

Valuing Seasonal Climate Forecasts in the Northern Australia Beef Industry

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ABSTRACT

Seasonal climate forecasts (SCFs) provide opportunities for pastoralists to align production decisions to climatic conditions, as SCFs offer economic value by increasing certainty about future climatic states at decision-making time. Insufficient evidence about the economic value of SCFs was identified as a major factor limiting adoption of SCFs in Australia and abroad. This study examines the value of SCFs to beef production system management in northern Australia by adopting a theoretical probabilistic climate forecast system. Stocking rate decisions in October, before the onset of the wet season, were identified by industry as a key climate sensitive decision. The analysis considered SCF value across economic drivers (steer price in October) and environmental drivers (October pasture availability). A range in forecast value was found (\$0–\$14 per head) dependent on pasture availability, beef price, and SCF skill. Skillful forecasts of future climate conditions offered little value with medium or high pasture availability, as in these circumstances pastures were rarely overutilized. In contrast, low pasture availability provided conditions for alternative optimal stocking rates and for SCFs to be valuable. Optimal stocking rates under low pasture availability varied the most with climate state (i.e., wet or dry), indicating that producers have more to gain from a skillful SCF at these times. Although the level of pasture availability in October was the major determinant of stocking rate decisions, beef price settings were also found to be important. This analysis provides insights into the potential value of SCFs to extensive beef enterprises and can be used by pastoralists to evaluate the cost benefit of using a SCF in annual management.


1. Introduction

The northern Australian beef industry contributes substantially to total Australian production (\$12 billion; [ABS 2018](#)) with Queensland accounting for 48% of beef and veal production in 2017–18 ([MLA 2018](#)). These extensive beef enterprises utilize the rangelands across Queensland, Northern Territory, and Western Australia featuring large paddock sizes, up to 16 000 ha ([Oxley](#)

[2006](#)), and low stocking rates. These enterprises are based on native pasture systems where producers aim to match the feed requirements of the herd to the availability of pasture to optimize beef production ([O'Reagain et al. 2014](#)). Management of these enterprises in many pastoral regions is occurring against a background of increasing variability in annual precipitation and pasture growth ([Cobon et al. 2019](#)).

The production system is seasonal with producers relying predominately on summer rainfall (November–April) to drive productivity through the dry season (May–November). Matching stocking rates through variable wet and dry seasons is an ongoing challenge with supplementary feeding of protein and carbohydrate being impractical due to the vast size of properties and cattle herds.

Stocking rate decisions have a major impact on land resource condition, pasture yield and composition, soil

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loss, pasture burning opportunities, and growth of woody weeds (Johnston et al. 2000), and hence enterprise profitability (McKeon et al. 2000; Ash et al. 2000; Stafford Smith et al. 2000). Seasonal climate forecasts (SCFs) may help to inform adjustments of stocking rates to match expected seasonal outcomes through minimizing losses in poor years and maximizing profits in good years (Cobon et al. 2017; Crean et al. 2015; Hayman et al. 2007; McIntosh et al. 2005).

In reviewing the value of SCFs in Australian agriculture Parton et al. (2019) found a wide range of values but the majority were positive. Since the early 1980s, when the role of SCFs in agriculture was first recognized, Parton et al. (2019) reviewed a total of 86 studies (8 from the beef industry that realized a mean farm-level value of $\$5.10 \text{ ha}^{-1} \text{ yr}^{-1}$) and found that 1) value was associated with the type of forecast (operational, hypothetical, experimental), method of estimating value, farm versus field scale, level of forecast skill, and approaches taken in defining “with” and “without” forecast scenarios; 2) most of the studies have been on wheat production (53%) and the level of nitrogen fertilizer to apply, and that other industries are worthy of further study incorporating a wider variety of farm decisions; 3) it is important to develop ways to include risk in analysis of the value of SCF; and 4) descriptive studies with producers should provide more confidence about the actual, rather than potential, value of SCFs and highlight some of the issues that are limiting their application in Australian agriculture.

Previous research into the potential use of SCFs in northern beef systems has largely focused on stocking rate decisions (Ash et al. 2000; McKeon et al. 2000; O'Reagain et al. 2011; Stafford Smith et al. 2000). Other 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 that are required for decision-making, such as forecast type and timing (Ash et al. 2000; Keogh et al. 2006).

Quantifying the economic value of the use of SCFs in stocking rate decisions provides useful information to drive management change. Studies investigating value utilize many different methodological strategies. These include various forecast types (e.g., theoretical, operational), forecast characteristics (e.g., lead time, length), and forecast variables (e.g., rainfall, growth days). All these factors introduce considerable variability between reported forecast values.

For example, McIntosh et al. (2005) investigated cash flow implications of using forecast information for a northern beef production system in Dalrymple shire in

Queensland and found that forecast use increased annual cash flow from the “without forecast” strategy by $\$12,785$ – $\$29,608$. Using a different approach, O'Reagain et al. (2011) examined five strategies to adjust stocking rates over a 12-yr field trial. One strategy used the Southern Oscillation index (SOI) phase forecast to vary stocking rates in November. The greatest annual accumulated gross margin (AGM) found was $\$28,490$ per 100 ha, which was for a strategy that did not use SOI forecast information but adjusted stocking rates in May based on current available pasture. The strategy that used the SOI forecast recorded a lower AGM [$\$26,595 (100 \text{ ha})^{-1} \text{ yr}^{-1}$] than the strategies that did not use a forecast to inform decisions. Using another approach, Stafford Smith et al. (2000) used simulation modeling to consider the impact of using various forecasts on annual cash flow of a cattle station in northeast Queensland. Their primary finding was that production benefits of a forecast did not readily translate to economic benefit at the whole of enterprise scale.

