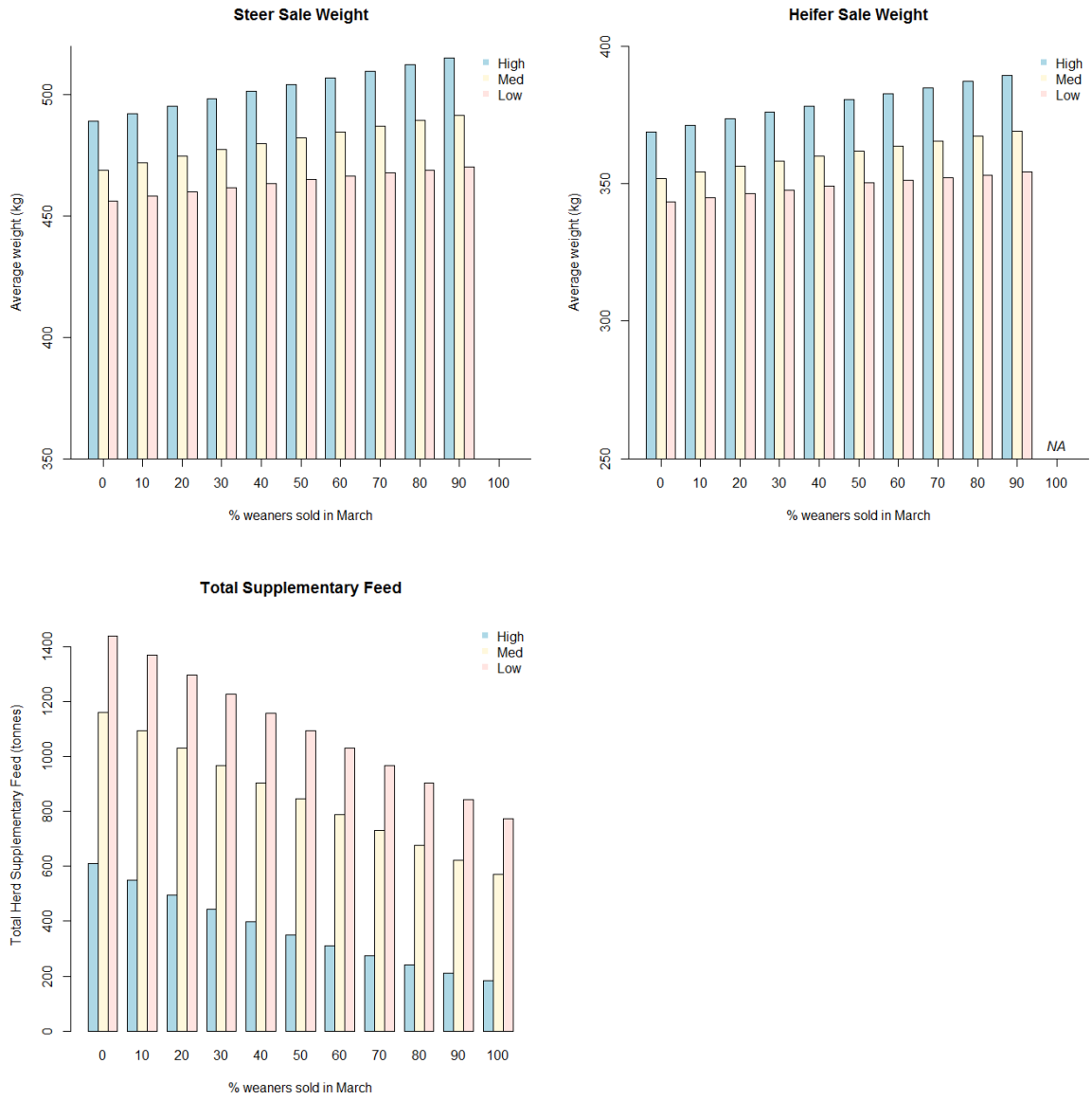


Figure 9 Mean steer and heifer weights at sale in November and total supplementary feed (1889–2015) for high, medium and low starting pastures for each of the 11 weaner selling decision points (0, 10, 20, …, 100%).

Two parameter combinations were used to investigate the potential impact of different climate states on the amount of supplementary feed feed: a 'worst-case' (low starting pasture and retaining all weaners, i.e. 0% sell) and a 'best -case' (high starting pasture and selling all weaners, i.e. 100% sell) (Figure 10). 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, of the wet climate state years with a tendency for higher supplementary feed requirements in dry and average years (Figure 10). For the best-case scenario, a weaker association between dry years and higher supplementary feed requirements was found, but again this was not for all dry classified years (Figure 10). These results indicate that there is a climate signal in biophysical data produced and hence potential value of SCFs.

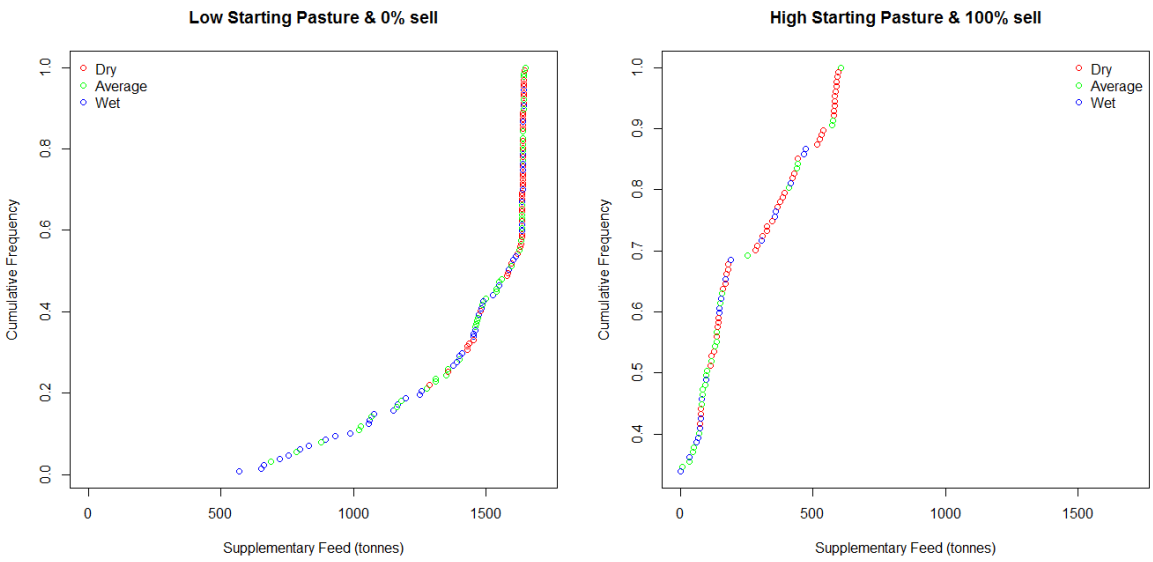


Figure 10 Annual supplementary feed requirements by November according to dry, average and wet classifications. Left is a 'worst-case' scenario with the model fit with low starting pasture and retaining all weaners. Right is a 'best-case' scenario with high starting pasture and 100% sell of weaners in March.

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 be first evaluated and subsequently compared with the decision made with a forecast. Figure 11 shows the without-forecast sell decision evaluated for each combination of the decision drivers (Table 4).

These results indicate limited difference between the decision to sell weaners with or without debt. This is likely due to small debt value used ($225 000), which is representative of average farm debt (Department of Agriculture and Water Resources, 2017). Given these limited differences, these results and the following results will focus on the no-debt values.

The without-forecast decision illustrates the influence of the decision drivers. Low pasture availability (top row; Figure 11) encourages selling of almost all weaners, regardless of other price drivers. Only when both weaner and supplementary feed prices are low does the decision shift to retain weaners, selling 30%.

Greater sensitivity to prices can be seen with medium March pasture availability (middle row; Figure 11). When weaner prices and supplementary feed prices are low or medium, the without-forecast decision is to sell less than 100%. However, when weaner prices are high and/or supplementary feed prices are high, the without-forecast decision is to sell 100% of the weaners.

Finally, with high pasture availability, the without-forecast decision has the greatest sensitivity to prices. As weaner and supplementary prices increase, so too does the percentage of weaners sold. Equally, no weaners are sold if weaner and supplementary prices are low.

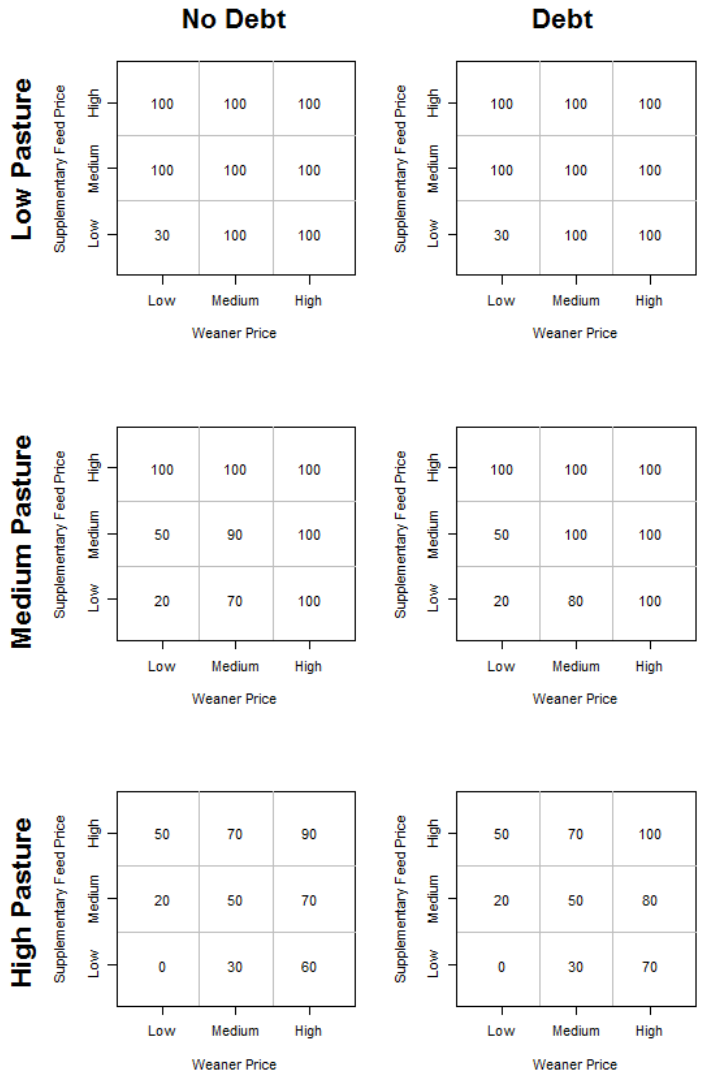


Figure 11 Without-forecast percentage weaners sold decision. No debt and debt in the two major columns, representing cash flow position, three levels of current pasture availability (low, medium, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and weaner price (low, medium, high) in the internal columns.

