Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Northern 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 northern Australia. The key decision identified by industry was how many livestock to carry through the wet season (October to April). A total of 13 stocking rate strategies (8, 9, …,20 animals/100 ha) were analysed. The timing of this decision was October for a rainfall forecast of the wet season ahead (October to April). Rainfall over this period can influence the level of pasture production and thus animal weight and level of pasture utilisation. 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 October–April rainfall received at Charters Towers over the period 1900 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 and beef production data from the biophysical production model *GRASP*. 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 pasture availability in October to be captured and outcomes to be explored in dry, average and wet climate states. Other key decision variables, namely beef prices and likelihood of pasture over-utilisation, 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 October had a substantial influence on the optimal stocking rate decision. High and medium pasture availability led to a decision of stocking at the highest rate (20 steers/100 ha) based on a low likelihood of pasture over-utilisation. Even a skilful forecast of future climate conditions offered little value in these circumstances as pastures were rarely over-utilised. In contrast, low pasture availability provided conditions for alternative stocking rates to be considered and for climate forecasts to be influential. The optimal stocking rate under low pasture availability 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 October was the major determinant of the stocking rate decision, beef price settings were also found to be important. Under low prices, the dominant decision tended towards higher stocking rates. This was triggered by the prospect of low income from selling steers versus higher income from retaining them for sale in April. Equally, when prices were high and pasture availability low, there was a tendency to destock in order to take advantage of high income from selling cattle now and avoiding costs associated with pasture over-utilisation.

Value of forecasts

Of the nine combinations of pasture availability and steer prices considered, only four yielded value from inclusion of SCFs. Forecasts of dry, average and wet climate states had different economic value. A climate forecast of average conditions was found to be of limited economic value under all decision 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 low and medium levels of pasture availability, with the extent also dependent on beef prices. The maximum value of a dry forecast occurred under medium pasture availability and improved returns by $11.80/steer. The maximum value of a wet forecast also occurred under low pasture availability and improved returns by $13.90/steer. Improved forecast skill was naturally found to be positively related to forecast value, although the extent to which 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 wet forecast under low level of starting pasture availability was valuable as a departure from a low stocking rate to a higher rate 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 northern 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 et al., 1996; Parton and Crean, 2016).

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

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

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

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

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

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

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

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

1.2 Project objectives

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

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

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

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

1.3 Case study approach

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

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

This report contains findings of the northern 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 describe the production system within which SCFs were evaluated. 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, each of the 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 Northern beef production system

2.1 Industry overview

Beef production makes an important contribution to the Australian economy with an estimated value of $12.14 billion (ABS, 2018) for cattle and calves in 2016–17. 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 of 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 North Australia Beef Research Council (NABRC), the Southern Australia Meat Research Council (SAMRC) and the Western Australia Livestock Research Council (WALRC). Beef production within the NABRC was the focus of this case study.

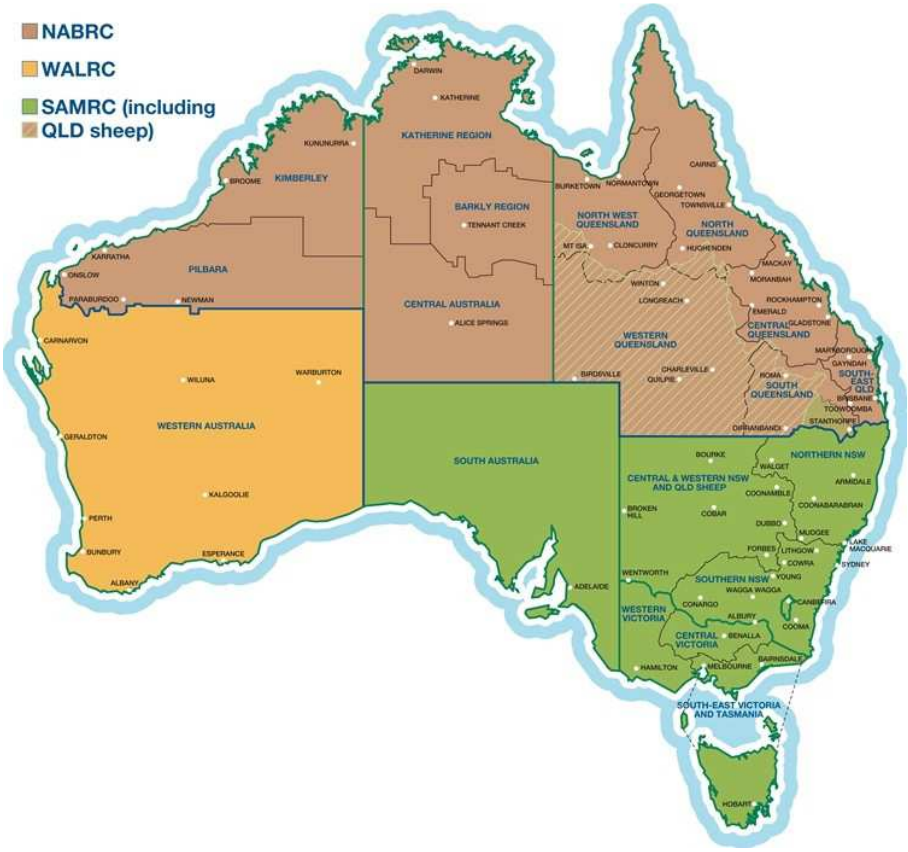

Figure 1 Regionalisation of MLA research councils (SAMRC, 2016)

2.2 Producing beef in northern Australia

Beef from northern Australia contributes substantially to total Australian production with Queensland alone accounting for 47.3% of beef and veal production in 2015–16 (MLA, 2018). These extensive beef enterprises utilise the rangelands across Queensland, Northern Territory and Western Australia. Features of this production system include large paddock sizes, up to 16 000 ha (Oxley, 2006), low stocking rates and are operate in a highly variable climate.

These enterprises are based on native pasture systems, where the core goal of production is the conversion of feed into animal weight gain. To optimise beef production, producers aim to match the feed requirements of the herd to the availability of pasture. Within this system management also includes the sustainable long-term management of native pastures for year-on-year productivity with many complex and interacting factors required for sustainable native pasture management (O'Reagain et al., 2014).

Northern beef enterprises are generally self-replacing breeding herds and operate on a production scale longer than a season (e.g. 39–45 months for a heavy bullock) with large-scale herd changes (e.g. changing core breeding herd or calving timing) a strategic decision implemented across many years.

Pasture supply within these dryland operations is intimately linked to climatic conditions, in particular rainfall. Annual, inter-annual and decadal rainfall is highly variable in the rangelands (McKeon et al., 1990) and can be extreme (wet and dry). This variability in rainfall leads to variability in pasture supply (Figure 2) with producers needing to manage, in particular, low rainfall seasons to minimise degradation of the pasture base and to maintain animal health.

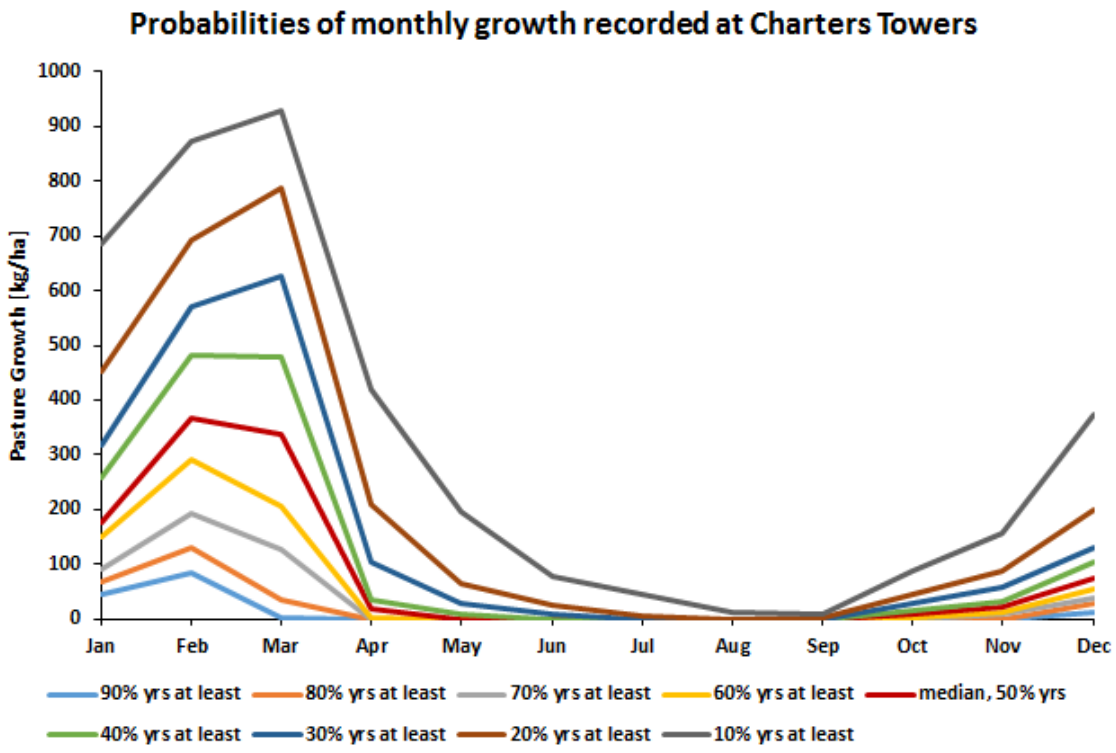

Figure 2 Modelled annual pasture growth for an average set of soil, pasture and land parameters in the Charters Towers region. Daily climate was taken from SILO and run in *GRASP* (Littleboy and McKeon, 1997). The monthly output from *GRASP* was analysed in Australian Rainman (Clewett et al., 2003).

Figure 2 highlights the seasonal context of production with producers relying predominately on summer rainfall (November through March) to drive productivity through the dry season (May to December). Matching stocking rates through variable wet and dry seasons is an ongoing challenge for northern beef producers with supplementary feeding to correct mineral deficiencies the only viable option, as the vast size of properties and herd sizes makes feeding protein and carbohydrate unviable.