In this study forecast value was explored over a range of both environmental and market conditions. This provides a wider picture of potential value depending on prevailing conditions. The method uses a theoretical forecast framework. 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 value of using SCF in annual decision making based on known forecast skill. The analyses were conducted using state-contingent theory applied through discrete stochastic programming (Crean et al. 2013; Crean et al. 2015). The approach explicitly represents activities and returns in each climate state, captures the trade-offs between climate states, and reflects the probabilistic outputs of operational forecast systems which convey information about the likelihood of each climate state. The optimal with and without forecast decisions were estimated using the same optimization process removing potential bias in the results.

To conduct this analysis a case study was designed for an extensive beef production enterprise in northern Australia.

2. Methods

a. Production system and key decision point

Consultation with industry was undertaken following the approach of Cashen and Darbyshire (2017) to capture important features of the northern beef production system and identify key decision points. A small group of industry experts and practitioners were invited to

participate based on industry reputation and experience. The group defined the production system that best reflected local conditions in the area and described key decision points. Subsequently, each of the decision points within the system were explored in terms of sensitivity to various decision drivers including seasonal climate forecasts. A single key decision point was then selected for analyses.

The system described by the practitioners focused on a self-replacing *Bos indicus* herd based in Charters Towers, Queensland (20°05'S, 146°16'E) with herd and site characteristics shown in Table 1. Stocking rates were set between 8 and 20 steers per 100 ha, which represents typical limits applied in this production system but does not fully represent the limits possible in extreme wet and dry years.

The hypothetical production system described included calving (birthing of calves) from October to January with two rounds of mustering (rounding up the cattle into one central location): round 1 in April–July and round 2 in August–October (Fig. 1). Destocking decisions are made during these mustering periods.

The key decision identified was “What stocking rate should be set prior to the wet season?” where “stocking rate” is the number of cattle per land unit. This decision occurred in October at the end of round 2 mustering. Cattle could be sold at this time. A secondary selling time for cattle was seven months later in April.

For the stocking rate decision in October, three key decision drivers were identified by the practitioners:

- 1) Current cattle prices: High prices encourage destocking; low prices discourage destocking.
- 2) Pasture availability: Low availability encourages destocking; high feed availability discourages destocking.
- 3) SCF of rainfall for October–April: Dry (i.e., poor pasture growth) encourages destocking; wet (i.e., good pasture growth) discourages destocking.

The potential value of SCFs was evaluated through selecting the optimal stocking rate that maximized returns. This was repeated under each setting of the decision drivers (steer prices and pasture availability). An overview of the methodology is outlined in Fig. 2. Three key components are provided to the economic model to evaluate the potential value of SCFs: forecast probabilities, biophysical production, and economic settings (costs and prices).

b. Biophysical model

The link between stocking rates, climatic conditions, pasture, and beef production was captured through using the Grass Production (GRASP) model (Littleboy and McKeon 1997; Day et al. 1997). GRASP is a dynamic,

TABLE 1. Key characteristics of the beef cattle production system. Values sourced from industry and supported by other industry relevant case studies, e.g., Holmes (2011), McGowan 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 (animal equivalent)	6000
Main target market	Store steers and cull heifers
Weaning rate (%)	60
Weaning weight (kg)	180
Growth rate (kg head ⁻¹ yr ⁻¹)	127

pasture-animal growth model that has been applied to evaluate the effects of various grazing management practices in Australia (McKeon et al. 2009) and has been validated for conditions at Charters Towers (Ash et al. 2015). GRASP was run from 1900 to 2015 to simulate the different stocking rates and pasture levels. Climate data (1900–2015) were sourced from the Scientific Information for Land Owners (SILO) patched point dataset (Jeffrey et al. 2001) for station 34084 (Charters Towers). Three discrete climate states were identified based on the lower, middle, and upper tercile of rainfall (October–April) received at Charters Towers (1900–2015). Each year was then classified as belonging to one of these climate states. A dry state was categorized by rainfall less than 435 mm, average as rainfall between 435 and 630 mm, and wet as rainfall in excess of 630 mm (Fig. 3). The output from GRASP was classified as dry, average, or wet and then averaged for each state for input into the economic model.

The animal production system modeled was based on young steers (castrated males) assuming an adult equivalent weight of 401 kg in October, the beginning of the simulation period. Animal performance and average pasture utilization were assessed in April, seven months after the start of the simulation. Three levels of initial pasture growing conditions (low, medium, and high) were tested. To represent these three levels, five key parameters were reset annually on 1 October (Table 2) with the remaining modeling parameters kept consistent with those of Ash et al. (2015). Thirteen stocking rates (from 8 to 20 steers per 100 ha at an increment of 1) were assessed. In total, 39 scenarios were simulated.

c. Seasonal climate forecasts

A probabilistic climate forecast system was used. Eleven different levels of probabilistic forecast skill consisting of 10% increments from 0% to 100% based on a hypothetical forecast system were created for each

	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
Reproductive cycle¹							Calving			Joining		
Animal classes²	→	Weaner			Weaner			Calf				→
Pasture quantity			Low							High		
Animal management	Round 1 muster				Round 2 muster							
Sell steers³	Sell steers				Sell steers							
Cull cows/heifers³	Cull cows/heifers				Cull cows/heifers							