4.2.2 Perfect-forecast decision

The weaner sell decisions for perfect forecasts of dry, average and wet climate states (100% skill) were evaluated similarly to the without-forecast decision. That is, evaluating the sell decision for different values for pasture availability, weaner prices and supplementary feed prices as well as the additional variable of climate forecast state (Figure 12).

Considering a low March pasture availability (top row; Figure 12), similar to the without-forecast decision, the predominant decision is to sell 100% of weaners. A few notable differences in the selling decision do begin to emerge between the climate states for low and/or medium weaner and supplementary feed prices. For instance, with low weaner and supplementary feed prices, the dry state decision is to sell 100% of weaners, the average state decision is to sell 40% and the wet state decision is to sell 0%.

Considering medium March pasture availability, greater differences in the selling decision between the climate states are more apparent. In particular, differences arise for low and/or

medium weaner and supplementary prices. Generally, more weaners are sold for a dry state and less for a wet state forecast.

Finally, with a high pasture availability the sell decision varies with both prices settings and climate states. Across climate states, the relative sell decision was to sell more weaners when weaner and supplementary feed prices were both high. Between climate states, more weaners are sold under a dry state with fewer animals sold for an average state and fewer again under a wet state.

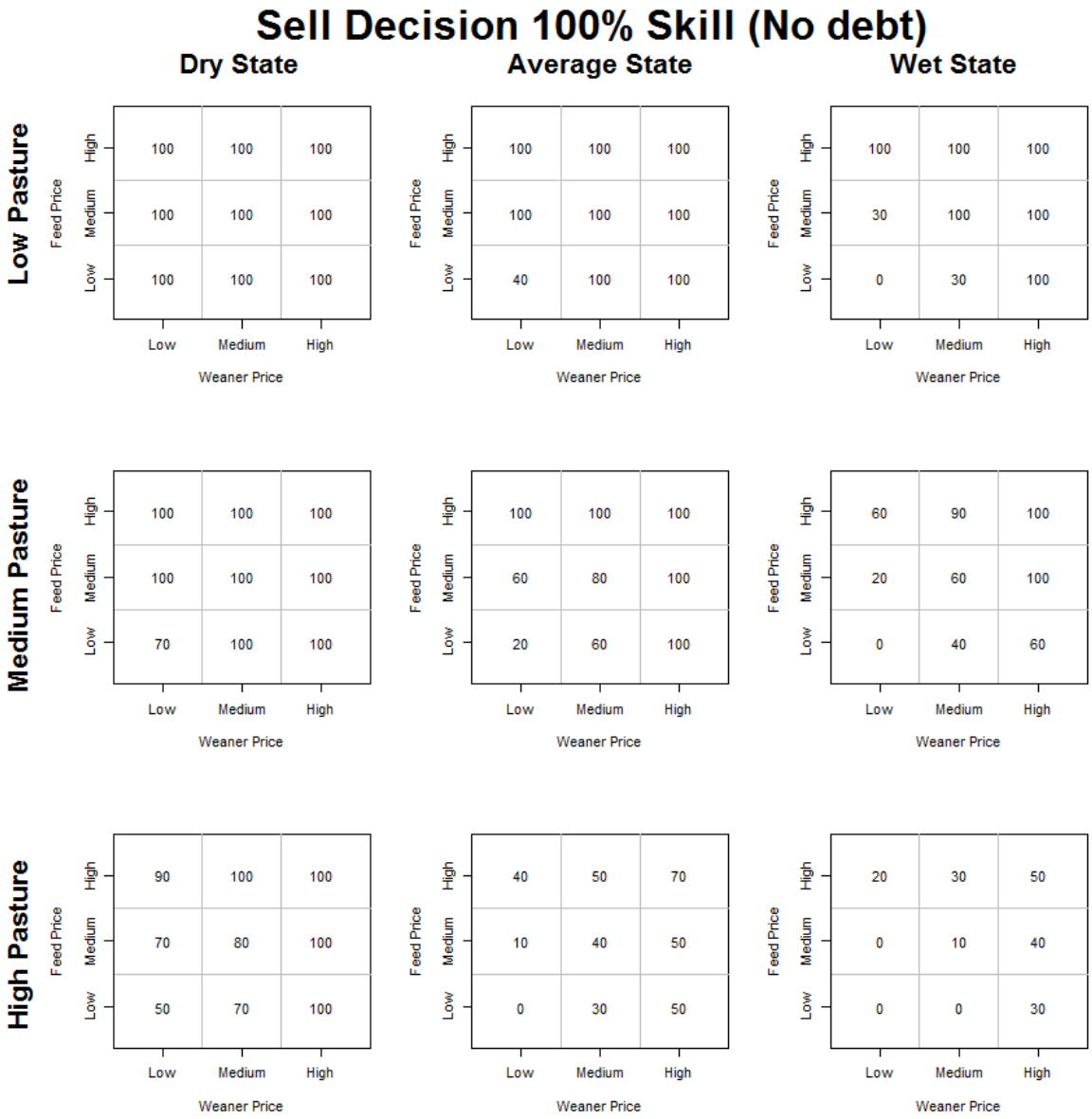


Figure 12 Percent of weaners sold given a perfect forecast. Forecast states (dry, average and wet) in the three major columns. Pasture starting conditions (low, medium, high current pasture availability) in the three major rows. Supplementary feed prices (low, medium, high) in the internal rows. Weaner 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 driver settings to deliver financial returns. If pasture availability is low in March, there is limited value of a perfect forecast for any of the climate states as demonstrated by mostly $0/ha value in Figure 13. Some gain in a perfect forecast under low

pasture conditions was found if weaner and supplementary feed prices are low for a dry forecast or low or medium for a wet forecast.

As pasture availability increases from low through medium to high, so too does the number of price settings which will return value of the forecast (non-zero values in Figure 13). High pasture availability in March yielded the most value across a range of price and climate state settings.

Most value was found for either dry or wet forecasts while limited value of an average state forecast (middle column; Figure 13) was found with value of the forecast ranging from $0–$6.20/ha.

The greatest value for a perfect forecast was $28.80/ha for a dry forecast with high pasture availability in March, low weaner prices and high supplementary feed prices. Under these circumstances 90% (Figure **12**) of weaners are sold with the forecast, shifting from the without-forecast position of selling 50% (Figure 11).

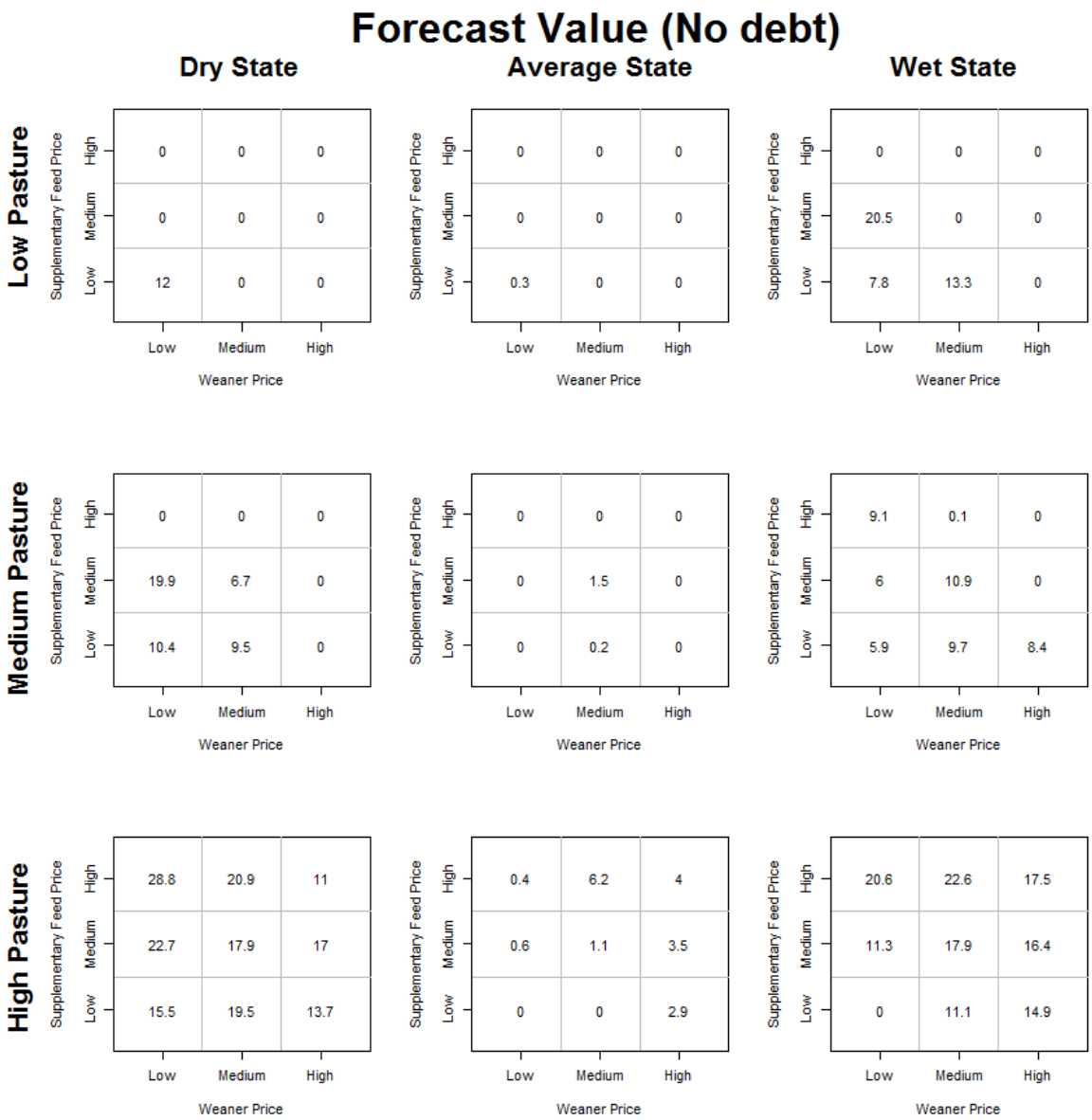


Figure 13 Perfect-forecast relative value compared to the without-forecast return ($/ha). Dry, average and wet states in the three major columns, three levels of current pasture availability (low, medium, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and weaner price (low, medium, high) in the internal columns.

4.2.4 Imperfect-forecast value

The value forecasts with different levels of skill were assessed for each climate forecast (dry, average, wet), each pasture availability level and different price settings for weaner and supplementary prices (Figure 14, Figure 15 and Figure 16). These plots provide greater detail for the results in Figure 13, illustrating the value of forecasts with various skill levels. Where value was found, value increases as skill increases. Most value was found for wet forecasts then dry forecasts for low and medium starting pastures (Figure 14 and Figure 15). High pasture availability yielded value in both dry and wet forecasts, with dry forecasts more often demonstrating value (Figure 16).