Animal management primarily occurs during two mustering periods, either side of the wet season. During mustering, the herd is gathered for animal sales, health checks, weaning, castrating and other management actions. These mustering times provide an opportunity to adjust stocking rates to match current and expected conditions.

2.3 Description of production system and key decision point

Industry consultation was undertaken to describe the production system and key decision points. Further information on the consultation process is contained in

Appendix 1: Industry engagement.

The northern beef case study focused on a self-replacing *Bos indicus* herd on a 30 000 ha farm based in Charters Towers, Queensland (Figure 3). The system is based on 6000 animal equivalent with herd and site properties shown in Table 1.

Table 1 Mean physical, biological and economic parameters for the northern Australia beef case study. Values sourced from Holmes (2011), McGowan M et al. (2014) and Ash et al. (2015)

Location	Charters Towers
Climate	Semi-arid tropics
Mean annual rainfall (mm)	650
Property size (ha)	30 000
Pasture type	Native pastures with an open savanna canopy of trees
Herd size (AE)	6000
Main target market	Store steers and cull heifers
Weaning rate (%) #	60
Weaning weight (kg) #	180
Growth rate (kg/head/year) #	127

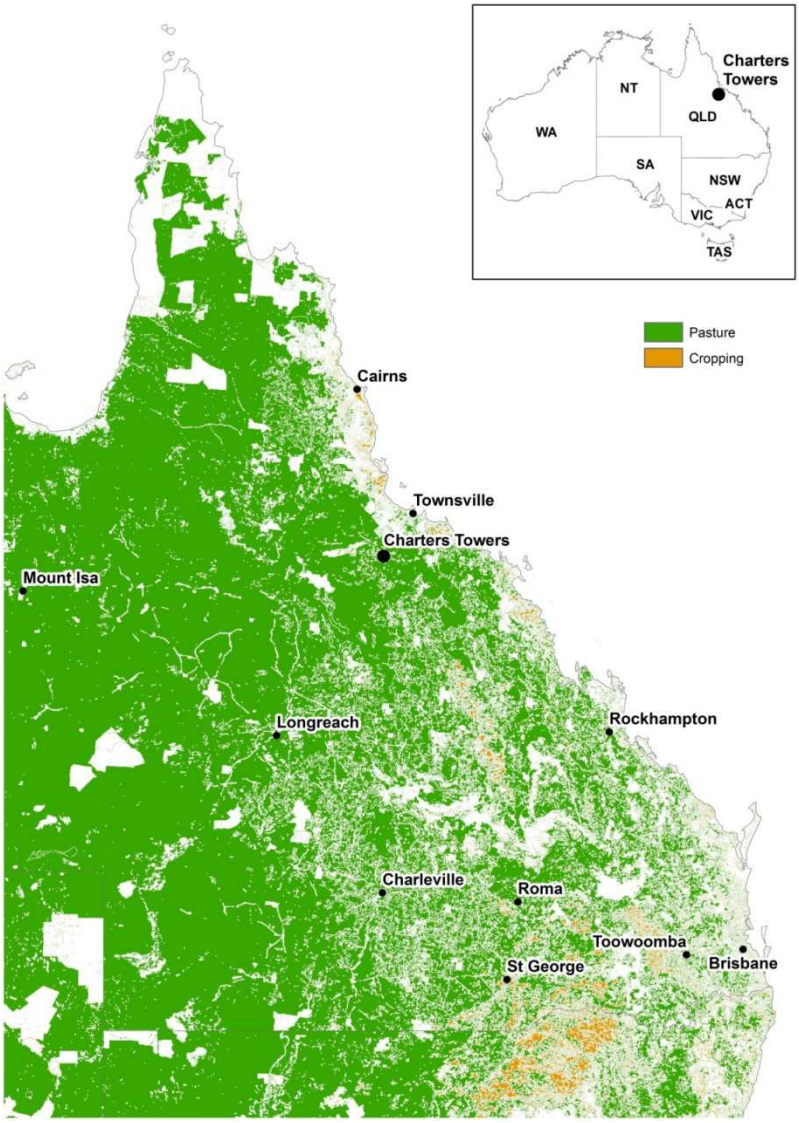

Figure 3 Map showing the location of Charters Towers, the case study site

In this system calving occurs from September to February with two rounds of mustering; the first in May to June and the second in August to September (Figure 4). Destocking decisions are made during these mustering periods, providing an opportunity to better match stocking rates to current and expected conditions. A more complete description of the production system is in Appendix 2: Production summary .

Figure 4 Broad system characteristics of northern beef case study

	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
Reproductive cycle[1]										X Joining		X
							X Calving			X		
		X Wean		X	X Wean		X					
Animal classes[2]	→						X Calf					→
		X Weaner		X								
					X Steer							→
Pasture quantity			X Low						X	X High		X
Animal management	Round 1 muster				Round 2 muster							
Sell steers[3]	Sell steers				Sell steers							
Cull cows/heifers[3]	Cull cows/heifers				Cull cows/heifers							

[1] Weaning will occur at one of two times depending on pasture availability.
[2] assuming calves are weaned at the first weaning opportunity.
[3] additional selling or holding of animals may occur in October, in particular greater selling across animal classes if conditions are poor.

2.3.1 Decision point

The key decision point for this system was:

What stocking rate will I set prior to the wet season?

The time of the decision was in October. The secondary selling time for retained steers was seven months later in April.

Setting the stocking rate, or allocating the number of steers to sell in October, is not a simple decision. Three key decision drivers were identified:

1. Current steer prices: low prices discourage destocking, high prices encourage destocking.
2. Pasture availability: low availability encourages selling, high availability discourages destocking.
3. Rainfall forecast for October through April: wet (i.e. good pasture growth) discourages destocking, dry (i.e. poor pasture growth) encourages destocking.

Figure 5 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: Industry engagement.

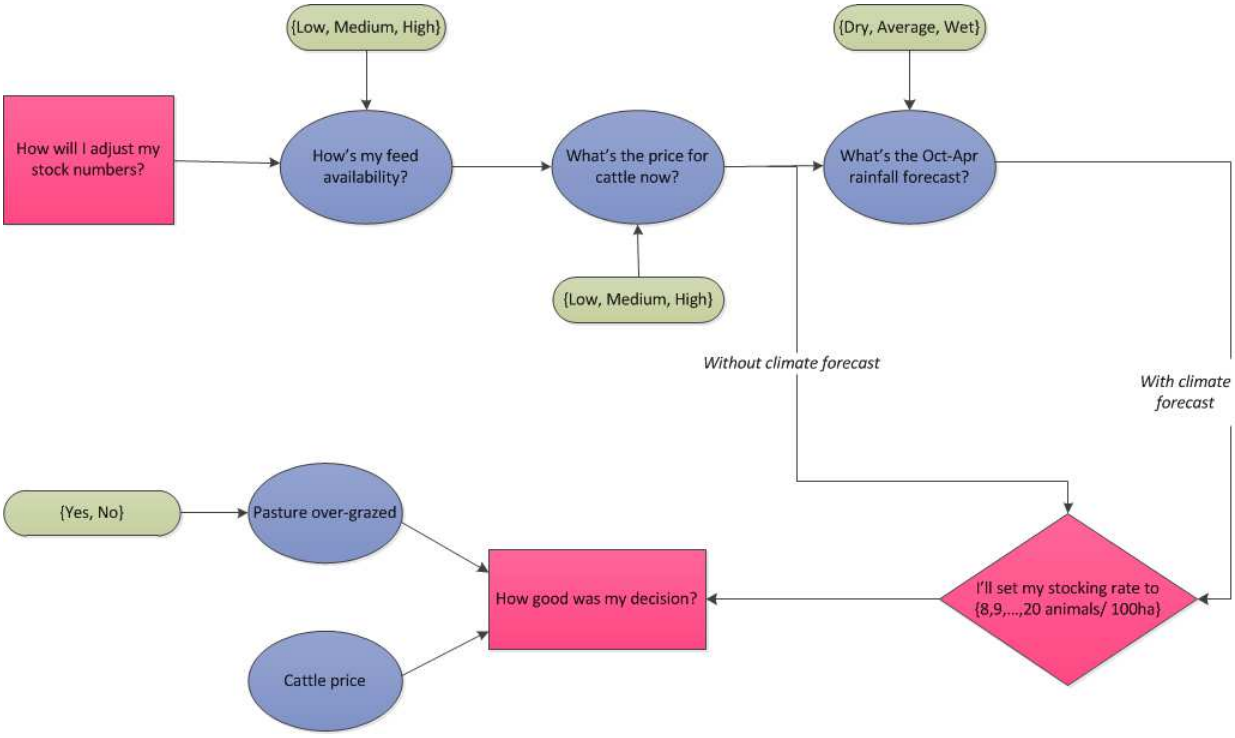

Figure 5 Decision pathway for setting the stocking rate in northern beef systems in October including an evaluation of the decision made.

2.4 Previous studies of SCFs in northern beef production systems

Adjustment of grazing pressure is a key management decision within northern beef systems and has a major impact on resource condition, pasture yield and composition, soil loss, burning opportunities, growth of woody weed and hence enterprise profitability. There are many options for managing grazing pressure (Johnston et al., 2000; Stafford Smith, 1992), including using a SCF to adjust stocking rates. Due to complexities of on-farm experiments to detail the impact of various pasture management strategies, simulation modelling is frequently used to examine potential implications of different management strategies, although not exclusively (e.g. O'Reagain et al., 2011). To enable assessment of whole-of-enterprise management of northern beef cattle (Ash et al., 2000; McKeon et al., 2000; Stafford Smith et al., 2000), these simulation models typically use linked models to simulate pasture growth, resource condition, soil loss, burning opportunities, liveweight change (e.g. *GRASP*; (Littleboy and McKeon, 1997)) with property economics (e.g. Herd-Econ; (Smith and Foran, 1992)).

Inclusion of SCFs into decision-making processes within Australia's northern beef systems 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 use of SCFs in northern beef systems has been previously examined by a number of studies (Ash et al., 2000; McKeon et al., 2000; O'Reagain et al., 2011; Stafford Smith et al., 2000) and largely focused on stocking rate decisions. Research attention has been directed to understanding the management decisions that may be sensitive to SCFs (Buxton and Smith, 1996), how forecasts are related to production variables such as live weight gain (McKeon et al.,

2000) and the attributes of the forecasts which are useful for decision-making such as forecast type and timing (Ash et al., 2000; Keogh et al., 2006).