FIG. 1. Timing of the annual reproductive cycle, pasture quantity, and management of the beef production system. Superscript numbers are 1: weaning will occur at one of two times depending on pasture availability; 2: assuming calves are weaned at the first weaning opportunity; and 3: additional selling or holding of animals may occur in October, in particular greater selling across animal classes if conditions are poor.

of the three climate states (dry, average, wet). These probabilistic forecasts were incorporated into the discrete stochastic programming 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 without forecast and with forecast probabilities are defined in Eq. (1):

$$\sigma = \frac{\pi_{s|f} - \pi_s}{1.0 - \pi_s}, \quad (1)$$

where $\pi_{s|f}$ is the posterior probability of state s given forecast f (i.e., with forecast) and π_s is the prior probability (i.e., without forecast) of state s . Note that π_s was set to of 0.33 for each tercile, representing the historical probability of the occurrence of state s .

Forecast skill σ was set to predetermined levels and was rearranged to provide posterior probabilities according to each skill level [Eq. (2)]:

$$\pi_{s|f} = \sigma(1.0 - \pi_s) + \pi_s. \quad (2)$$

Using this definition of forecast skill, 0% skill equates to climatology where each state has a 33% chance of occurring. An example, applying this equation to a forecast of a dry state with an assumed skill of 20%, results in posterior probabilities assigned to dry, average, and wet states of 47%, 27%, and 27%, respectively [Eq. (3)]:

$$\begin{aligned} \text{Dry} &= \pi_{\text{dry}|f} = \sigma(1.00 - \pi_{\text{dry}}) + \pi_{\text{dry}} \\ &= 0.20(1.00 - 0.33) + 0.33 = 0.47, \\ \text{Avg} = \text{Wet} &= \frac{(1.00 - \pi_{\text{dry}|f})}{2} = \frac{(1.00 - 0.47)}{2} = 0.27. \end{aligned} \quad (3)$$

Table 3 provides the weighting between the climate states for the 11 skill levels for a dry forecast state.

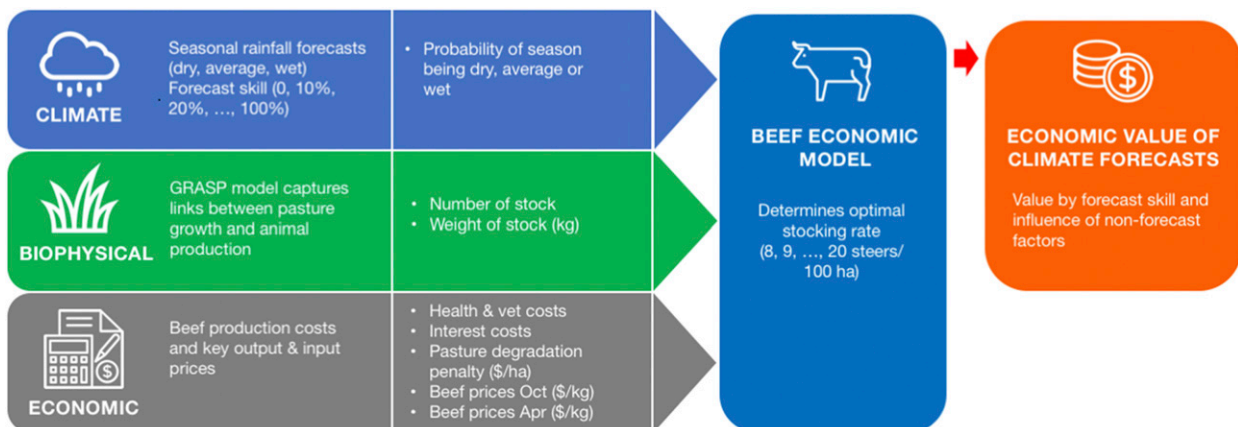


FIG. 2. Methodological overview. Generation of biophysical data, beef production costs, beef prices, and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal stocking rate based on maximizing returns.