As in Figure 13, limited value was shown with low pasture availability in March (Figure 14). Where value was found, skill needed to be over approximately 30%. The greater value in forecasts with medium pasture availability in March is further demonstrated in Figure 15. Forecasts with 20% of greater skill start to demonstrate some value. Again, the greater value of a forecast, particularly dry and wet forecasts, was demonstrated for high pasture availability in March (Figure 16). Skill over approximately 20% was required to yield value from the forecasts.

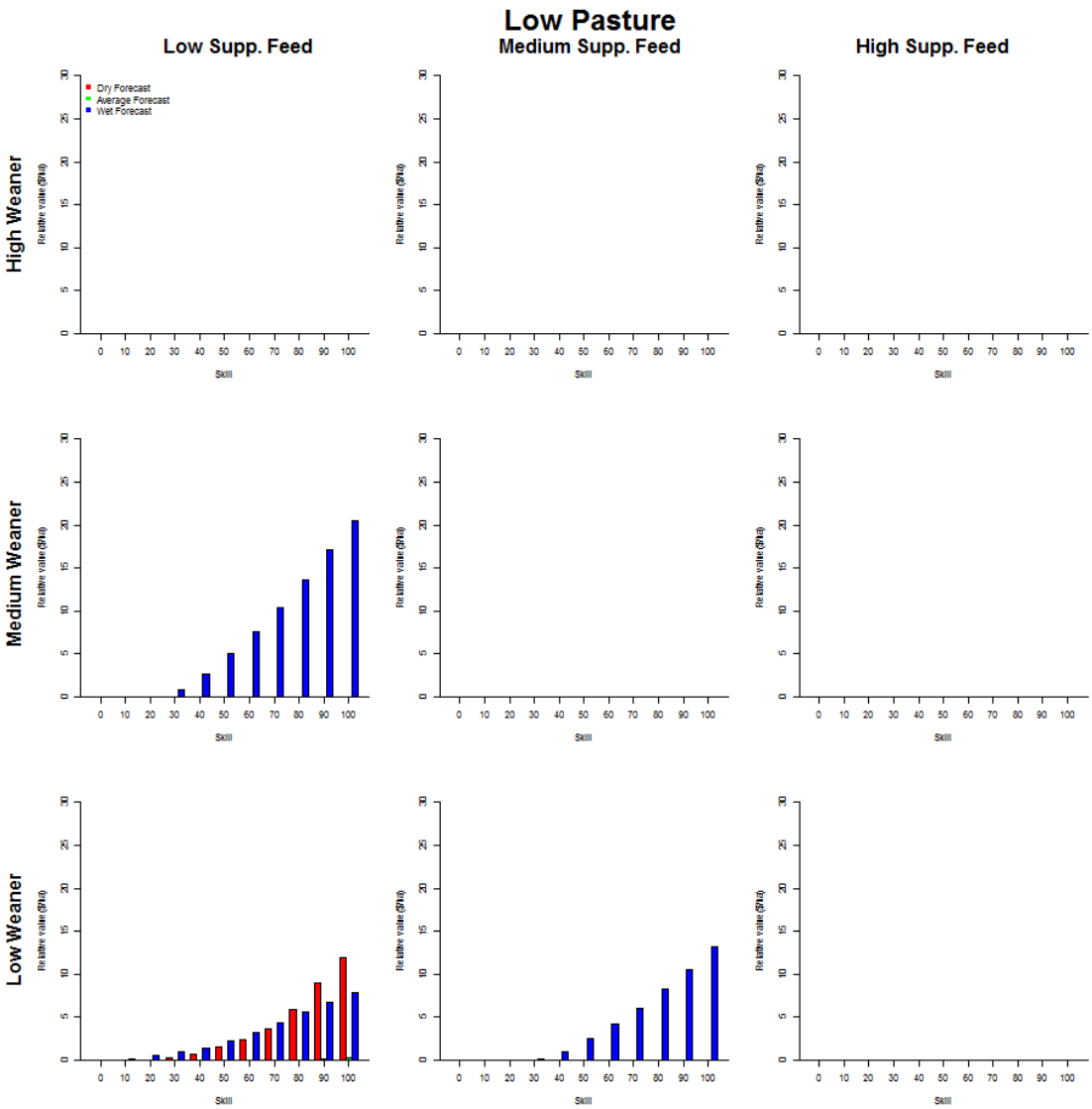


Figure 14 Value of forecast ($/ha) for low pasture availability in March. Supplementary feed prices (low, medium, high) are the three columns of plots, weaner price (low, medium, high) in the three rows of plots. Red, green and blue represent dry, average and wet climate forecast. Forecast skill, grouping dry, average

and wet forecasts, increases on the x-axis from 0 to 100% with 0% the without forecast and 100% the perfect forecast.

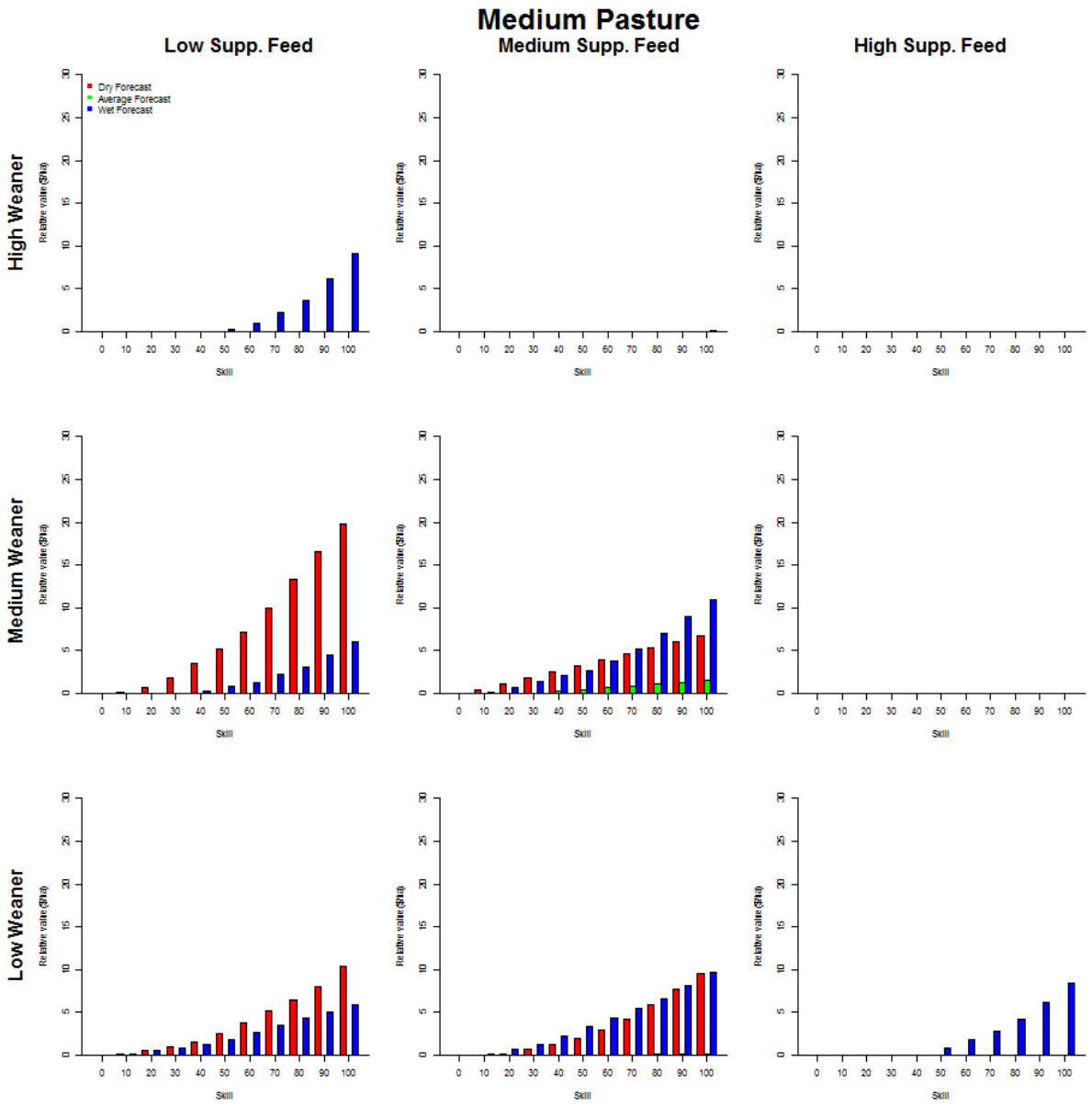


Figure 15 Value of forecast ($/ha) for medium pasture availability in March. Supplementary feed prices (low, medium, high) are the three columns of plots, weaner price (low, medium, high) in the three rows of plots. Red, green and blue represent dry, average and wet climate forecast. Forecast skill, 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.