A few studies have examined the economic value of SCFs within northern Australian beef systems. Using simulation modelling, McIntosh et al. (2005) investigated stocking rate decisions for a beef production system in Dalrymple shire in Queensland. They used various forecast systems to adjust stocking rates. They found incorporation of forecast information into the decision increased annual cash flow from the no-forecast strategy by $12 785 to $29 608.

O'Reagain et al. (2011) examined five strategies to adjust stocking rates over a 12-year field trial on a commercial property about 70 km south-west of Charters Towers. One strategy used the SOI phase forecast to vary stocking rates in November. Over the period of the experiment the accumulated gross margin (AGM) was calculated for each grazing strategy. The greatest AGM found was $28 490/100 ha for a variable stocking rate strategy which adjusted stocking rates in May based on current available pasture. A fixed moderate stocking rate strategy, which set stocking rates to keep pasture utilisation at approximately 25% of the long-term pasture production, recorded a similar AGM of $28 279/100 ha. The strategy that used the SOI forecast recorded a lower AGM than these strategies that did not use SCF of $26 595/100 ha.

Stafford Smith et al. (2000) used simulation modelling to consider the impact of using various forecasts on annual cash flow of a cattle station in north-east Queensland. Their primary finding was that production benefits of a forecast (Ash et al., 2000; McKeon et al., 2000) did not readily translate to economic benefit at the whole-of-enterprise scale. They also found that selling strategies were sensitive to market prices, with trading strategies relatively favoured over the constant stocking rate strategy as this allowed responses to prices.

3 Methods

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

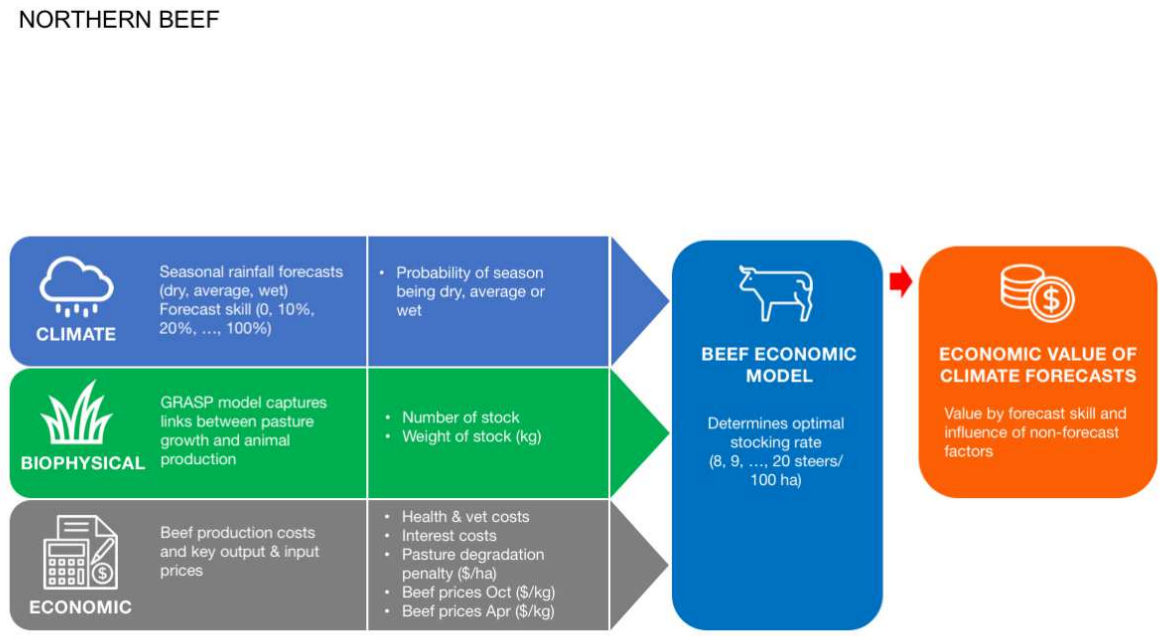

Figure 6 Methodological overview. Generation of biophysical data, beef production costs, beef prices and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal stocking rate based on maximising returns.

3.1 Beef biophysical simulation model

The link between stocking rates, climatic conditions, pasture and beef production was captured through detailed biophysical modelling using the *GRASP* model (Littleboy and McKeon, 1997). *GRASP* is a dynamic, pasture-animal growth model that has been applied to evaluate the effects of various grazing management practices in Australia (McKeon et al., 2009). *GRASP* uses climate data as input information and a suite of mathematical equations to simulate changes in pasture dynamics. The soil water balance is based on four soil layers and includes sub-models of tree transpiration, pasture transpiration, soil evaporation, run-off and through-drainage. A full description of various modelling components, including assumptions, strengths and limitations is provided elsewhere (Day et al., 1997). The model has been validated for various soils and climates in Queensland including for the conditions at Charters Towers (Ash et al., 2015). However, like other similar livestock production models, *GRASP* does not represent the impact of nitrogen cycle (drought carryover, length of wet season, burning, legumes), species differences (root/shoot ratio, leaf/stem ratio, detachment rates), species composition (annuals, perennials, forbs), tree dynamics (growth, litter, browse, death), germination and pests and diseases (pasture or animal) and as such it tends to optimise biophysical performance.

Climate data for the case study was sourced from SILO patched point dataset (Jeffrey et al., 2001) for station 34084 (Charters Towers). The modelling followed a per hectare approach which can then be scaled up to property size. A total of 39 scenarios were tested, involving three levels of initial pasture growing conditions (low, medium and high) and 13 levels of stocking rates (from 8 to 20 steers/100 ha at an increment of 1). Five key parameters were reset annually (1st October) to assess the three levels of pasture (Table 2) with the remaining default modelling parameters kept consistent with those of Ash et al. (2015) to retain the previously validated model setup. All scenarios were simulated for 116 years (1900–2015). The animal production system modelled was based on young steers assuming an adult equivalent weight of 401 kg in October. Animal performance and average pasture utilisation for each scenario were assessed in April, seven months after the start of the simulation.

Table 2 Pasture composition attributes used in the *GRASP* modelling.

Pasture Scenario	Initial total standing dry matter (kg/ha)	Average daily re-growth (kg/ha)	Transpiration efficiency (kg/ha/mm)	Maximum nitrogen uptake (kg/ha)	Initial plant density (% basal area)
Low	385	3	10	10	1
Medium	1448	6	12	12	2.5
High	2153	15	18	25	5

3.2 Beef production costs

The production costs of the system, including beef herd health, selling and feeding costs for the model were based on values in Martin (2016). Detailed production costs used are included in Appendix 3: Gross margin values. An annual interest rate of 10% was applied to production costs.

3.2.1 Pasture over-utilisation penalty

Within the *GRASP* model under fixed stocking rate strategies, animals are able to heavily graze pastures. This would, over time, lead to pasture degradation and an unsustainable and less profitable system. The analysis conducted here only considers the implications of production decisions over seven months and as such this long-term degradation was not captured.

The analysis included a cost for the over-utilisation of pastures to better capture the production and economic impacts of climate variability, particularly the downside risks associated with high stocking rates in dry years. *GRASP* modelling output was supplemented using results from O'Reagain et al. (2011) who evaluated the long-term economic impact of various grazing strategies at a property 70 km from Charters Towers. Two strategies in their study were pertinent to this assessment: (1) a moderate stocking rate used to reflect the sustainable long-term carrying capacity of the site which was stated to be approximately 25% utilisation of the average annual long-term pasture production; and (2) a heavy stocking rate, set at twice that of the moderate stocking rate equating to approximately 50% utilisation of annual average long-term pasture production.

Using this information, an index was created for each simulation run to reflect whether the pastures were over-utilised or not. This used the monthly *GRASP* pasture utilisation output for October to April (the forecast and decision period). The average utilisation across these months was calculated and, if it exceeded 25%, the simulation was marked to indicate that the pastures were over-utilised:

$$\text{Over-utilisation} = \sum_{Oct}^{Apr} \overline{pasture\ utilisation} \geq 25\%$$

This approach was undertaken to best reflect the designation applied in O'Reagain et al. (2011). When pasture was classified as over-utilised a financial penalty, or cost, was applied to returns. The results from O'Reagain et al. (2011) were used to set the value of the penalty which was taken as the difference in the annualised net present value between the moderate and heavy stocking rate strategies ($639 per 100 ha).

3.3 Key input costs

Model sensitivity to steer price in October was conducted to evaluate the value of SCFs under different price scenarios.

Stock prices were sourced for 2006–2015 from the MLA Queensland Monthly Saleyard Cattle Indicators (MLA, 2017) and adjusted to real prices using (ABARES, 2015). Stock prices used were medium and heavy steer prices in October, the first selling option and medium and heavy steer prices in April, the second selling option. Sensitivity to October price was tested for three possible prices, low, medium and high. These were calculated as the 10th, 50th and 90th percentiles of the price data (Table 3).

Steer prices in April were fixed. This was implemented as prices in April are unknown when the stocking rate decision in October is made. The 50th percentile of steer prices in April was used to set the April price (196 medium steers, 208 heavy steers c/kg live weight).

Table 3 Stock prices in October sourced from MLA (2017).

	Low	Medium	High
Medium steer 400–500 kg (c/kg live weight)	168	192	220
Heavy steer 500–600 kg (c/kg live weight)	183	196	226

3.4Seasonal 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 were identified based on the lower, middle and upper tercile of October–April rainfall received at Charters Towers over the period 1900 to 2015. Each year was then classified as belonging to one of these climate states: drywas categorised by rainfall less than 435 mm, average as rainfall between 435 mm and 630 mm, and wet as rainfall in excess of 630 mm (Figure 7).