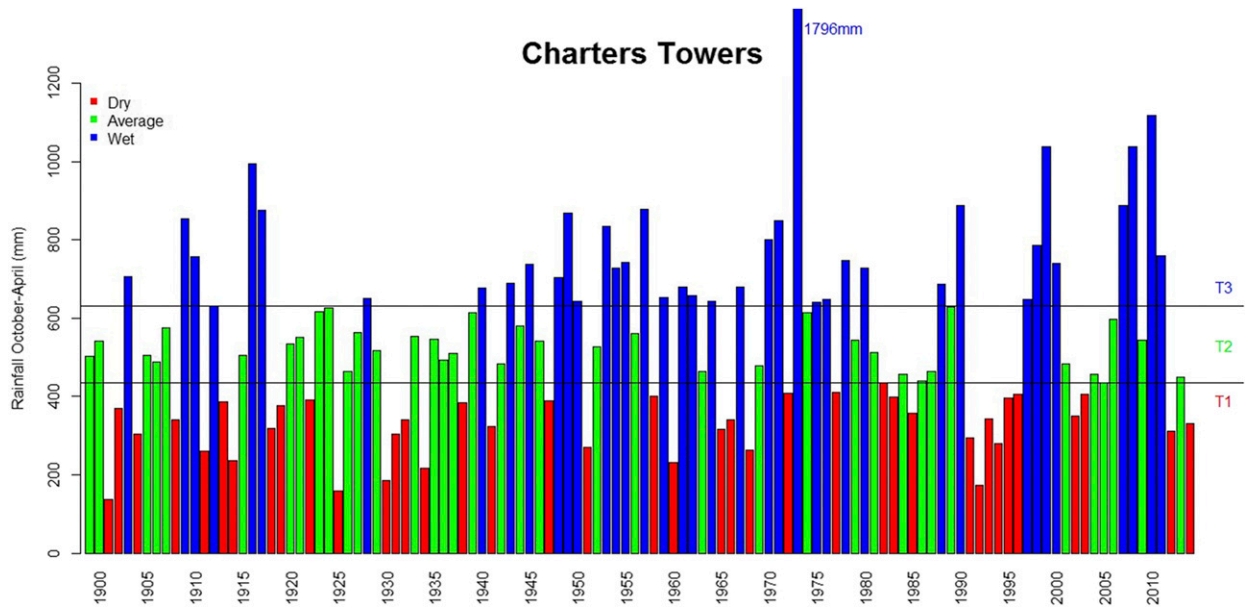


FIG. 3. Total rainfall for October–April at Charters Towers for 1900–2015 sourced from SILO (Jeffrey et al. 2001). Each year is classified into one of three terciles (dry, average, and wet).

d. Economic model

The economic model evaluated the profitability of different stocking rate strategies for different price and pasture settings. This was achieved by applying a consistent set of prices and costs to the biophysical outputs. The model was used to investigate the optimum decision and hence profitability for the three forecast states (dry, average, wet) and for 10 levels of forecast skill (10%, 20%, . . . , 100%). The same optimization process was used to evaluate the “without forecast” decision (0% skill), which assumed climatology with a 33% chance of each climate state occurring. Value was then determined, for each forecast state and each forecast skill level, as the marginal benefit between the farm returns of the optimal decisions made with and without a forecast. This valuation process was repeated across three market (steer prices) and three environmental (starting pasture) levels.

1) BEEF PRODUCTION COSTS

The production costs of the system including beef herd health and selling and feeding costs for the model were based on values in Martin (2016) with gross

margin details in the online supplemental material (see Table S1). An annual interest rate of 10% was applied to production costs.

2) KEY INPUT COSTS

Sensitivity analyses to steer price in October were conducted to evaluate the value of SCFs under different price scenarios. Medium and heavy steer prices in October and April for 2006–15 (MLA 2017) were used and adjusted to real prices (ABARES 2015). Sensitivity to the 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 4).

Steer prices in April were fixed to the 50th percentile of April steer prices (196 medium steers, 208 heavy steers cents kg⁻¹ live weight). This was implemented as prices in April are unknown when the stocking rate decision in October is made.

3) PASTURE OVERUTILIZATION COST

Within the GRASP model under fixed stocking rate strategies animals are able to heavily graze pastures.

TABLE 2. Pasture composition attributes used in the GRASP modeling.

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

TABLE 3. Example calculation of weightings of each climate state for a dry forecast state for skill levels 0%–100% that were applied to the economic model.

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

This would, over time, lead to pasture degradation and an unsustainable and less profitable system. The analysis conducted here only considered the implications of production decisions over seven months, to account for seasonal decisions, and as such the potential costs of long-term degradation needed to be captured.

Thus, an overutilization financial penalty was applied. For each simulation year and scenario, pastures were assessed for overutilization. Pastures were considered overutilized if the average pasture utilization from October to April, the simulation period, exceeded 25%. Results from O'Reagain et al. (2011) were used to set the value of the penalty. Using their results, a cost of \$639 per 100 ha was applied if pastures were classified as overutilized (the financial implication between setting a moderate and high stocking rate).

e. Analyses

Agricultural production levels representing dry, average, and wet climate states were obtained by classifying yearly (1900–2015) production outputs (pasture production, animal weight, pasture over utilization) according to one of these three climate states. The years classified each of the three states were averaged to represent each climate state in the economic model.

The economic model maximized returns by choosing the stocking rate that had the highest return weighted for each three climate states according to the prescribed forecast skill for each pasture and price setting. The economic model takes the form of a discrete stochastic programming problem, as outlined by Crean et al. (2013), which can be solved through adapting a conventional linear programming model [Eq. (4)]. The model is subject to normal constraints on the use of land and capital so that input usage can never exceed availability.

$$\text{Max } E[Y] = \sum_{s=1}^S \pi_s y_s, \quad (4)$$

where $E[Y]$ is the expected return, π_s is the probability of state s , and y_s farm income in state s .

The weighted or expected return ($E[Y]$) is simply the sum of economic returns in each state ($y_{\text{dry}}, y_{\text{avg}}, y_{\text{wet}}$)

multiplied by the probability of each state occurring ($\pi_{\text{dry}}, \pi_{\text{avg}}, \pi_{\text{wet}}$). The optimal stocking rate without a climate forecast is the one which provided the highest expected return with the probability of each state occurring set to 33%.

The introduction of a climate forecast with skill greater than 0% leads to a revision of the probabilities to reflect the forecast skill (Table 3) and the expected return is re-evaluated. The change to a climate state weighting due to different levels of forecast skill may lead to a change in the stocking rate decision compared to the without forecast decision (e.g., sell a greater/fewer number of steers in October) and this creates economic value from forecast use. The potential value (\$ per steer) of SCFs was calculated as the marginal difference between returns with and without the forecast [Eq. (5)]. 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 the optimal decision with (y_{sf}^*) and without the forecast (y_{so}^*) is the same:

$$V_f = \sum_{s=1}^3 \pi_{s|f} y_{sf}^* - \sum_{s=1}^3 \pi_s y_{so}^*, \quad (5)$$

where V_f is the value of forecast f , $\pi_{s|f}$ is the probability of state s given forecast f , while y_{sf}^* is the net return in state s resulting from implementing the optimal stocking rate based on forecast f , π_s is the probability of state s (without a forecast), and y_{so}^* is the net return in state s resulting from implementing the optimum stocking rate without a forecast.