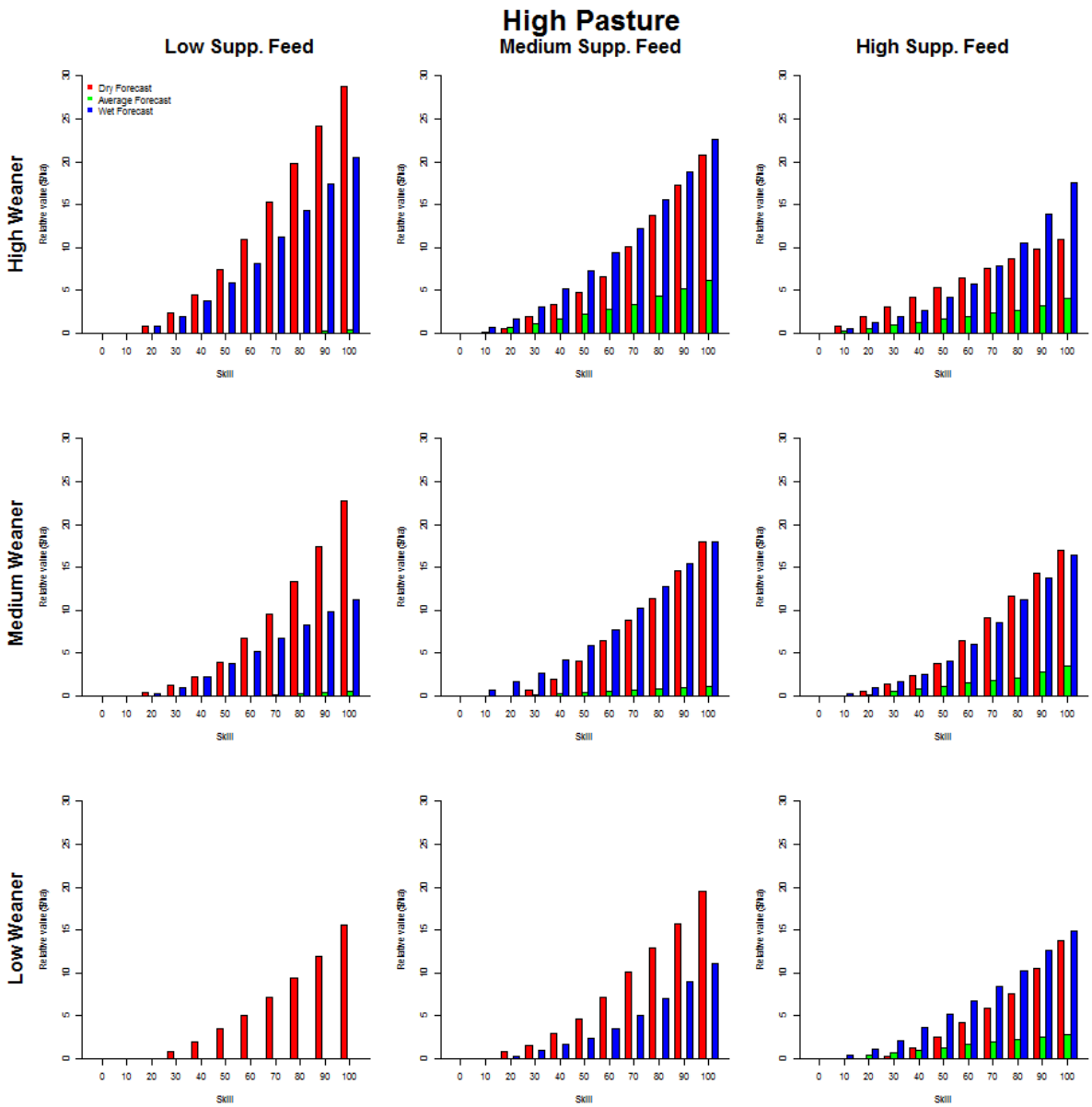


Figure 16 Value of forecast ($/ha) for high pasture availability in March. Supplementary feed prices (low, medium, high) are the three columns of plots, weaner price (low, medium, high) in the three rows of plots. Red, green and blue represent dry, average and wet climate forecast. Forecast skill, grouping 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 different pasture availability and for each of the forecast states (dry, average, wet). The range represents the range across different weaner and supplementary prices. For all skill levels, nil value is possible with the only exception for high pasture in March and a dry forecast. 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, as too is the greater value in a forecast with increasing pasture availability in March.

Table 5 Range of value of the forecast ($/ha). Range is across different weaner 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%

Low	Dry		0–0	0–0	0–0.3	0–0.7	0–1.5	0–2.5	0–3.6	0–5.9	0–8.9	0–12
	Ave		0–0	0–0	0–0	0–0	0–0	0–0	0–0	0–0.1	0–0.2	0–0.3
	Wet		0–0.1	0–0.5	0–0.9	0–2.7	0–5	0–7.5	0–10.4	0–13.7	0–17.1	0–20.5
Med	Dry		0–0.4	0–1.1	0–1.8	0–3.5	0–5.2	0–7.2	0–10	0–13.3	0–16.6	0–19.9
	Ave	NA	0–0	0–0	0–0.1	0–0.3	0–0.5	0–0.7	0–0.9	0–1.1	0–1.3	0–1.5
	Wet		0–0.2	0–0.8	0–1.4	0–2.3	0–3.4	0–4.4	0–5.5	0–7	0–9	0–10.9
High	Dry		0–0.8	0–2	0.4–3.1	1.2–4.4	2.6–7.4	4.2–11	5.9–15.4	7.6–19.8	9.9–24.1	11–28.8
	Average		0–0.2	0–0.7	0–1.2	0–1.7	0–2.2	0–2.8	0–3.3	0–4.3	0–5.3	0–6.2
	Wet		0–0.8	0–1.7	0–3	0–5.2	0–7.3	0–9.4	0–12.3	0–15.6	0–18.8	0–22.6

5 Discussion

The key decision identified by industry was how many weaners to sell in March and how many to carry through winter to sell as yearlings in November. 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.

5.1 Optimal decisions made without seasonal climate forecasts

Pasture availability in March strongly influenced the optimal decision. With low pasture availability the predominant decision was to sell all weaners, regardless of climate forecast state and, in most instances, regardless of price settings. These conditions resulted in little value of a perfect forecast (Figure 13) and hence even less value from an imperfect forecast (Table 5). These results indicate that when conditions are poor in March, it is difficult to improve the profitability of the system regardless of seasonal evolution.

Although the level of pasture availability in March was the major determinant of SCF value, supplementary feed and cattle price settings and the particular climate state (dry, average or wet) modified the economic outcomes of production.

The influence of feed and cattle prices can be clearly seen in the results. With low weaner and supplementary feed prices, the dominant decision tended towards holding weaners to sell as yearlings (Figure **12**). This appears to be a rational decision as income from weaners is smaller and any supplementary feeding will be less expensive, allowing for greater returns to be yielded when animals are sold as yearlings. Equally, when weaner and supplementary feed prices are both high, there is a tendency to sell weaners (Figure **12**). Again, this appears rational as higher income from weaners is obtained and feeding animals to higher weights will be expensive under this scenario.

5.2 Optimal decisions made with seasonal climate 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. The maximum value of a forecast of average conditions was $6.20/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.

When pasture availability was high in March, the sell decision varied with climate forecast state and price settings (Figure **12**), indicating that producers have more options to respond when the start to the weaner growing period is strong. A medium level of pasture availability in March led to some value of a perfect forecast, depending on price settings (Figure 13).

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 high pasture availability in March, low weaner prices and high supplementary prices, the without-forecast decision was to sell 50% of weaners. With a perfect **dry** forecast, the optimal decision changes to selling 90% of weaners, 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 $28.80/ha under this scenario.

A scenario of low pasture availability in March, low weaner prices and medium 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 weaners, largely due to poor pasture conditions. With a perfect wet forecast, the optimal decision changed to selling just 30% of weaners. 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 $20.50/ha under this scenario.

These examples highlight the maximum possible value of SCFs 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 20–40% skill (Figure 14, Figure 15 and Figure 16). Table 5 provides the range of value of SCFs for different price settings. Under all skill levels and almost all pasture and climate state scenarios, the range in value includes $0/ha. This highlights the influence of price settings on the potential value of SCFs. The only scenario that differed was for high pasture availability and a dry forecast. This scenario is the only one for which a SCF consistently provides value for skill 30% or greater.

Industry consultation identified cash flow as an important factor in making livestock selling decisions. When cash flow is poor, there is an incentive to sell weaners to improve cash flow. Here cash flow was not found to be an important decision driver when evaluating the potential value of a forecast. This finding is in part an artefact of the methodological approach.

This analysis considered the potential value of SCFs relative to a without-forecast decision environment. The without-forecast decisions do differ slightly between the no debt and debt analyses which represent cash flow differences in the analysis, with some increased selling of weaners under the debt analysis (Figure 11). However, the relative benefit of a SCF to these without-forecast decision settings did not meaningfully differ between the two debt level settings. That is, the selling decision was moderately different, however, the relative benefit of including SCFs in improving income was similar regardless of debt position. In addition to the relative benefit structure of the methodology limiting the importance of cash flow, the debt burden incorporated into the analysis was not large compared with turnover. The $225 000 debt figure used represents average debt levels for beef specialists in New South Wales (Department of Agriculture and Water Resources, 2017) and was deemed appropriate for this case study. For individual circumstances where debt levels are much larger or there are other significant constraints on cash flow, the value of a forecast would be expected to reduce notably as holding animals to sell as yearlings will not, in most circumstances, provide sufficient returns to cover operational costs and the costs of servicing high debt levels. These producers have limited ability to respond to different seasonal conditions or forecasts and thus would not be the target audience for inclusion of SCFs into their decision-making.

5.3 Limitations and assumptions

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 with different systems (i.e. autumn calving systems) and for different production areas with different climate profiles.

The modelling for the case study attempts to capture the key characteristics of the real decision environment. A number of simplifications were adopted to reduce the complexity of the modelling and analysis. A key simplification was to limit the number of selling opportunities to two time periods (March and November). In reality, beef producers in southern Australia have several selling opportunities throughout the season, including selling stock in winter as feeder stock or buying feeder stock. Stocking rate decisions that result in the sale of too many or too few animals, in the light of changes in seasonal conditions, could be somewhat rectified, with associated costs. These additional selling and buying opportunities were not included in the analysis but would potentially reduce the value of SCFs as producers are able to make ongoing modifications of stocking rates. For example, if no weaners were sold and the season evolved as dry, these stock could be sold prior to November and losses minimised. While these changes would not be cost-free (e.g. dry conditions may lower stock prices due to widespread selling), the loss associated with the initial decision can be lowered.

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, weaner price, supplementary price) and future information that is unknown at the decision time (climate state, price of steers/heifers in 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 steers/heifers 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 at the time of selling to of the likely price of steers/heifers in November (e.g. greater market access leading to higher demand for beef). With additional information changing the likely price of cattle in November, this would likely change the with- and without-forecast selling decision. This was investigated through a sensitivity analysis to November cattle prices using historically low (10th percentile) and high (90th percentile) prices (Appendix 5: Perfect forecasts with low/high November 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, if it is known that cattle prices in November will be higher, fewer weaners will be sold. Conversely, if prices are expected to be low in November, more weaners are sold. This shows the value of information in decision-making but it should be noted that future conditions cannot be precisely known.

Sensitivity analyses of weaner and supplementary feed prices were not contingent on the climate state. That is, it was not assumed that prices modify in-step with different climate conditions. For instance, in a dry season weaner prices could be lower due to greater selling of animals. This non-state contingent design was purposeful. State-based relationships to historical prices (weaner and supplementary feed) were not found. This may be the result of several factors. Cattle prices are related to stock availability and in recent years the national herd numbers have been historically low. As such, increased selling in dry years did not trigger oversupply or a dip in prices. Supplementary feed prices may not increase in dry seasons as supply is related to the previous season which may have been good. Equally, prices may be high in a wet season due to poor supply. Relationships to the dry forecast, in particular, may not be evident as the definition of dry in this case study was the lower tercile of rainfall, not drought conditions. Under the particular conditions of broad drought, prices linked to seasonal conditions may be appropriate.

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 (i.e. accuracy) score for March to May rainfall in the Holbrook region is approximately 60%, equivalent to 20% using the definition of skill in this study.

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Appendix 1: Industry engagement

Engagement for the development of a case study for southern beef 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 southern beef 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 theoretical representative farm system. The group selected Holbrook with a self-replacing herd as a representative for southern Australian beef specialists and allocated a farm size of 700 ha.