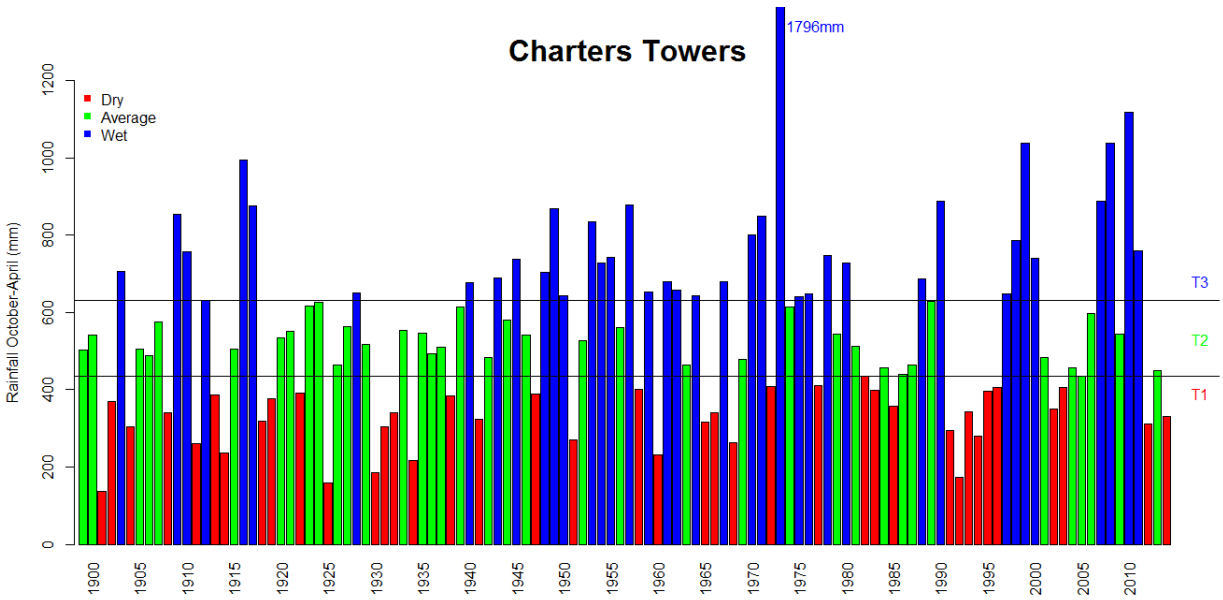

Figure 7 Total rainfall for October through April at Charters Towers for 1900–2015 sourced from SILO (Jeffrey et al., 2001). Dry, Average and Wet represent terciles 1, 2 and 3.

Agricultural production levels representing dry, average and wet climate states were obtained by classifying yearly outputs (1900 to 2015) of pasture, pasture utilisation and beef production data from the *GRASP* production model (see section 3.1). Resulting yearly data for each state (39 years) were then averaged to represent each climate state within the economic model. This categorisation is a critical part of the approach because variations in production across climate states provide the necessary, but not sufficient, conditions for forecasts to offer value in decision-making.

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

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

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

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).

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

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).

$$\text{Dry} = \pi_{dry|f} = \sigma\left(1.00 - \pi_{dry}\right) + \pi_{dry} = 0.20(1.00 - 0.33) + 0.33 = 0.47$$

$$\text{Avg} = \text{Wet} = \frac{\left(1.00 - \pi_{dry|f}\right)}{2} = \frac{(1.00 - 0.47)}{2} = 0.27 \qquad \text{[Equ 3]}$$

Using this definition of forecast skill, 0% skill equates to climatology where each state has a 33% chance of occurring. Table 4 provides an example of weighting between the climate states for the 11 skill levels for a dry forecast state.

Table 4 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 *GRASP* 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 pasture utilisation under the different stocking rate strategies. This was achieved by applying a consistent set of prices and costs (beef prices in October and April) to the biophysical outputs, incorporating baseline information on beef production costs and taking into consideration the costs of pasture over-utilisation.

The profitability of each stocking rate strategy was assessed under each forecast state (dry, average, wet). The economic model maximises returns by choosing the stocking rate that has the highest return weighted across the three climate states according to 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.

$$Max\ E[Y] = \sum_{s=1}^{S} \pi_s y_s \qquad \text{[Equ 4]}$$

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

The model is also subject to normal constraints on the use of land 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 4 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 number of steers in October) and this creates economic value from forecast use.

A more detailed description of the economic model is contained in Appendix 4: 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 $/steer.

The value was assessed for several different decision settings (pasture scenario, October beef prices) and for 11 levels of forecast skill for each of the three climate forecasts (dry, average, wet). This produced 297 results representing various decision environment settings, forecasts and forecast skill levels (Table 5).

Table 5 Variables and value levels assessed to evaluate forecast value

Variable	Values tested
October pasture availability	low, medium, high
Steer 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) stocking rate decision was reported for all variable values (October pasture availability and steer price). Subsequently, the perfect-forecast (100% skill) stocking rate decision for the three forecast states was similarly reported. The potential value ($/steer) of the perfect forecast was calculated as the difference in with-forecast and without-forecast returns. This represents the largest potential value of climate forecasts for each climate state. Finally, probabilistic forecast value ($/steer) relative to the without-forecast decision were calculated for each different decision environment setting.

4 Results

4.1 Biophysical modelling

Data from the *GRASP* biophysical model showed marked differences between animal weight and initial pasture levels particularly when comparing low pasture availability with medium and high (Figure 8). This indicates that it is difficult to reverse a poor start in October. April steer weights progressively decrease as stocking rates increase. Again, this is particularly evident for low initial pasture conditions (Figure 8). The lower observed weights at higher stocking rates are expected as more animals are consuming the same feed thus weights decrease.

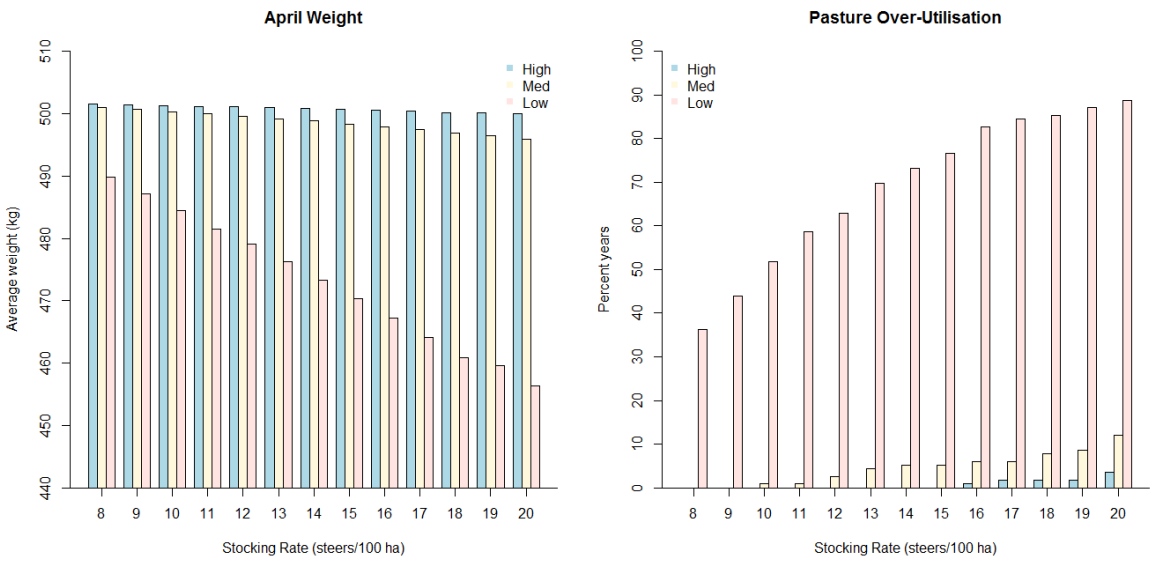

Figure 8 Mean steer weight in April and percentage of years which recorded pasture over-utilisation (1900–2015) for low, medium and high pasture availability for each of the 13 stocking rates.

Some of the weight gain results may have been achieved through pasture over-utilisation. This means short-term weight gain would be achieved at the cost of long-term pasture degradation and thus poor production outcomes in the following years. To assess this, the percentage of years which pastures were over-utilised (average utilisation ≥25%) was reported by stocking rate and pasture availability (Figure 8). As stocking rates increased so too did the instances of over-utilisation of pastures, which was particularly evident for low pasture availability.

The impact of the three climate states (dry, average and wet) on sale weight in April and instances of pasture over-utilisation were investigated (Figure 9 and Figure 10). The differentiation between the climate states differed with starting pasture conditions. Low pasture availability showed the greatest difference in weight by climate state while limited differences in weight were found for average and high initial pasture conditions (Figure 9). In general, a wet climate state led to higher animal weights, followed by average and dry climate states.