The potential value of SCFs was assessed for all the decision settings (pasture levels, steer prices) and for 11 levels of forecast skill for each of the three climate forecasts (dry, average, wet). A total of 297 results were

TABLE 4. Stock prices in October sourced from MLA (2017).

	Low	Medium	High
Medium steer 400–500 kg (cents kg ⁻¹ live weight)	168	192	220
Heavy steer 500–600 kg (cents kg ⁻¹ live weight)	183	196	226

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

produced representing various decision environment settings, forecasts, and forecast skill levels (Table 5).

The value of the forecast system was calculated for a 100% skill. This was achieved by multiplying the forecast value for each forecast state by 33%, the likelihood of each forecast state eventuating [Eq. (6)].

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 V_F denotes a forecast system and q_f is the frequency with which each forecast occurs, then the value of a forecast system with three possible forecasts can be defined as

$$V_F = \sum_{f=1}^3 q_f V_f, \tag{6}$$

where V_F is the value of the forecast system, f is the forecast state (dry, average, wet), and V_f is the optimal value for forecast state f .

3. Results and discussion

a. Biophysical modeling

Data from the GRASP model showed marked differences between animal weight and pasture availability, particularly when comparing low pasture availability with medium and high (Fig. 4). This indicates that it is difficult to reverse a poor start in October. April steer weights progressively decreased as October stocking rates increased as too did the instances of pasture overutilization, again this was particularly evident for low initial pasture conditions (Fig. 4).

b. Economic modeling—Optimal stocking rates

The optimal stocking rate decision was evaluated for 100% skillful forecasts and without a forecast (0% skillful) for each combination of the decision drivers (Fig. 5). High pasture availability lead to the same decision to stock steers at the highest stocking rate (20 steers per 100 ha) regardless of steer price or forecast state. For medium initial pasture availability, the stocking rate decision remained the same with and a without forecast except under a dry forecast state with high steer prices, where greater destocking was the optimal decision (9 steers per 100 ha). The greatest change in stocking rate from the without forecast decision was with low pasture availability and this differed between steer prices.

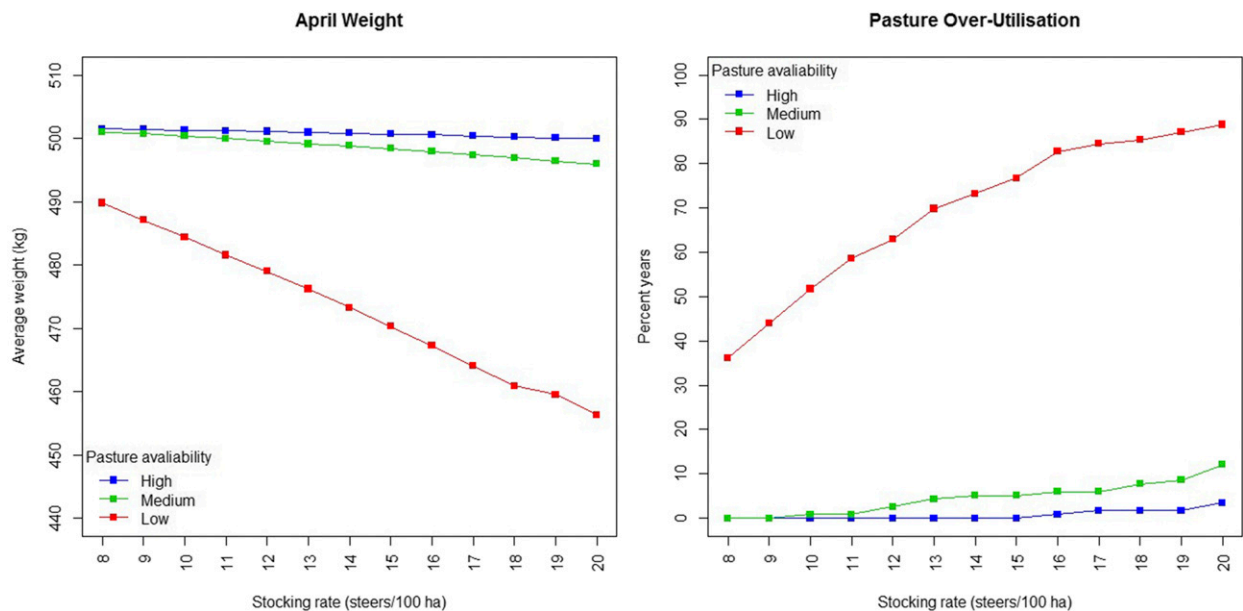


FIG. 4. (left) Mean steer weight in April and (right) percentage of years that recorded pasture overutilization (1900–2015) for low, medium, and high pasture availability for each of the 13 October stocking rates.