Two calving systems were discussed: autumn calving, which was considered as the traditional approach; and winter/spring calving, considered by the participants as a more progressive system. It was noted that there are likely greater differences between these two systems than between sites using the same system. The group highlighted that converting between autumn and spring calving systems takes many years and is a strategic decision that cannot be changed over the timeframe of a seasonal climate forecast (months).

1.1 Autumn calving

The general cycling of an autumn calving system was defined to have calving occurring from mid-February to mid-April. As such, cows are lactating through the autumn and winter months. This coincides with when cows have the highest energy demand and pasture growth is low. As such, the herd, particularly the lactating cows, need sufficient feed. Commonly, winter feed is sourced from hay and silage cut from the previous spring. Typically, autumn calving systems are closed with limited feed bought into the system. The peak spring pasture growth is utilised by weaners (about 3–6 months old) and yearlings (about 15–18 months). In this system, typically half the weaners are sold in January (8–10 months) and the rest are carried through to later selling opportunities (e.g. November). By selling a proportion of weaners early, the risk of insufficient volume of stored feed, which is needed to meet lactating cows demand, is minimised.

For the purpose of this assessment, the representative farm with an autumn calving system was set with a stocking rate of 400 cows.

1.2Winter/spring calving

The general cycling of a winter/spring calving system was defined to have calving occurring from mid-July to mid-September. The spring peak in pasture growth coincides with the cows lactating period, with high energy demand by cows occurring at the same time as high pasture growth. Less hay and silage making occurs in this system as more pasture is used by the animals, with feed more frequently bought in over winter. Note, that as cows are not lactating through winter their energy demand is lower through winter than in the autumn calving system. In this system, typically only a small proportion of weaners are sold in March and the bulk are carried through to later selling opportunities (e.g. November). By selling a smaller proportion of weaners early, a greater number of animals are carried through winter.

The same farm details as the autumn calving system were used in the winter/spring system with the number of cows increased to 500 to reflect the higher intensity of these systems.

2 Decision point

The group identified that the decision of how many weaners to sell was sensitive to seasonal climate forecast information for both autumn and winter/spring calving systems. The number of weaners sold was classified as the critical climate-sensitive decision as this sets the number of animals carried through low feed conditions and also sets the number of animals available for future selling opportunities. In evaluating this decision economically, a comparison between profit gained from selling weaners must be compared with the alternative potential profit of holding stock to sell later at higher weights.

A seasonal rainfall forecast close to the sale time, January (March) for autumn (winter/spring) calving systems can provide an indication of likely upcoming pasture availability and hence assist with decisions around stocking rates.

Decision point:

How many weaners to sell versus how many to carryover?

The timing for this decision differs between autumn and winter/spring systems, reflecting the difference in weaner age at the same time of year. As such, the timing of the decision is different between the systems, as is the relevant rainfall forecast period (Table 6).

Table 6 Decision point timing and forecast periods for autumn and winter/spring calving

Calving system	Decision time	Forecast period
Autumn	January	January, February, March
Winter/spring	March	March, April, May

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

1. Cash flow: low cash flow encourages selling, good cash flow discourages as much selling.
2. Relative price of weaners: good prices encourage additional selling, low prices discourage selling.
3. Feed availability: low pasture and/or low stored feed encourages selling, high feed availability discourages selling.
4. Rainfall forecast: wet (i.e. good pasture growth) discourages selling, dry (i.e. poor pasture growth) encourages selling.

Figure 17 illustrates this decision-making process, 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.

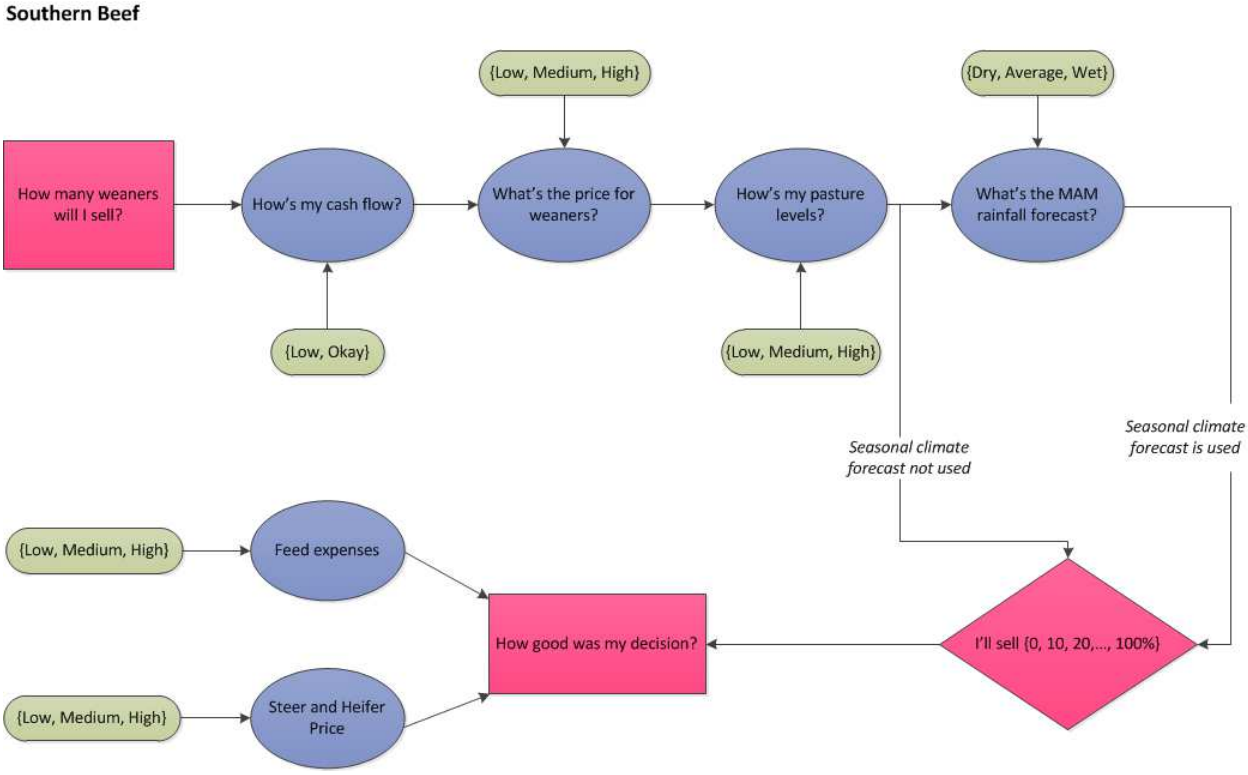


Figure 17 Decision pathway for proportion of weaners sold in southern beef systems including an evaluation of the decision made

3 Selling decision

Selling decisions based on different values of the four drivers were estimated through consultation with industry for autumn (Table 7) and winter/spring calving systems (Table 8). A clear difference between the systems can be seen in the first two rows of Table 7 and Table 8, which represent average conditions with different cash flow positions. Under these average circumstances, autumn calving systems are set up to sell a large proportion of weaners, 50% (75%) with okay (low) cash flow. For the winter/spring calving system, a lower percentage of weaners are sold under average circumstances with 10% (45%) sold under okay (low) cash flow. These selling options represent the 'business-as-usual' selling decision.

Table 7 Autumn calving sell decisions with different options for the key drivers as determined in consultation with industry. Seasonal rain forecast is for the three months January, February and March. *industry values determined through the workshop, the remaining values were determined subsequently and confirmed by the participants at a later date.

Cash flow position	Price weaners	Feed available	Seasonal rain forecast	%sell
*Okay	Average	Average	Equal chance	50
*Low	Average	Average	Equal chance	75
OK	Low	Low	Dry	85
Low	Low	Low	Dry	85++
OK	Low	Low	Equal chance	50
*Low	Low	Low	Equal chance	75
OK	Low	Low	Wet	40
Low	Low	Low	Wet	75
OK	High	Low	Dry	90
Low	High	Low	Dry	90++
OK	High	Low	Equal chance	75
Low	High	Low	Equal chance	85
OK	High	Low	Wet	75
Low	High	Low	Wet	85
OK	Low	High	Dry	<40
Low	Low	High	Dry	65
OK	Low	High	Equal chance	35
Low	Low	High	Equal chance	50
*OK	Low	High	Wet	35
Low	Low	High	Wet	50
OK	High	High	Dry	75
*Low	High	High	Dry	75
OK	High	High	Equal chance	65
Low	High	High	Equal chance	75
*OK	High	High	Wet	65
*Low	High	High	Wet	75

Table 8 Winter/ spring calving sell decisions with different options for the influential factors as determined in consultation with industry. Seasonal rain forecast is for the three months March, April and May. *industry values determined through the workshop, the remaining values were determined subsequently and confirmed by the participants at a later date.

Cash flow position	Price weaners	Feed available	Seasonal rain forecast	%sell
*Okay	Average	Average	Equal chance	10
*Low	Average	Average	Equal chance	45
*OK	Low	Low	Dry	50
*Low	Low	Low	Dry	85++
*OK	Low	Low	Equal chance	20
*Low	Low	Low	Equal chance	75
*OK	Low	Low	Wet	10
*Low	Low	Low	Wet	65
OK	High	Low	Dry	50
Low	High	Low	Dry	85++
OK	High	Low	Equal chance	70
Low	High	Low	Equal chance	75
OK	High	Low	Wet	10
Low	High	Low	Wet	70
OK	Low	High	Dry	10
Low	Low	High	Dry	45
OK	Low	High	Equal chance	0
Low	Low	High	Equal chance	40
*OK	Low	High	Wet	0
*Low	Low	High	Wet	40
OK	High	High	Dry	30
Low	High	High	Dry	60
OK	High	High	Equal chance	10
Low	High	High	Equal chance	50
*OK	High	High	Wet	0
*Low	High	High	Wet	75

Appendix 2: Gross margin values

Table 9 Productions costs used in the economic analyses with an enterprise unit of 100 cows