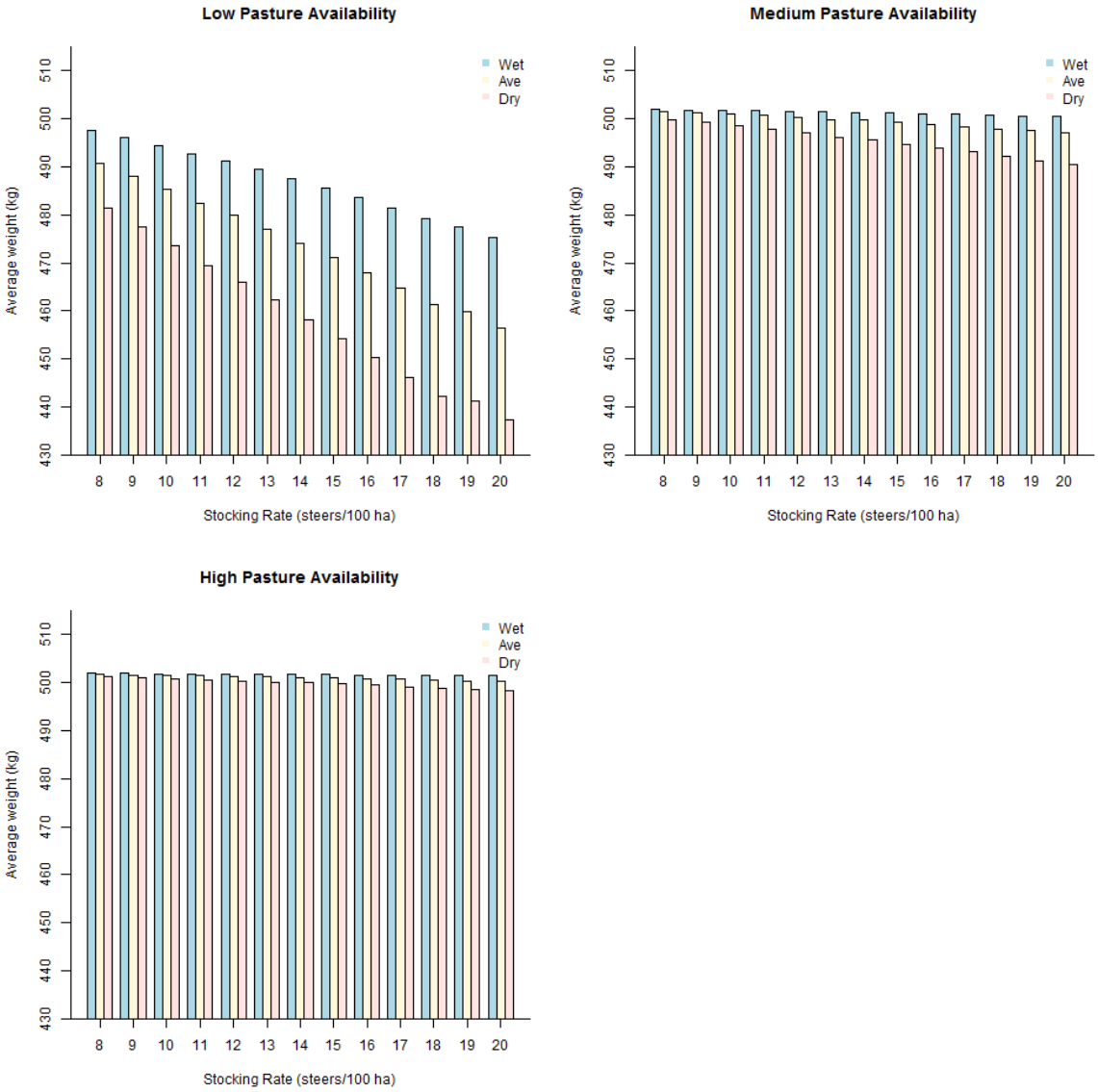

Figure 9 Mean steer weight in April (1900–2015) by climate state (dry, average, wet) for low, medium and high initial pasture levels for each of the 13 stocking rates.

The instances of pasture over-utilisation by climate state are plotted in Figure 10. For low pasture availability the instances of over-utilisation was greatest for the dry climate state followed by average and wet states. For medium pasture availability the dry climate state led to the most instances of pasture over-utilisation. Very few instances of pasture over-utilisation were recorded for high pasture availability. Note, the individual average and wet climate state years which did record pasture over-utilisation for high pasture availability had skewed rainfall distributions towards the early part of the forecast period, leading to the recorded result.

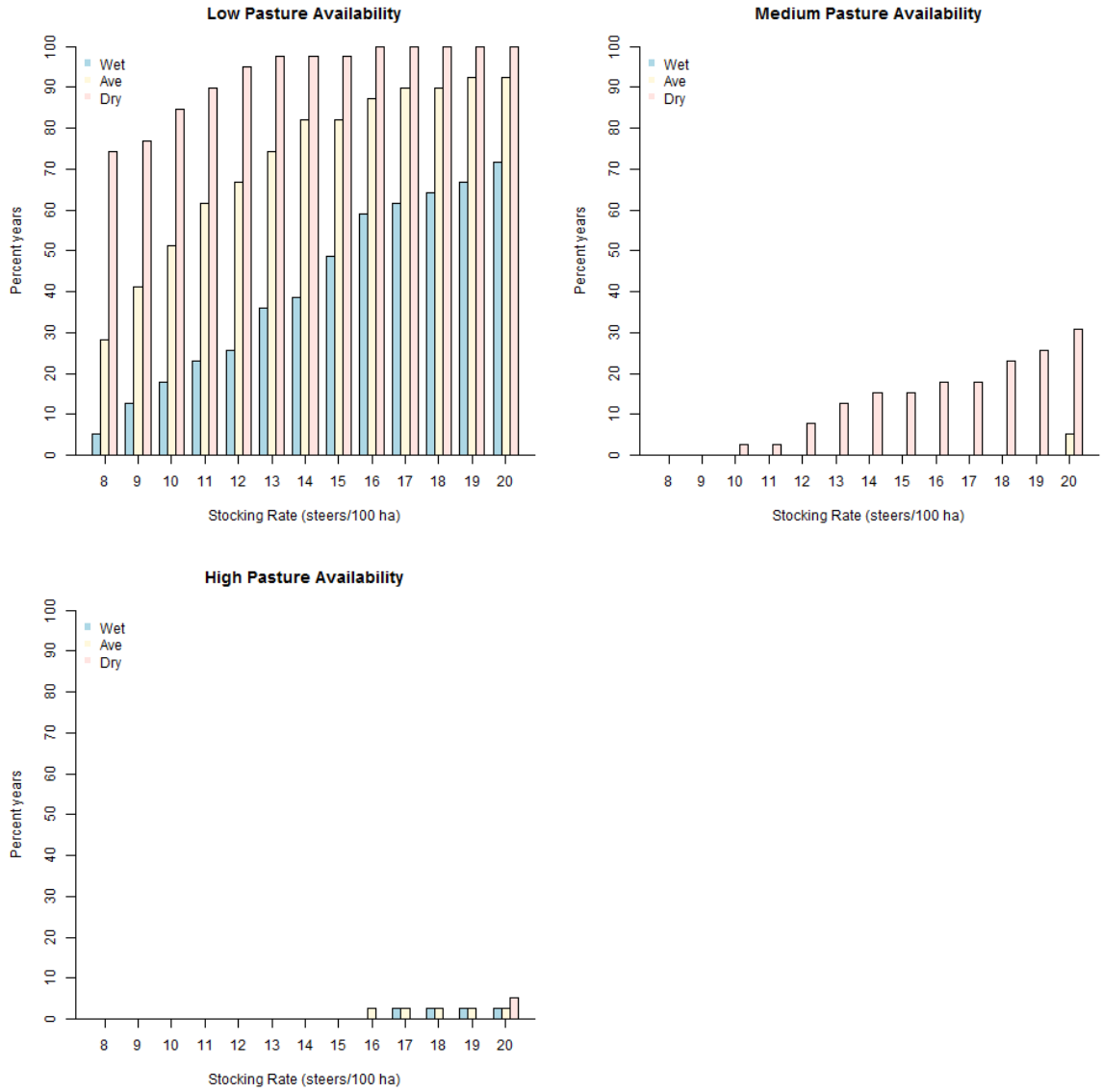

Figure 10 Percentage of years (39 years) which recorded pasture over-utilisation (1900–2015) by climate state (dry, average, wet) for low, medium and high pasture availability for each of the 13 stocking rates.

4.2 Economic modelling

4.2.1 Without-forecast decision

The optimal stocking rate decision without a forecast (0% skill) must be first evaluated prior to calculating the potential value of SCFs. Figure 11 shows the optimal without-forecast stocking rate decision for each combination of the decision drivers (Table 5). The without-forecast decision illustrates the influence of the decision drivers. High and medium pasture availability (bottom row; Figure 11) lead to the decision to stock steers at the highest stocking rate (20 steers/100 ha) regardless of steer prices. When pasture availability was low, lower stocking rates were selected when steer prices were medium or high in October.

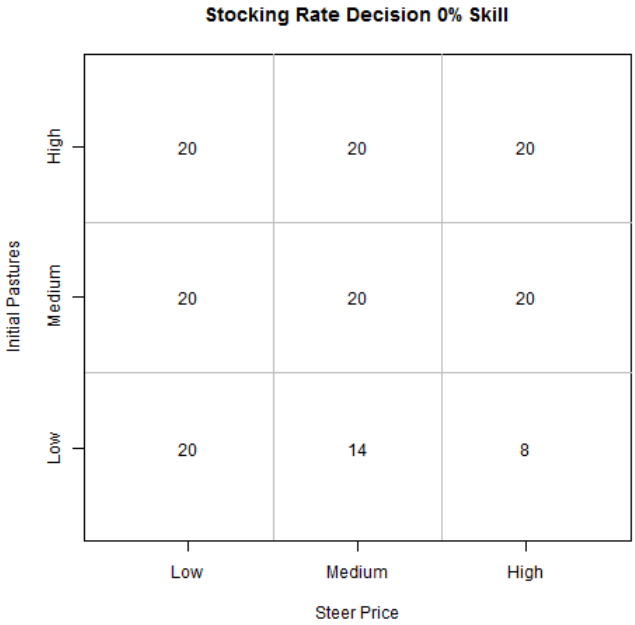

Figure 11 Optimal without forecast stocking rate decision (steers per 100 ha). Three levels of pasture availability (low, medium, high) are represented in the three rows and steer price in October (low, medium, high) are represented in the columns. These figures were based on a farm size of 30 000 ha with 6000 animals.

4.2.2 Perfect-forecast decision

The optimal stocking rate decision for perfect forecasts of dry, average and wet climate states (100% skill) were evaluated for each setting of pasture availability, October steer price and climate forecast state (Figure 12).

For high pasture availability, the optimal stocking rate decision remained the same as the without-forecast decision for all three climate states (20 steers/100 ha). For medium initial pasture availability, the stocking rate decision similarly remained the same as the without-forecast decision except under a dry climate forecast state with high steer prices, where notable destocking was selected (9 steers/100 ha).

The greatest change from the without-forecast decision was for low pasture availability. Lower stocking rates were selected for the dry state (Figure 12), with the exception for when steer prices were high as the lowest stocking rate was already selected for the without-forecast decision (Figure 11). Higher stocking rates were selected under a wet climate state for medium and high steer prices. For an average climate state there was little change from the without-forecast decision.