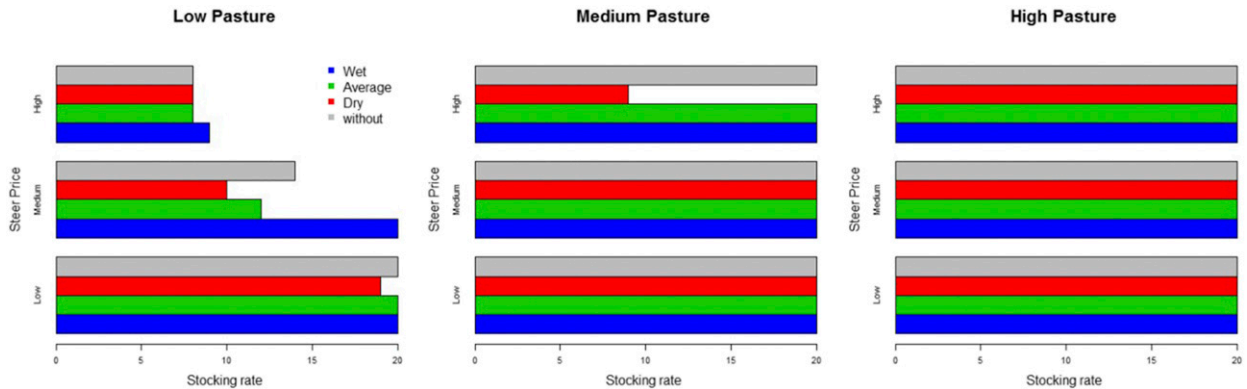


FIG. 5. Optimal stocking rate decision (steers per 100 ha) without (gray) and with a 100% skillful forecast. Steer price is for October.

c. Economic modeling—Forecast value

The value of a 100% skillful forecast system and each forecast state was calculated for each decision environment setting (Fig. 6). The importance of the decision driver settings to deliver financial returns is evident with many settings recording \$0 per head value (Fig. 6). No value was found when pasture availability was high and all but one result when pasture availability was medium. The greatest value was found for low pasture availability with the highest value (\$13.90 per head) found for a wet forecast with medium steer prices.

The overall forecast system value for a 100% skillful forecast, calculated by multiplying the forecast value by the probability of that forecast occurring (33%), ranged between \$0 and \$6.70 per head, depending on the decision environment settings (Fig. 7). Analyses of forecast system value with varying levels of skill illustrated that as skill decreased so too did value (Fig. 7).

The key production decision evaluated to estimate forecast value was what stocking rate to set for the wet season. This decision was a trade-off between selling

smaller animals earlier with a lower risk of pasture overutilization or selling animals later at higher weights but potentially risk incurring costs associated with pasture overutilization. The degree of the trade-off varied with different decision environment settings (pasture availability and steer price). SCF value ranged from \$0 to 13.90 per head dependent on decision environment settings, forecast climate state, and forecast skill. The value of the overall forecast system operating with 100% skill ranged between \$0 and 6.70 per head (Fig. 7). Contextualizing for a herd size of 6000, this maximum value for the farm was \$40,200 for one particular setting of the decision environment (low initial pasture and medium steer prices).

Results found here were similar to previous studies for northern Australian beef production systems. O'Reagain et al. (2011) evaluated several strategies to set stocking rates over a 12-yr field experiment. They found that the best strategy was to set stocking rates based on available forage, mirroring the importance of pasture availability found here (Fig. 7). However, the results here did find forecast value with low pasture

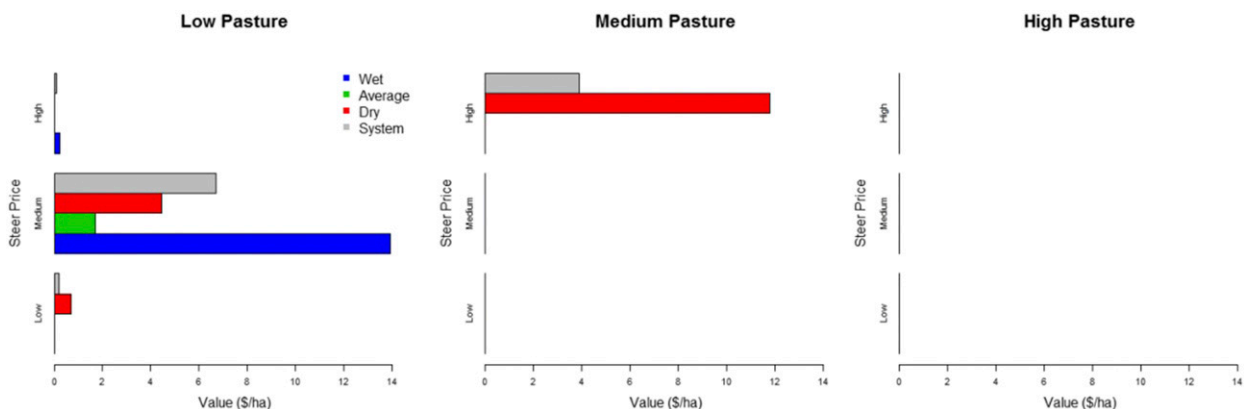


FIG. 6. A 100% skillful forecast system and forecast state value (\$ per head). Steer price is for October.