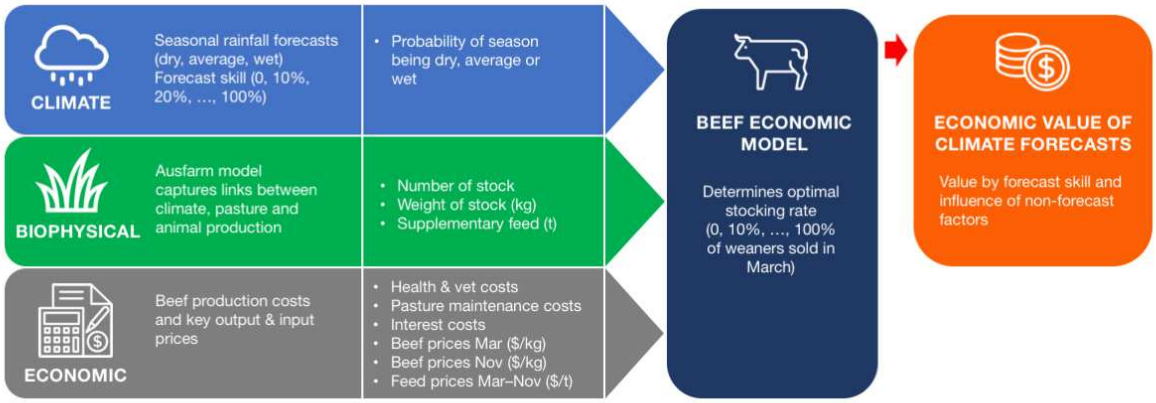
Variable costs	Cost (A$)	/unit
Livestock husbandry costs		
Vac – 5 in 1 for calves	0.50	/head
Vac – 5 in 1 boost yearlings	0.25	/head
Worm treat yearlings	1.00	/100kg
Pregnancy test	4.00	/head
Miscellaneous herd costs	4.00	/head
Total livestock husbandry costs	**16.05**	**100 cows**
Selling costs		
Replacement – bull	6000	/head
Commission	4%	/head
Yard dues	3.00	/head
MLA levy	5.00	/head
Freight costs to saleyard	8.00	/head
NLIS tags	2.90	/head
Total livestock selling costs	**66.96**	**100 cows**
Feeding costs		
Pasture maintenance	6000	**100 cows**
Supplementary feed pellets*		/tonne
10th percentile	159	
50th percentile	203	
90th percentile	267	
Supplementary feed lucerne hay – (bag)*		/tonne
10th percentile	210	
50th percentile	259	
90th percentile	386	
Total feeding costs	**60.00**	**100 cows**

Data source: https://www.dpi.nsw.gov.au/__data/assets/pdf_file/0003/175530/26-Young-cattle-15-20-mths.pdf

Appendix 3: Economic model

1 Overview of the modelling approach

SOUTHERN BEEF



2 Economic model description

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

A two-stage discrete stochastic programming (DSP) model was developed for the beef 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 weaners in March), 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 March to maximise the expected level of net farm income across climatic states. In algebraic terms, the main elements of the model are:

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

$$y_s = \sum_{j=}^{Jy} y_j\ c y_j\ x y_j + \sum_{n=}^{N} c_{2nsy} x_{2nsy} \qquad \text{[Equ 2]}$$

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 weaners under stocking rate j in Stage 1 ($/hd) – March

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

Model variables

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

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

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 herd and the number of weaners and yearlings 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 weaners in March ($/kg) multiplied by their live weight and x_{1j} is the number of male and female weaners sold. In Stage 2, the term $c_{2ns}\, x_{2ns}$ represents state-contingent revenue and costs. These are state-contingent because climatic conditions influence the live weight of yearlings 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. beef prices) were assumed to be independent of climatic conditions. A review of available beef and supplementary feed price data did not establish a correlation with March–November 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 weaners in March) 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 πs). 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 x^*_{sf} based on forecast *f*; and

y^*_{so} denotes net return in state *s* resulting from implementing the optimum stocking rate 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 (March) and the state-contingent tactical adjustments made in Stage 2 (November).

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:

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

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 eleven 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 percentage of weaners sold as forecast skill increases for each forecast state (dry, average, wet). The following three plots are for low, medium and high pasture availability in March, respectively.

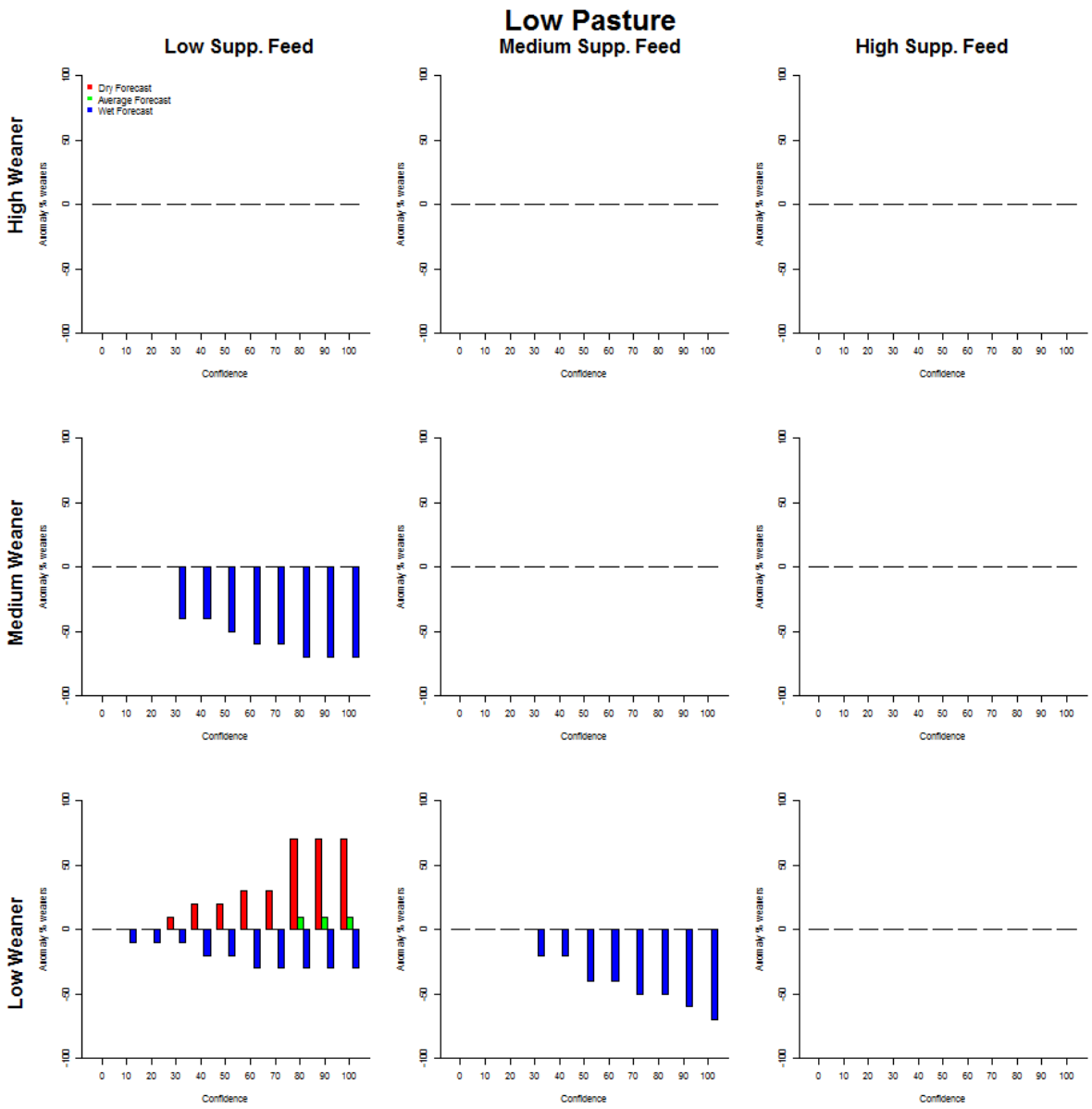


Figure 18 The change in the percentage of weaners sold based on increasing skill of probabilistic forecasts, relative to the without forecast sell decision (i.e. 0% skill) for low pasture availability in March. Red, green and blue indicate dry, average and wet forecasts.

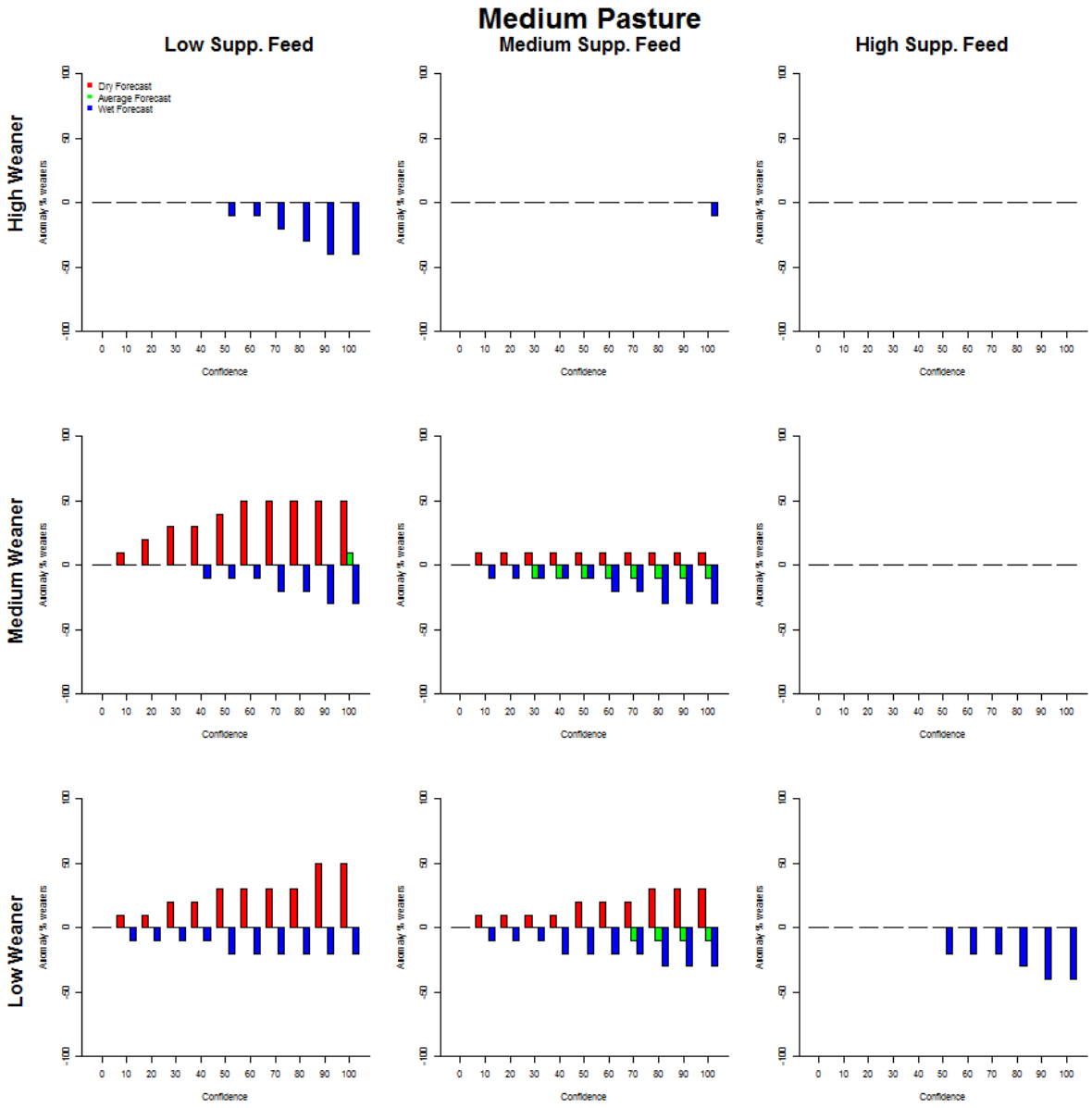


Figure 19 The change in the percentage of weaners sold based on increasing skill of probabilistic forecasts, relative to the without forecast sell decision (i.e. 0% skill) for medium pasture availability in March. Red, green and blue indicate dry, average and wet forecasts.