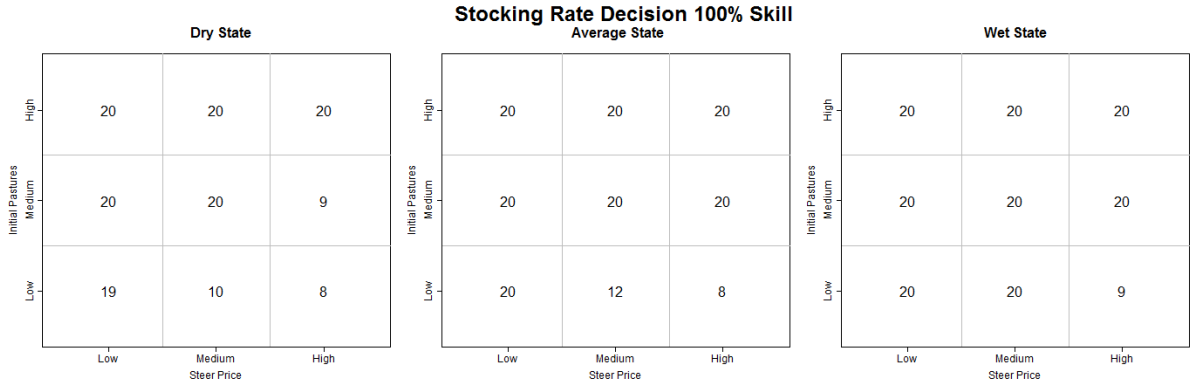

Figure 12 Optimal with forecast stocking rate decision (steers per 100 ha). Dry, average and wet climate states are represented in each box, the three levels of pasture availability in October (low, medium, high) are represented in the rows and steer price in October (low, medium, high) are represented in the columns. These figures were based on a farm size of 30 000 ha with 6000 animals.

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 (Figure 13). If pasture availability was high in October, no value of a forecast was found, regardless of steer price (top rows; Figure 13).

For medium pasture availability, value was only found for a dry forecast when steer prices were high ($11.80/steer). The greatest value was found with low initial pasture availability. The highest value was found for a wet forecast with medium steer prices ($13.90/steer). A dry forecast provided the next highest value, also with medium steer prices ($4.40/steer).

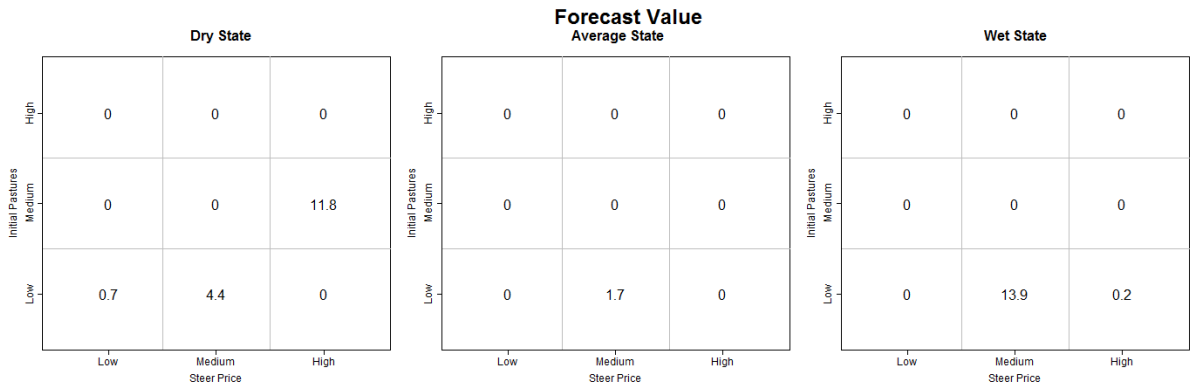

Figure 13 Perfect-forecast value ($/steer). Dry, average and wet states in the three boxes, three levels of current pasture availability (low, medium, high) in the three rows and steer price (low, medium, high) in the columns. These figures were based on a farm size of 30 000 ha with 6000 animals.

4.2.4 Imperfect-forecast value

The forecast value differed with forecast skill and for each climate forecast (dry, average, wet), pasture availability level and steer price (Figure 14). These plots provide greater detail of the results in Figure 13, illustrating the value of forecasts with various skill levels. For the few instances where value was found, it was mostly for dry or wet forecasts and increased as forecast skill increased (Figure 14).

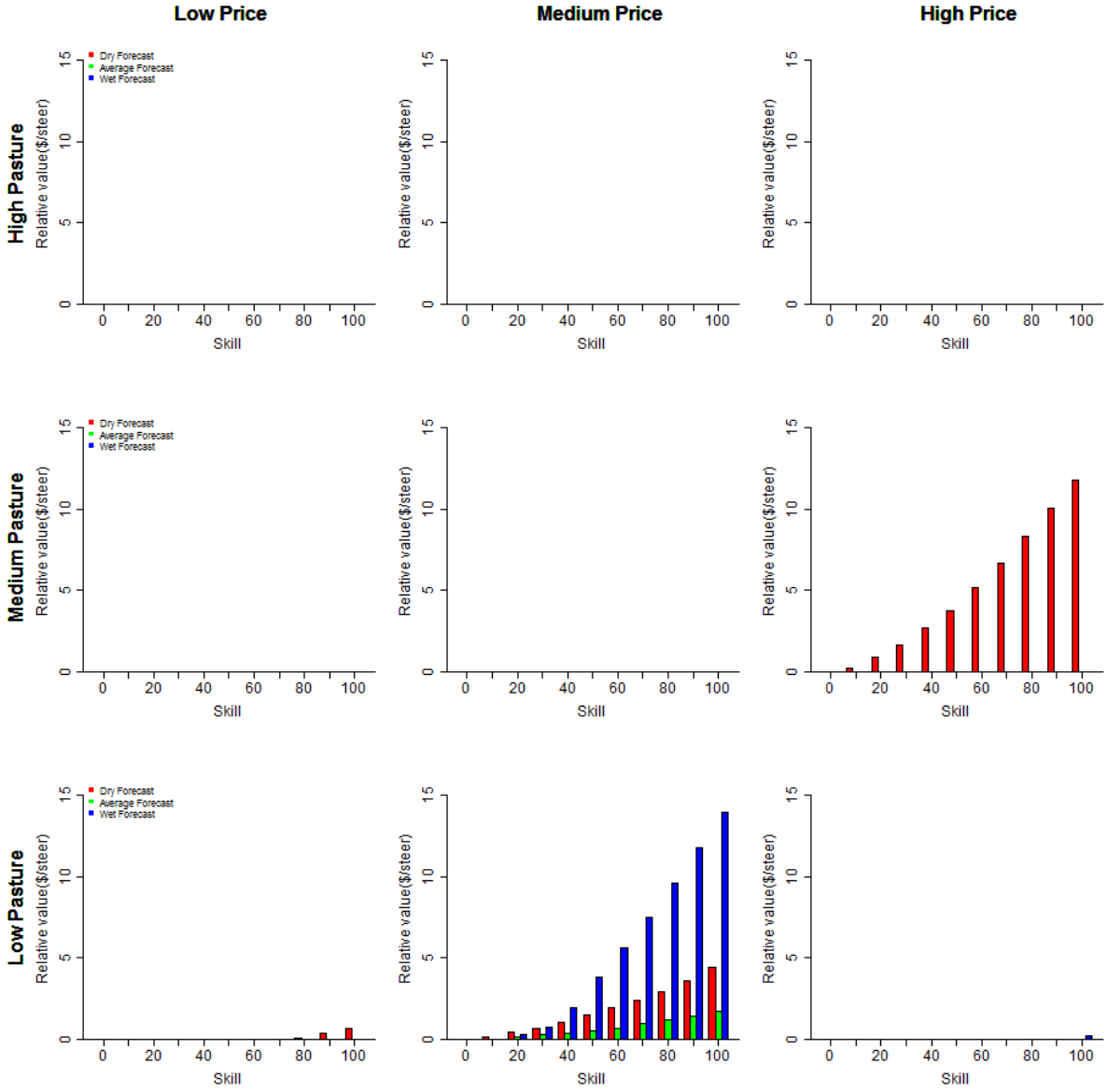

Figure 14 Imperfect forecast value ($/steer). Three levels of current pasture availability (low, medium, high) are in the three rows and three steer prices (low, medium, high) in the columns. Skill (%) is represented on the x-axis as calculated in Table 4. These figures were based on a farm size of 30 000 ha with 6000 animals.

5 Discussion

The key production decision sensitive to SCF identified by industry was what stocking rate to set for the wet season. This decision is a trade-off between selling smaller animals in October with a lower risk of pasture over-utilisation and selling animals later at higher weights but potentially risk incurring costs associated with pasture over-utilisation.

5.1 Optimal decisions made without seasonal climate forecasts

Pasture availability in October strongly influenced the optimal decision made without a forecast. With high and medium pasture availability, the decision was to stock at the highest allowable stocking rate, regardless of price settings (Figure 11). These results reflect that with medium or high pasture availability it is likely that sufficient feed will be available through the wet to avoid over-utilisation as indicated in Figure 8. As pasture over-utilisation is the major cost associated

with higher stocking rates, the model selected the maximum stocking rate as there was limited cost incurred to grow animals out to higher weights.

For low pasture availability in October, differences in stocking rates were seen with progressively more stock destocked for medium and high steer prices. This highlights a trade-off between a cost penalty associated with over-utilisation and the price obtained for lighter animals in October. Greater destocking at higher steer prices is logical as higher income can be generated in October and costs associated with pasture over-utilisation minimised. Overall, these results indicate that pasture conditions and pasture management through the dry season (up to October) will have a notable impact on stocking rate decisions made for the wet season.

5.2 Optimal decisions made with seasonal climate forecasts

Inclusion of perfect (100% skilful) forecasts of dry, average and wet conditions only changed the optimal stocking rate decision from the without-forecast decision for a few combinations of pasture availability and steer prices. The stocking rate decision did not alter for high pasture availability. For medium pasture availability, destocking compared to the without-forecast scenario was selected for a dry forecast with high steer prices (20 steers/100 ha reduced to 9 steers/100 ha) and yielded a maximum value of $11.80/steer but otherwise decisions were unchanged at this pasture level.

For low pasture availability and perfect (100% skilful) forecasts, different stocking rate decisions were made depending on climate forecast state. For a dry state, greater destocking was selected with a range in value between $0–4.40/steer, depending on steer price. Under a wet climate forecast state, higher stocking rates were selected with an associated value $0–13.90/steer, depending on steer price.