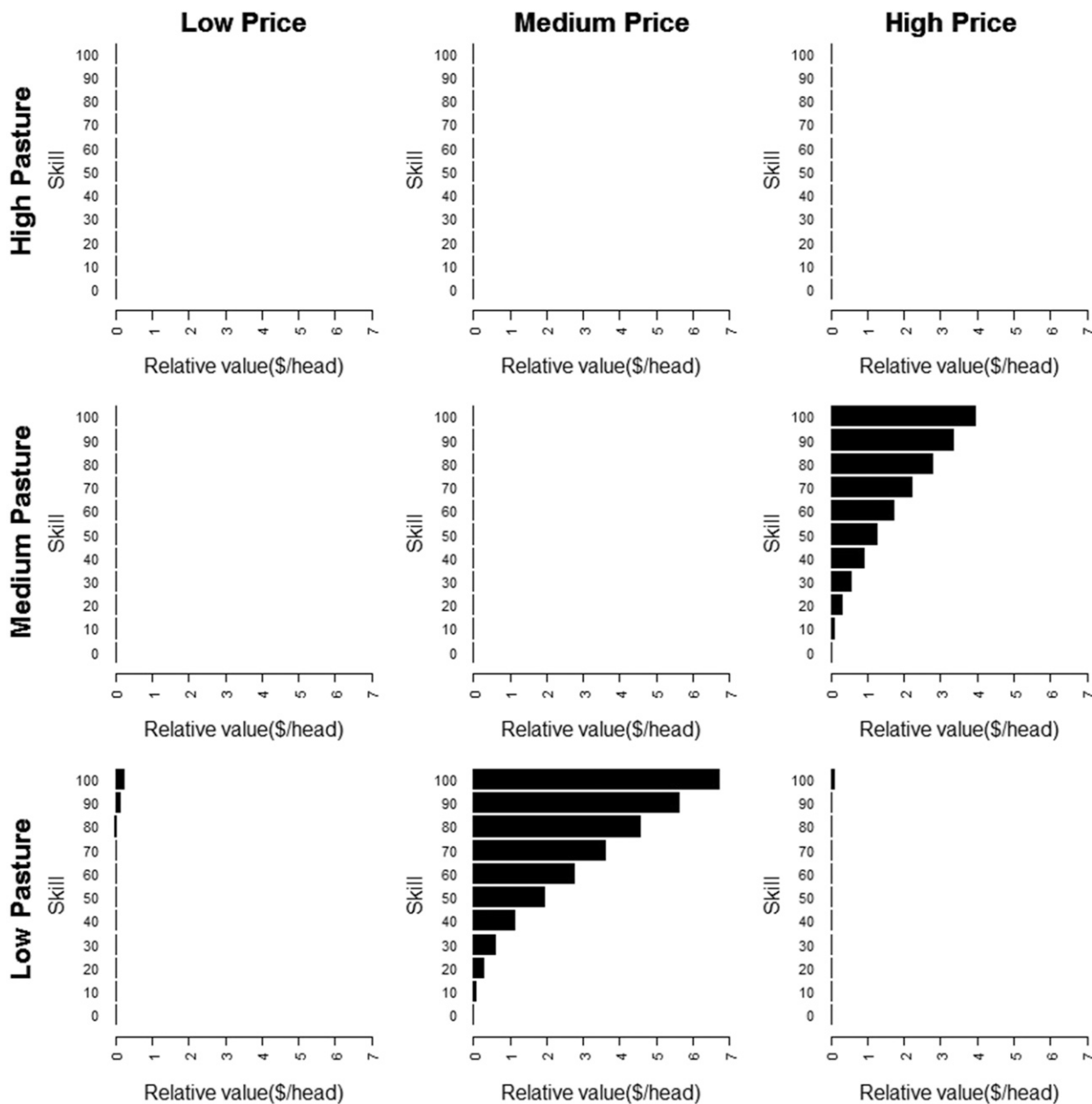


FIG. 7. Imperfect forecast system value (\$ per head). Three levels of current pasture availability (low, medium, high) are in the three rows and three steer prices (low, medium, high) in the columns.

availability. Similar to this study, [Stafford Smith et al. \(2000\)](#) used the GRASP model to evaluate forecast value in terms of whole farm economics using a different economic model (Herd-Econ). They found only modest improvements in cash flow through incorporating a forecast over their “without forecast” management strategies. In addition they also found that decisions were sensitive to market settings. The results found here support their conclusions with modest forecast value found, and steer prices at the time of the

decision found to be important, dependent on pasture availability.

[McIntosh et al. \(2005\)](#) found more forecast value in their assessment of a northern beef enterprise also utilizing the GRASP model. They found that all the forecast systems assessed improved annual cash flow. A 14%–33% improvement in cash flow above the “without forecast” scenario was found. The decision point assessed was stocking rate in July and the forecast period July–March, which differed from that used here.

Furthermore, increases to stocking rates were allowable in their assessment, again an aspect not included in this study.

Allowable stocking rates were restricted to between 8 and 20 steers per 100 ha, which represents typical limits applied in this production system. This resulted in a hard boundary for further changes to reduce or increase stocking rates based on climate forecast state. For example, the without forecast stocking rate decision for low pasture availability at high steer prices was 8 steers per 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. It should be appreciated that drastic reduction in stock numbers (e.g., to 0) was not considered as producers retain base herd numbers for future breeding. A similar circumstance was reflected for increasing stocking rates. A fixed upper boundary is a reasonable assumption as producers do not typically buy stock as a result of a SCF in this system.

This study explored a range of decision environment settings and forecast states to provide a landscape of forecast value. A key finding was that pasture availability followed by steer price were important influences on whether forecast value was found. Only 4 of 12 decision environment combinations resulted in forecast value (Fig. 7). With high and medium pasture availability, the decision was to stock at the highest allowable stocking rate, regardless of price settings. These results reflect that with medium or high pasture availability it is likely that sufficient feed will be available through the wet season to avoid pasture overutilization regardless of the climate state (dry, average, wet). Thus, the forecasting of these conditions was not valuable. This highlights that using a subset of the environmental and economic conditions to assess forecast value will likely misrepresent overall forecast value, either inflating or deflating value.