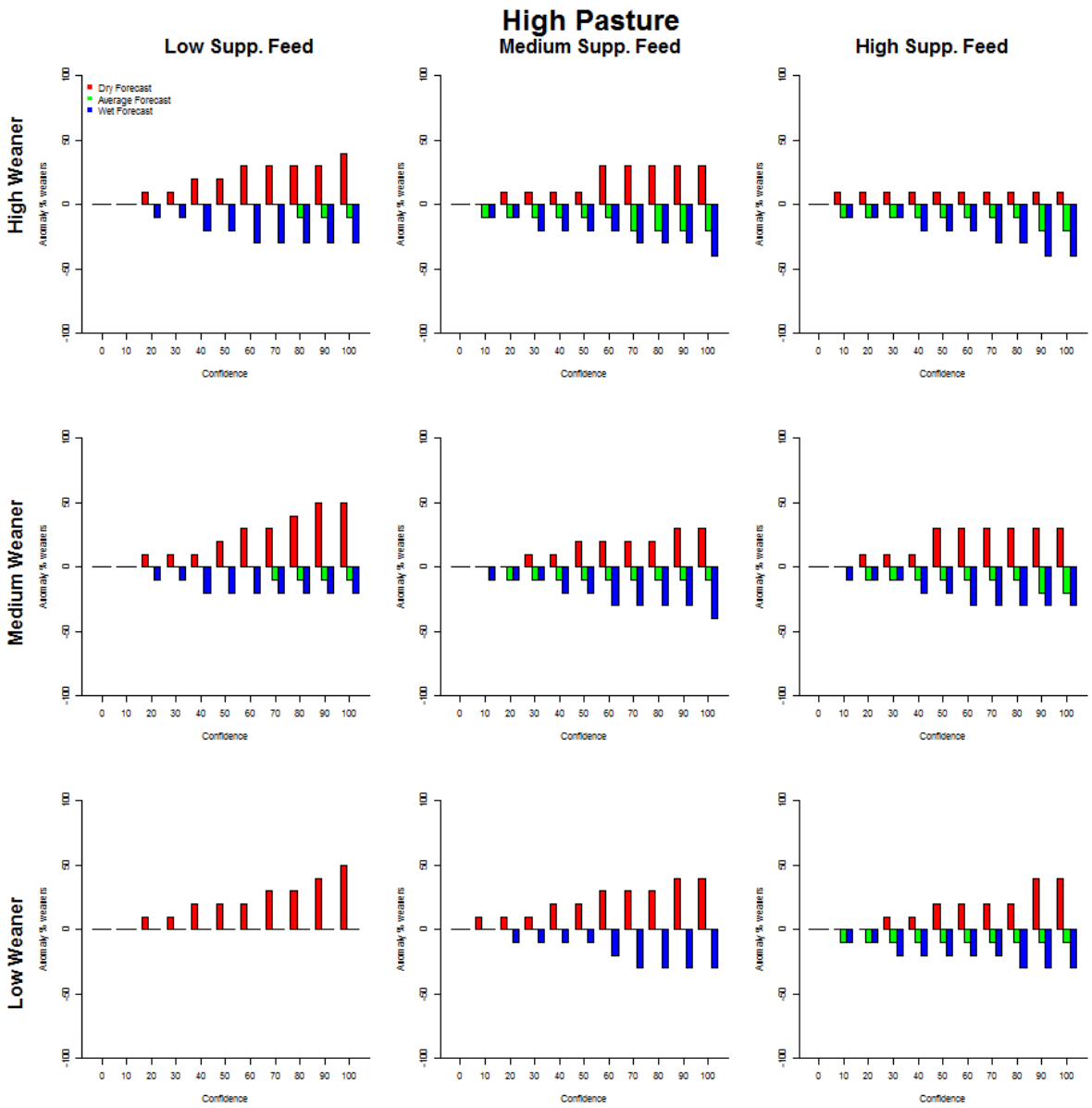


Figure 20 The change in the percentage of weaners sold based on increasing skill of probabilistic forecasts, relative to the without forecast sell decision (i.e. 0% skill) for high pasture availability in March. Red, green and blue indicate dry, average and wet forecasts.

Appendix 5: Perfect forecasts with low/high November prices

The perfect-forecast decision (Figure 21) and value of a perfect forecast (Figure 22) for low November steer and heifer prices (183 c/kg and 196 c/kg for heifers and steers, respectively). The perfect forecast decision (Figure 23) and value of a perfect forecast (Figure 24) for high November steer and heifer prices (219 c/kg and 228 c/kg for heifers and steers, respectively).

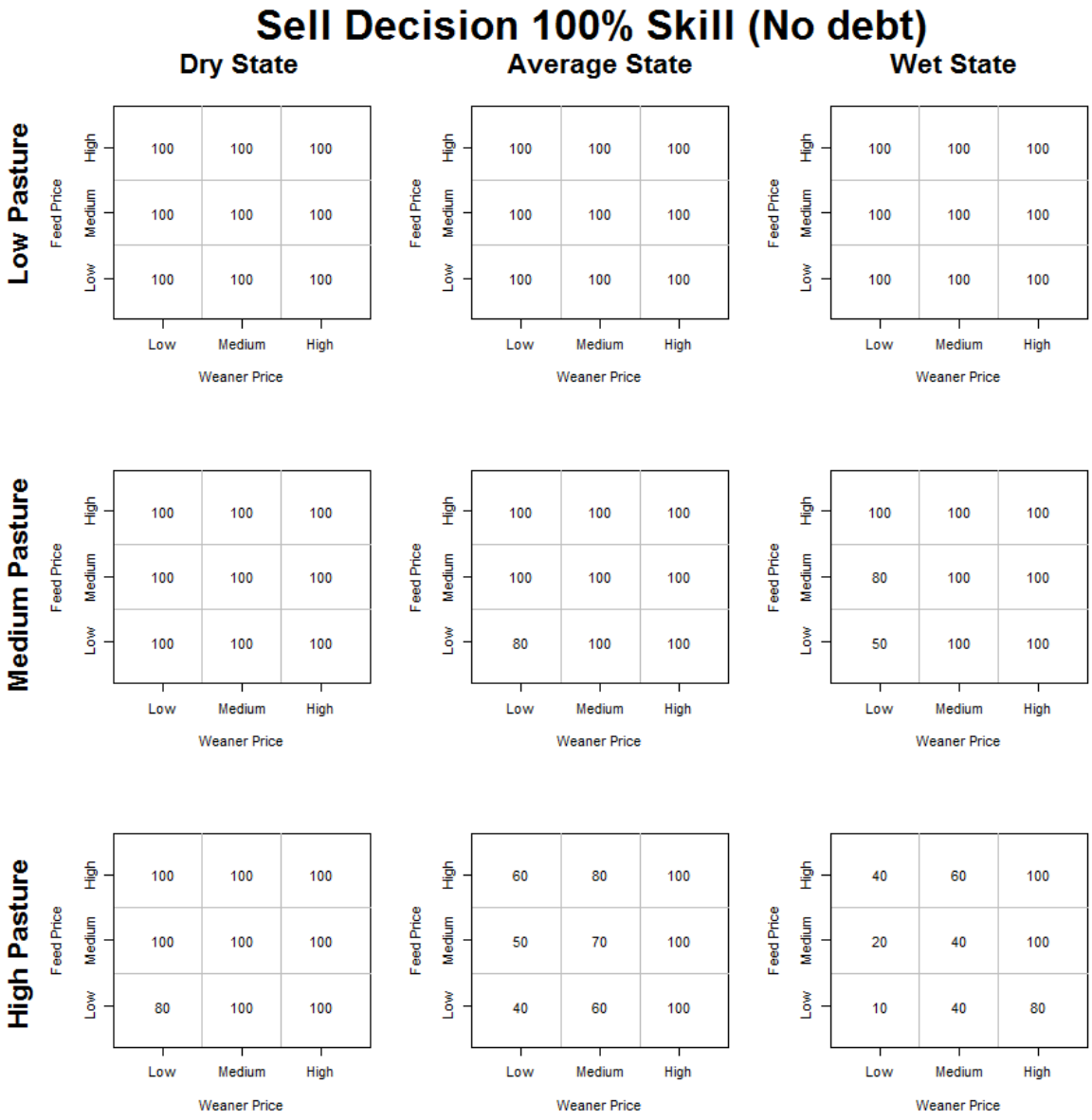


Figure 21 Perfect-forecast percentage weaners sold decision for low November heifer and steer prices. Dry, average and wet states in the three major columns, three levels of current pasture availability (low, medium, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and weaner price (low, medium, high) in the internal columns.