Some combinations for which value was not identified were constrained by the experimental design. Allowable stocking rates were restricted to between 8 and 20 steers/100 ha which represents typical limits applied in the system. This resulted in a hard boundary for further changes to lower or higher stocking rates based on climate state. For example, the without-forecast stocking rate decision for low pasture availability at high steer prices was 8 steers/100 ha, the lowest possible stocking rate option. Thus, under a dry forecast scenario further destocking could not be selected to respond to deteriorating conditions. A similar circumstance is reflected for increasing stocking rates. This upper boundary is less fluid as producers do not typically buy stock and this decision is centred on the degree of destocking. It should be appreciated that although a single-class steer-only model was used, it was used to represent a full herd. As such, drastic reductions in stock numbers (e.g. to 0) were not considered as producers will need to retain base herd numbers for future breeding.

A climate forecast of average conditions was found to be of limited economic value under all model settings. The single instance of value was $1.70/steer for a perfect average forecast (100% skilful). The low value of an average forecast state reflects the limited change in conditions compared to the without-forecast decision (i.e. based on climatology). As climatology is the average climate conditions, no change or a small change to the stocking rate decision with an average forecast state (middle tercile of climate data) is unsurprising.

Greater value of dry and wet forecast states was found (Figure 14). Two examples will be used to explore the different circumstances for which dry and wet forecasts have value. With medium pasture availability and high steer prices, the without-forecast decision was to stock at the maximum of 20 steers/100 ha. With a perfect **dry** forecast, the optimal decision changed to destocking to 9 steers/100 ha, driven by increased revenue from selling steers at high prices in October and a reduction of the costs of pasture over-utilisation, which was exacerbated due to dry conditions (Figure 10). A perfect forecast of a dry state resulted in an improvement in returns of $11.80/steer under this scenario.

A scenario of low pasture availability and medium steer prices provides an example of the benefit of a **wet** forecast. The without forecast decision in this scenario was to destock to 14 steers/100 ha, largely due to poor pasture conditions. With a perfect wet forecast, the optimal decision changed to keeping stock at the maximum 20 steers/100 ha. In this example, a wet forecast provided greater surety about the occurrence of additional pasture growth that occurs in a wet state, reducing likelihood of pasture over-utilisation (Figure 10). This reduced costs and, in association with medium steer prices, made holding stock more profitable. A perfect forecast of a wet state resulted in an improvement in returns of $13.90/steers under this scenario.

The above examples highlight the maximum possible value of SCF under different scenarios through assuming the forecast was perfect or 100% skilful. However, in reality SCFs are imperfect and different levels of skill were analysed to assess the value of improvements. Positive value of SCFs was obtained for four of the nine combinations of pasture availability and steer prices (Figure 14). Of these four, two scenarios recorded limited value (<$1/steer) and this was not realised until skill exceeded at least 80%. For the two scenarios with greater value, positive value was found for skill above 10–20%.

5.3 Comparison to previous findings

The forecast value found here is similar to previous studies that considered the value of SCFs to northern beef production systems. O'Reagain et al. (2011) evaluated several strategies to set stocking rates over a 12-year field experiment. They found the best strategy was to set stocking rates based on available forage, mirroring the importance of pasture availability found here. They further found that following a fixed, conservative strategy performed better than a variable approach using the SOI phase forecast system to set stocking rates. Again, the findings here support their findings with near $0 forecast value found for many decision variable settings (Figure 13). Similar to this study, Stafford Smith et al. (2000) used the *GRASP* model to evaluate if the incorporation of SCFs improve whole farm economics using a different economic model framework (Herd-Econ). They found only modest improvements in cash flow through incorporating a forecast over their baseline management strategies. In addition, they found that decisions were sensitive to market settings. The results found here support their conclusions.

McIntosh et al. (2005) found more forecast value in their assessment of a northern beef enterprise also utilising the *GRASP* model. They found that all the forecast systems assessed (SOI phase, SST, perfect rainfall and perfect growth index) improved annual cash flow. A 14–33% improvement in cash flow above the without-forecast scenario was found. For the maximum forecast value found here (low pasture and medium price; Figure 13) a similar improvement in returns was found (23%).

5.4 Limitations and assumptions

The case study design used particular parameter settings both within the *GRASP* production model and the economic model. *GRASP* has been used widely to investigate climate variability and climate change assessments for northern beef enterprises (Ash et al., 2000; McIntosh et al., 2005; McKeon et al., 2000; Stafford Smith et al., 2000) and limitations outlined (McKeon et al., 2009). For the *GRASP* 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, weaning timing and mustering timing may differ. Thus, this case study is simply an example of the potential value of SCFs, not a comprehensive assessment for all possible enterprise arrangements.

Profitability in northern beef production systems is generated by multi-year management leading to returns in beef production. The assessment of profits through a single wet season may not adequately capture the flow-on influences of decisions through the system. This includes pasture management and herd structure dynamics. The aim of this study was to investigate the potential of seasonal forecasts. This necessitated a restricted view of profitability based on a

single season to evaluate the benefit of including SCFs into decisions at the seasonal scale. *GRASP* is a simplified model with the live weight gain parameterised for animal live weight production. Here, only October to April values were considered with carry-over influence into later phases on the production not considered in order to evaluate a seasonal decision. These carry-over influences were thus not incorporated into the results.

GRASP uses a steer-only herd in the modelling process. In reality the herd will contain males and females in various age classes. For this application investigations were focused on the balance of pasture availability and animal weight gain, not on herd dynamics or breeding strategies (e.g. calving time) which operate on time horizons longer than a season. As such, *GRASP* is sufficient to capture the key linkages between pasture production, beef production and climate variability which were the focus of this study. Nonetheless, a more complex biophysical model would allow for more nuanced stocking rate decisions. The NABSA production model (Ash et al., 2015) was investigated for this purpose, however constraints and assumptions in the model, which was developed for multi-year assessments of management decisions and long-term climate, was not amenable for this application.

The pasture over-utilisation penalty was an important cost estimated in the economic model. There were two methodological steps which led to the penalty applied. These were the determination of whether pastures were over-utilised and the penalty ($) associated with over-utilisation. Both the values were derived using findings from O'Reagain et al. (2011) as described in section 3.2.1. Different derivation of determining when pastures were classified as over-utilised would influence the percentage of years classified as over-utilised and would change sensitivity to SCFs. For example, a 20% (30%) threshold rather than 25% would increase (decrease) instances of pasture over-utilisation increasing (decreasing) the cost associated with higher stocking rates, with SCFs likely to have greater (less) value for more (fewer) circumstances.

Similarly, modification to the penalty value would influence the value of SCFs. A higher penalty would increase the costs associated with pasture over-utilisation making lower stocking rates more profitable. In turn, a lower penalty value would further increase high stocking rates. Although the results were dependent on the determination of these values, O'Reagain et al. (2011) provided the best evidence to set these values due to the experimental design and proximity to the case study site (within 70 km). However, O'Reagain et al. (2011) did not specifically design their experiment to assess a cost penalty associated with pasture over-utilisation for a single season. Further research is required to provide viable alternate options to set these parameter values in the economic model.

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, steer prices in October) and future information that is unknown at the decision time (climate state, price of steers in April). 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 in April 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 about the likely price of steers in April (e.g. greater market access leading to higher demand for beef). Additional information regarding the likely price of cattle in April would likely change the without- and with-forecast stocking rate decision and may influence the value of SCFs.

April steer prices were not set to be contingent on the climate forecast state. That is, it was not assumed that April prices modify in-step with different climate conditions. For instance, in a dry season steer prices in April could be lower because of greater selling of animals due to lower animal condition and destocking into the dry season. This non-state contingent design was necessary as insufficient historical data was available to evaluate state-based relationships. If

April steer prices are related to climate conditions, it is likely that the value of SCFs is under-estimated in this assessment, in particular for dry forecasts.

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. However, the methodology outlined here provides a robust framework for further analyses of operational forecast systems.

Like operational forecasts, the theoretical forecasts used in this analysis provided an indication of the likely climate state (dry, average or wet), not the precise evolution of weather conditions. The value of a higher resolution forecast, such as a decile forecast, may be greater. This sets a challenge to the forecasting community. For instance, the Bureau of Meteorology currently operates on a two-state climate forecast (above or below median). The current percent consistent score for the Charters Towers region for October to December rainfall is approximately 70%, equivalent to 40% using the definition of skill in this study.

6 References

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Appendix 1: Industry engagement

Engagement for the development of a case study for northern beef was conducted in consultation with industry experts in CQ (Rockhampton), Dalrymple and Gulf (Charters Towers), CW Qld and Channel country (Longreach), Kimberley and Victoria River Downs (Kununurra), Pilbara (Broome) on the advice from MLA representatives (Tom Davidson and Irene Sobotta; 13 April 2016).

Workshops or interviews were held in Rockhampton (22/6/2016), Charters Towers (22/7/2016), Longreach (2–4/8/2016), Kununurra (23–24/8/2016) and Broome (25/8/2016) to explore the northern beef system and identify climate-sensitive decision points at a seasonal scale (months). Those present included advisers, consultants, producers, corporate managers and managers from pastoral houses.

1 Identifying climate-sensitive decision points

Discussions were focused to identify the annual management cycles, starting conditions (e.g. herd structure, husbandry, etc.) and timing of key decisions for the northern beef herd in general, and for variation that occurs across regions due to climate and land type. Once these workshops were completed, the project team selected a theoretical breeding property at Charters Towers as representative for northern Australia with a property size of 30 000 ha and herd size of 2700 AE.

The key climate-sensitive decision was adjusting stock numbers (sell, move, buy) from March to October, which depends on current livestock numbers, available feed supply, market prices and seasonal outlook. This usually occurs in two rounds of mustering, the first after the wet season from April to July, and the second prior to the wet season from August to November.

2 Decision point

Round 1 – April–June – How many livestock do we carry until round 2 (July–October)?

The timing of this decision is April to June for a seasonal climate forecast of July to September and August to October.

Round 2 – July–October – How many livestock do we carry until the end of the wet season (round 1 next year)?

The timing of this decision is July to October for a seasonal climate forecast of the wet season ahead (November to March).

Three variables are important to this decision and storylines around each variable follow:

Relative price (high or low): good prices encourage additional selling of livestock, low prices discourage selling.