Forecast value was mostly found for dry and wet forecasts (Fig. 6). Two examples will be used to explore the different circumstances for which dry and wet forecasts had value. With medium pasture availability and high steer prices, the without forecast optimal decision was to stock at the maximum of 20 steers per 100 ha. With a perfect dry forecast the optimal decision changed to destocking to 9 steers per 100 ha, driven by increased revenue from selling steers at high prices in October and a reduction of the costs of pasture overutilization, which was exacerbated due to dry conditions. A perfect forecast of a dry state resulted in an improvement in returns of \$11.80 per head 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 was to destock to 14 steers per 100 ha (Fig. 6), largely due to poor initial pasture conditions. With a perfect wet forecast the optimal decision changed to keeping stock at the maximum 20 steers per 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 the likelihood of pasture overutilization and this in association with medium steer prices made holding stock more profitable. A 100% skillful forecast of a wet state resulted in an improvement in returns of \$13.90 per head under this scenario.

A climate forecast state of average conditions was found to be of limited economic value under all settings. The single instance of value was \$1.70 per head for a 100% skillful average forecast. The low value of an average forecast state is a reflection of the limited change in conditions compared to the without forecast decision (i.e., based on average conditions). Nil or a small value with an average forecast state (middle tercile of climate data) when compared with average conditions is unsurprising.

The above examples highlight the maximum forecast value by assuming the forecast was 100% skillful. However, in reality operational forecasts are imperfect and different levels of skill were analyzed to assess forecast value for different levels of skill (Fig. 7). The use of theoretical rather than operational forecasts was preferred in this case so that the value of forecast improvements could be determined. However, the results can be used to provide a broad estimate of operational forecast value once their skill level is determined.

For example, the current accuracy of the Australian Bureau of Meteorology operational forecasts for the Charters Towers region for October–December rainfall is approximately 70% using percent consistent with above/below median forecasts (www.bom.gov.au/climate/ahead/outlooks/skill/). This is equivalent to 40% using the definition of skill in this study. At this operational skill level, the forecast system value was \$0–\$2.00 per head.

The case study presented here used particular parameter settings within the GRASP production 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). The farm characteristics set in GRASP were developed in consultation with industry to provide a representative farm. These characteristics will likely be different from other individual farms. For instance, weaning and mustering timing may differ. Thus this case study is simply an example of the potential value of SCF

not a comprehensive assessment for all possible enterprise arrangements.

GRASP uses a steer-only herd in the modeling process. In reality a herd will contain males and females in various age classes. For this application the focus was 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 was 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 Northern Australia Beef Systems Analyser (NABSA) production model (Ash et al. 2015) was investigated for this purpose; however, the constraints and assumptions in the model, which was developed for multiyear assessments of management decisions and long-term climate, were not amenable for this application. Enduring profitability in northern beef enterprises is generated by multiyear management; however, forecast value was assessed over a single wet season to match the seasonal scale of climate forecasts. The approach used here may not capture flow on influences of the decision through time. This includes impacts on pasture management and herd structure dynamics. The aim of this study was to investigate the potential value of seasonal forecasts and thus a restricted view of profitability based on a single season was used to evaluate value on decisions at the seasonal scale. A cost penalty was applied in relation to pasture overutilization to account for future losses to ensure the model was not optimized for a single season of production.

The pasture overutilization penalty was an important cost estimated in the economic model. There were two methodological steps in determining the penalty. These were the determination of whether pastures were overutilized and the cost penalty associated with overutilization. Both the steps were derived using findings from O'Reagain et al. (2011). Different derivation of determining when pastures were classified as overutilized would influence the percentage of years classified as overutilized and might alter forecast value. For example, a 20% threshold rather than 25% would increase instances of pasture overutilization, increasing the cost associated with higher stocking rates, with the forecast likely to have greater value for more decision environment circumstances.

Similarly, modification to the penalty value would influence forecast value. For example, a higher cost associated with pasture overutilization would make lower stocking rates more profitable. Although the results were dependent on the determination of these values, O'Reagain et al. (2011) provided the best available

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 determine a cost penalty associated with pasture overutilization for a single season. Further research is required to provide viable alternate options to set these parameter values in the economic model.

An interesting line of future enquiry would be to set April prices to be contingent on forecast climate state. That is, allow April prices to modify in step with different forecast climate conditions. For instance, steer prices in April in a dry season could be lower due to higher selloff of animals earlier (i.e., from October to April) due to the dry conditions. The non-state-contingent design of this study was required as insufficient historical price data were available to evaluate state-based relationships. If April steer prices are related to climate conditions it is likely that the value of SCF is underestimated in this assessment, in particular for dry forecasts. As more historical data are accumulated, this prospect should be evaluated.

The analyses presented here outlined an approach to evaluate the potential value of seasonal climate forecasts to northern Australian beef enterprises. The results highlight that under a few decision settings there was value in using forecast information in setting stocking rates prior to the wet season. The results can be used to inform annual management planning and also avenues of future research regarding SCF value to pastoral industries. Inclusion of other decisions that may benefit from forecast information, the level of skill required to generate sufficient value, the use of other metrics such as soil moisture and pasture growth, and other users of forecast information should be considered in such an analysis.

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