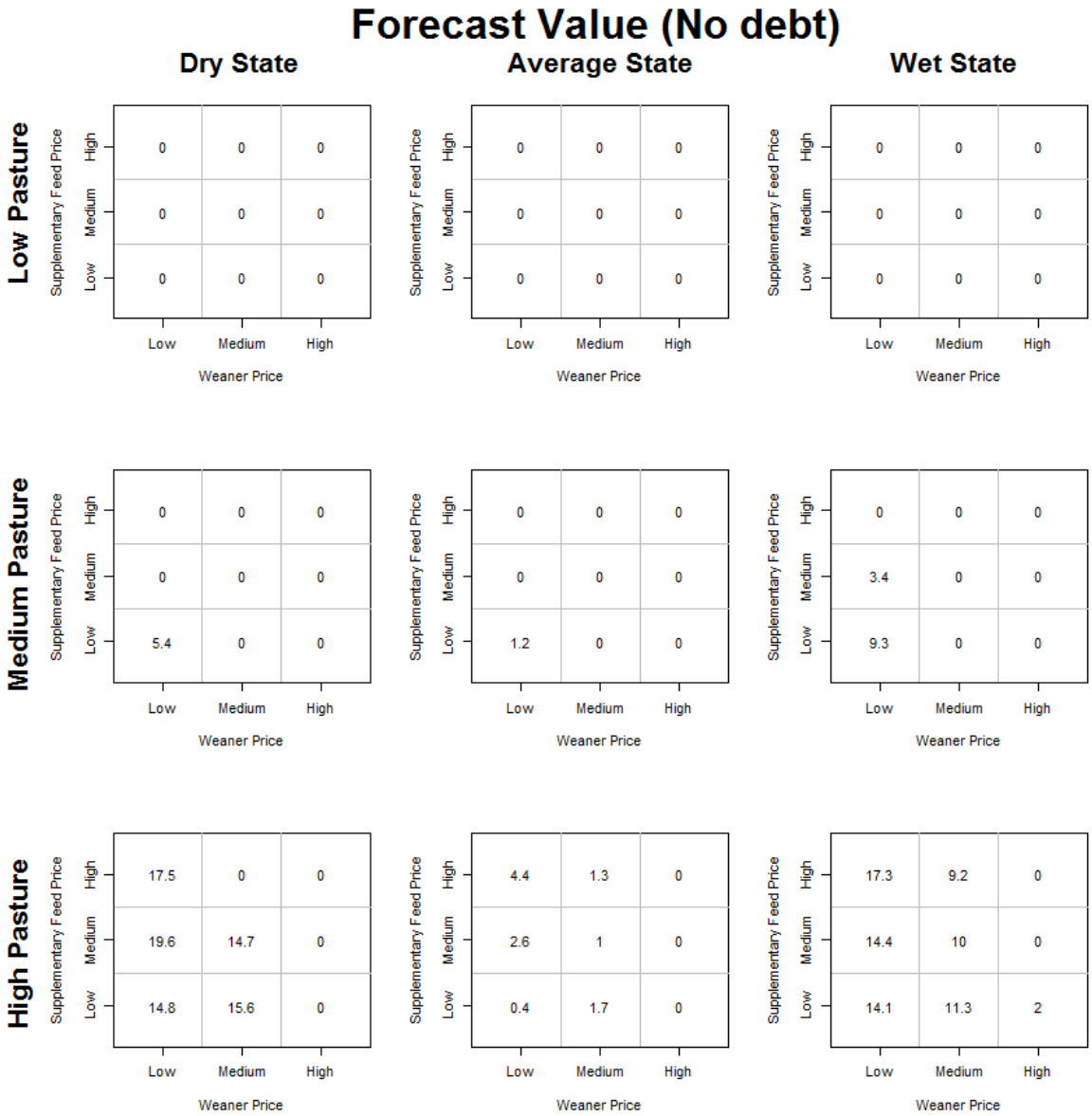


Figure 22 Perfect forecast relative value compared to the without-forecast return ($/ha) for low November heifer and steer prices. Dry, average and wet states in the three major columns, three levels of current pasture availability (low, medium, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and weaner price (low, medium, high) in the internal columns.

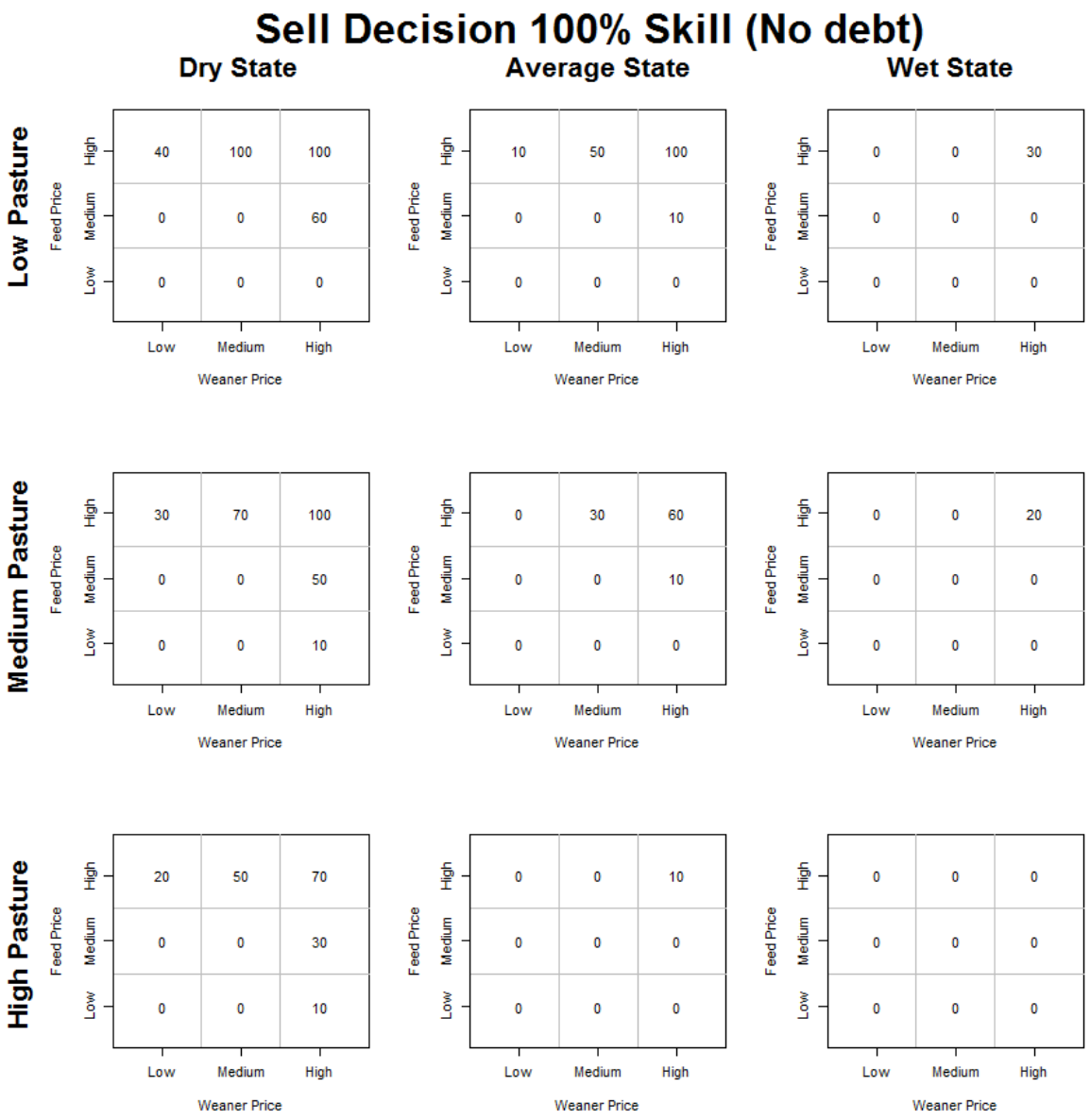


Figure 23 Perfect-forecast percentage weaners sold decision for high November heifer and steer prices. Dry, average and wet states in the three major columns, three levels of current pasture availability (low, medium, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and weaner price (low, medium, high) in the internal columns.

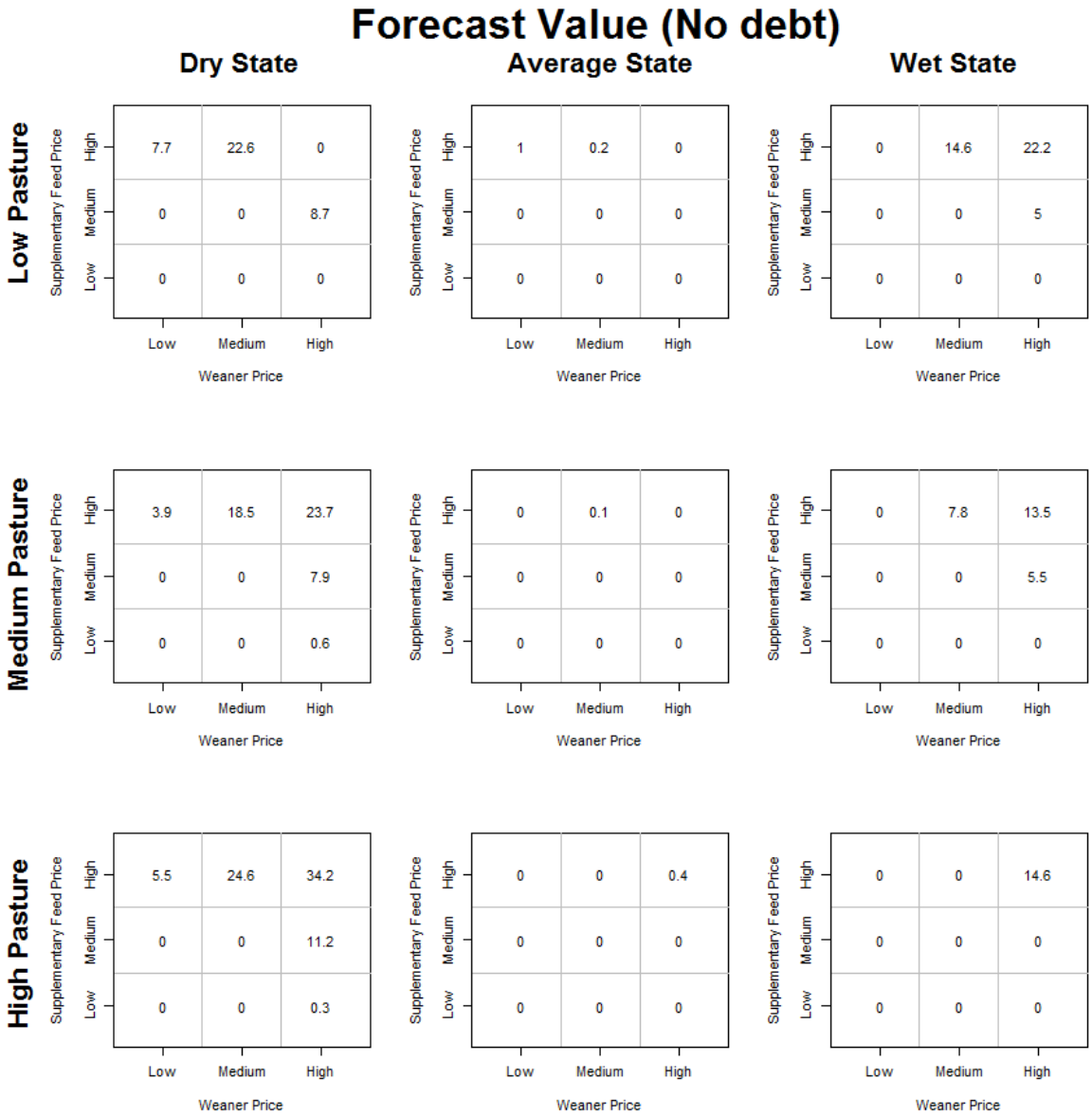


Figure 24 Perfect-forecast relative value compared to the without forecast return ($/ha) for high November heifer and steer prices. Dry, average and wet states in the three major columns, three levels of current pasture availability (low, medium, high) in the three major rows, supplementary feed prices (low, medium, high) in the internal rows and weaner price (low, medium, high) in the internal columns.