Feed availability (high or low): Low pasture (in paddock) encourages selling, high feed availability discourages selling.

Rainfall forecast (wet, dry, average): Wet (i.e. good pasture growth) discourages selling, dry (i.e. poor pasture growth) encourages selling.

Figure 15 illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including seasonal climate forecast information against decisions made without this information.

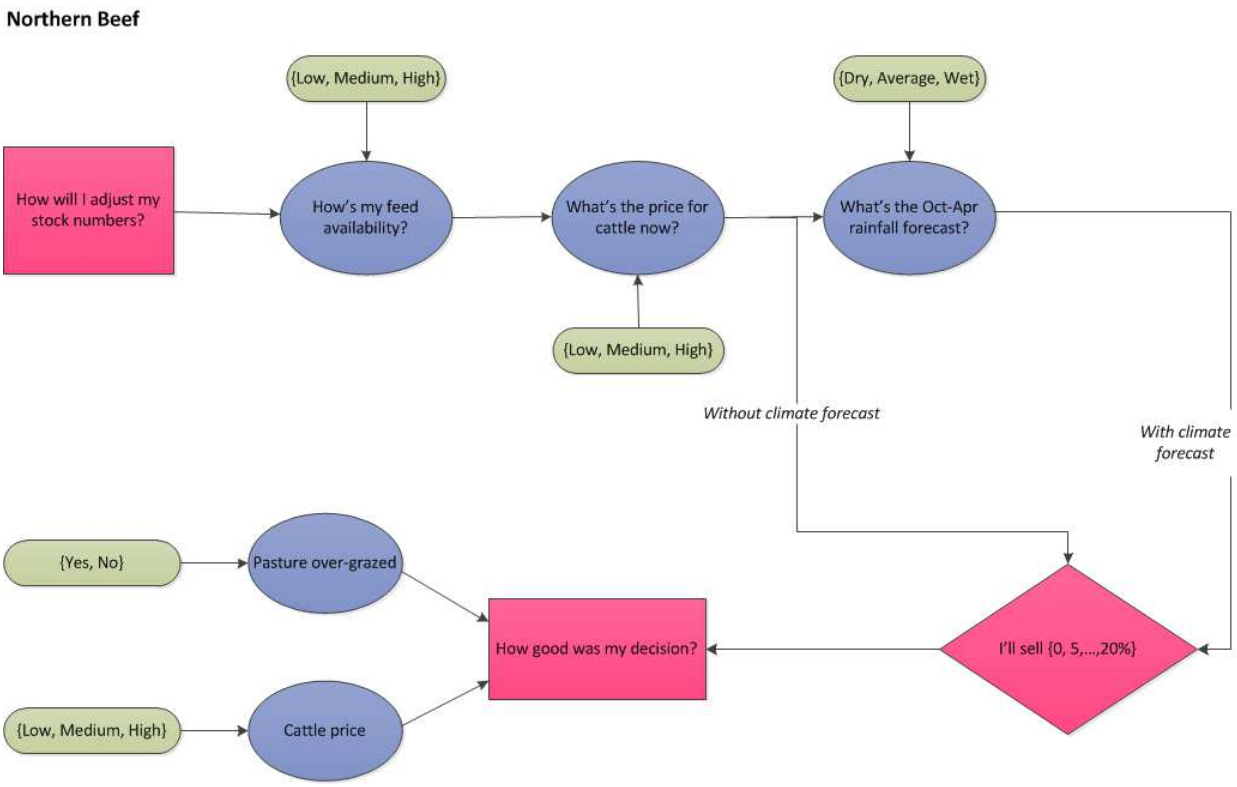


Figure 15 Decision pathway for proportion of livestock sold in northern beef systems including an evaluation of the decision made.

3 Selling decision

The northern beef herd is usually mustered in two rounds (i.e. round 1 March–June, round 2 July–October). Depending on the quantity of available pasture, current herd numbers or stocking rate, market prices and the prospects of future rainfall, livestock are kept on the property or sold in the domestic or overseas markets. During the November to March period there is limited livestock management activity because cows are calving (mustering causes mis-mothering), wet season causes difficulties with access, heat causes stress for livestock and humans, and stockmen are released for annual leave. As such, most stations operate on skeleton staff from December to March. Therefore the key livestock decision during the round 2 muster relates to how many livestock are carried through the wet season until the round 1 muster next year.

Appendix 2: Production summary

Figure 16 shows in more detail the major management decisions made for northern Australian beef enterprises. This calendar was compiled based on advice from producers in Charters Towers, Kununurra and Broome regions along with industry researchers (Mick Sullivan, DAF Rockhampton and; Peter O'Reagain, John Bushell, Karl McKellar, David Smith Charters Towers DAF).

Figure 16 Herd management calendar for a control mated, pregnancy tested or foetal aged herd selling store steers and cull heifers as yearlings (15–20 months) in central Queensland. In the north-east (Charters Towers) and north-west (Kimberley) these management activities may be 1–2 months later and management such as control mating, pregnancy testing, foetal aging and herd segregation are less common.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cow status	Wet	Wet	Wet	Wet	Dry pregnant	Dry pregnant	Dry pregnant	Dry pregnant	Calving & wet	Calving & wet	Calving & wet	Calving & wet
Management activity	Brand	Bulls out of heifers 24 Feb (12 weeks mating)	Bulls out of cows 24 Mar (16 weeks mating) Mop up branding		Weaning Pregnancy testing	Select heifers for joining at next mating				Check and vaccinate bulls		Bulls in 1 Dec
Movements			Draft off cows that failed to calve		Draft cull cows for sale & fattening							
Marketing		Empty cows retained previous year for finishing										
		Cows that failed to calve i.e. dry at branding or weaning										
					Fat cows culled at PD							
		Yearling steers i.e. previous year's weaners										
		Yearling cull heifers										

Appendix 3: Gross margin values

Table 6 Productions costs used in the economic analyses based on information in Martin (2016)

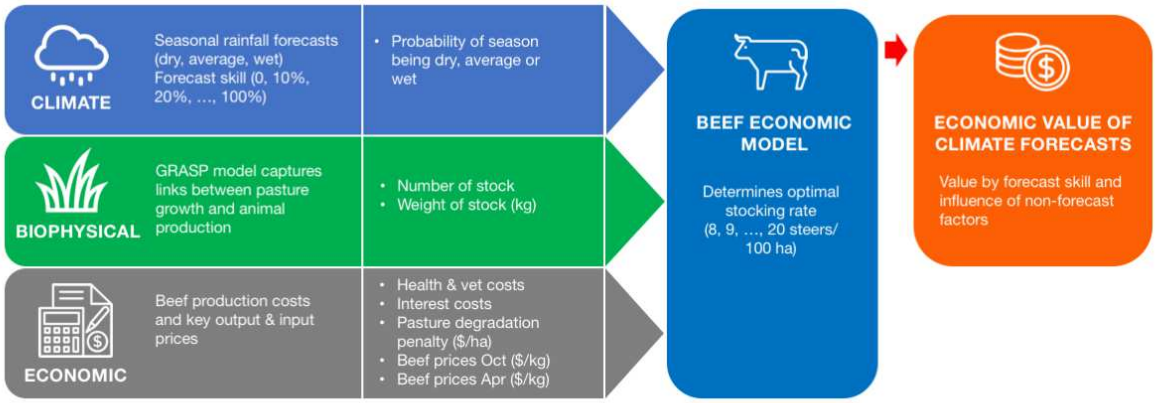
Variable costs	Cost (A$)	/unit
Enterprise expenses*		
Livestock materials and veterinary chemicals	3.36	/AE
Cattle purchases	12.60	/AE
Freight	6.72	/AE
Pasture chemicals	0.84	/AE
Total enterprise costs	**23.52**	**/AE**
Degradation costs of over-utilisation (>25%)	285,364	/30,000ha^
Livestock selling cost		
Commission	5%	/head
MLA levy	5.00	/head
Freight costs to saleyard	10.00	/head

^sourced from O'Reagain et al. (2011)
AE is animal equivalent

Appendix 4: Economic model

1 Overview of the modelling approach

NORTHERN BEEF



2 Economic model description

The economic model used key outputs from the *GRASP* 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 pasture utilisation under different stocking rate strategies. This was achieved by applying a consistent set of output (beef prices in October and April) 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 (13 stocking rate strategies – 8, 9, 10……..20 head per 100 ha in October), s is the state of nature (tercile rainfall - dry, avg and wet) and $x_2\ (s, x_1)$ represents Stage 2 decisions (number and weight of stock sold, pasture over-utilisation cost incurred). 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 return across climatic states. In algebraic terms, the main elements of the model are:

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

$$y_s = \sum_{j=1}^{J} c_{1j}\, x_{1j} + \sum_{n=1}^{N} c_{2ns}\, x_{2ns} \qquad \text{[Equ 2]}$$

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 young steers under stocking rate *j* in stage 1 ($/hd) – October

c_{2js} the net return from activity *n* chosen in state *s* in Stage 2 (older steer price, pasture over-utilisation cost) – April

Model variables

x_{1j} the number of young steers *j* sold in Stage 1 – October

x_{2ns} the level of activity *n* chosen in state *s* in Stage 2 (yearling – sales, likelihood of pasture over-utilisation – probability) – April

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 number of steers available for sale. The DSP model was solved using the What's Best!® 14.0 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 young steers in October ($/kg) multiplied by their live weight and x_{1j} is the number of young steers 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 older steers and the likelihood of pasture over-utilisation.

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 and outputs (e.g. beef prices) were assumed to be independent of climatic conditions. There was insufficient historical data available to determine the extent of correlation between seasonal conditions and April steer prices within the study area.

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 producers to consider state-contingent responses, something readily observed in practice. Third, with operational forecasts being probabilistic in nature, rational producers 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 which 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 relative to the without-forecast scenario. Model restrictions ensure that the overall probability of the occurrence of each climatic state is the same as its historical probability of occurrence (i.e. the prior probability π_s). This restriction ensures that the model is valuing improved knowledge about the occurrence of each state.

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

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

where:

y^*_{sf} denotes the net return in state *s* resulting from implementing the optimal stocking rate 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 (October) and the state-contingent tactical adjustments made in Stage 2 (April).

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 and steer prices).