Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Sugar 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 sugarcane farms. The key decision identified by industry was when to harvest the ratoon 3 crop (the last crop to be harvested). Two options were analysed, on time or early. The timing of this decision is early September for a September–October rainfall climate forecast. Rainfall over this period can influence yield and cane sugar content and can increase harvesting costs. A skilful climate forecast is potentially valuable if it helps sugar growers to make a better harvest time 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. Six discrete climate states were identified based on September– October rainfall received at Ayr over the period 1893 to 2017. Two climate states were based on the lower and middle tercile of rainfall data representing dry and average climate states, respectively. The upper tercile was split evenly into four categories representing mild wet, moderate wet, severe wet and extreme wet climate states. Each year was classified as belonging to one of these six climate states. Agricultural production levels (cane yield, sugar content) for each of these climate states were obtained from outputs from the biophysical production model *APSIM*. These outputs were combined with sugar production costs and built into an economic model to capture the links between climatic conditions, yield and sugar content. The economic model was used to select the most profitable harvest time decision.

In order to systematically assess the value of forecast skill, a hypothetical forecast system of the six climate 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 six climate states. Increasing forecast skill results in a higher probability of a particular climate state evolving, providing more certainty about future conditions.

Value of forecasts

Forecasts of the different climate states had varying economic value. A climate forecast of dry or average conditions had no economic value as the with-forecast decision did not alter from the without-forecast decision (to harvest on time). This was also the case under the mild wet forecast. The reason for these findings was that there were no production or economic drawbacks to harvesting on time and hence no reason to alter harvest time, no matter how skilful the forecast.

In contrast, moderate wet, severe wet and extreme wet states all resulted in some adverse effects either on production and/or harvest time. Skilful forecasts of these states were consequently found to be of value. Moderate, severe and extreme wet forecasts had maximum values of $448/ha, $1358/ha and $2358/ha, respectively. Improved forecast skill was naturally found to be positively related to forecast value.

This high forecast value for a perfect forecast was found for irregular events. That is, each of these finer wet state categories are only expected to occur every 1 in 12 years. Evaluation of the forecast system, found by weighting forecast value by relative likelihood of climate state occurrence, found a much lower overall value of $0–$347/ha, depending on forecast skill.

Key findings

A general finding was that skilful forecasts of irregular events were found to be of considerable value. Noting that the likelihood of the wet climate states is low (1 in 12 years), this value would not be realised frequently. Nonetheless, this highlights that skilful forecast of unusual events would be valuable.

It is important to recognise that the decision investigated here represents only part of the risk sugar 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 sugar growers more generally.

Contents

Glossary of terms

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

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

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

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

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

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

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

1 Introduction

1.1 Background

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

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

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

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

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

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

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

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

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

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

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

1.2 Project objectives

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

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

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

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

1.3 Case study approach

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

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

This report contains findings of the sugar 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 were 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 Sugar production system

2.1 Industry overview

Sugar production makes an important contribution to the Australian economy, with the 2015/16 season valued at $1.47 billion (ABS, 2016). The Australian sugar industry is export-oriented. Approximately 80% of all sugar produced is exported while most refined sugar is sold domestically (Australian Sugar Milling Council, 2018). Australian sugarcane grows in high-rainfall and irrigated areas along coastal plains and river valleys on 2100 km of Australia's eastern coastline, between Grafton in New South Wales and Mossman in far north Queensland (Figure 1). Queensland accounts for about 95% of Australia's raw sugar production and New South Wales approximately 5%.

Approximately 4600 cane growers produce sugarcane on 380 000 ha suppling 24 sugar mills (Australian Sugar Milling Council, 2018). The industry produces up to 35 million tonnes of sugarcane and can produce up to 4.5 million tonnes of raw sugar. Approximately 85% of the raw sugar produced in Queensland is exported, generating up to $1.75 billion in earnings in 2017 (Australian Sugar Milling Council, 2018).

Figure 1 Australia's sugar production regions (Australian Sugar Milling Council, 2018)

2.2 Producing sugar in Australia

Sugarcane is a tall tropical perennial grass and a C4 plant, which is efficient photosynthetically allowing the plant to store sugar (sucrose) as juice in its stalks. Sugarcane in Australia is grown as a dryland or irrigated crop requiring approximately 1500 mm of water per season (rain and/or irrigation). The majority of farms use irrigation water to supplement rainfall.

Sugarcane is grown on an approximately four-year cycle. In the first year, sugarcane is planted and harvested by cutting the cane off at ground level. From this stubble, a 'ratoon' crop emerges, which grows from the remaining buds and once mature, is similarly harvested. Typically, three ratoon crops will be grown from one planting. After the sugarcane crop cycle has

completed, growers may choose to fallow the paddock or plant a break or complementary crop to improve soils and manage weeds, pests and disease (Creighton, 2012).

The sugarcane harvest season occurs over many months from June to December. Many factors influence harvest timing including farm site, climatic conditions, timing of planting and the difference in time to maturity between plant and ratoon crops.

The sugarcane produced and harvested by growers is milled to produce raw sugar, which may be refined further to make food products (e.g. crystal sugar, golden syrup, treacle). Typically, growers receive payment for cane based on commercial cane sugar (CCS) percentage per tonne of sugarcane that is extracted from the cane and the global price of raw sugar. Hence, profits are driven by cane yield, CCS percentage and the price of sugar.

2.2.1 Commercial cane sugar

Commercial cane sugar (CCS) percentage varies depending on several factors including climatic conditions, the crop phase (plant or ratoon crops), time of harvest in the previous year as well as cane variety and farm location, although these influences are less important (Lawes et al., 2002). Oliveira et al. (2017) used data mining techniques to weigh the importance of soil, weather, agricultural practices and crop variables in determining CCS. Of the 28 variables evaluated, the variables with the greatest, and similar, predictive capacity were summed degree days, mean minimum temperature and total precipitation, all during the maturity phase.

The relationship between cumulative rainfall and sugar has been considered in greater detail by Cardozo et al. (2015). They investigated the impact of rainfall for the 120 days prior to harvest on CCS for a range of cultivars grown in Brazil. They found a negative exponential relationship with, as an extreme example, a –7% difference in CSS between high rainfall accumulation in the 120 days prior to harvest (approximately 800 mm) and low rainfall (approximately 80 mm).

2.3 Description of climate-sensitive point

Industry consultation was undertaken to describe the production system and key decision points that are sensitive to climatic conditions. Further information on the consultation process is contained in Appendix 1: Industry engagement.

The case study for this analysis was a cane farm in Ayr, Queensland, based in the Lower Burdekin River delta region (Figure 2). The production system was based on paddock rotation between plant and ratoon crops, and fallow/break crop for an irrigated farm (Figure 3).

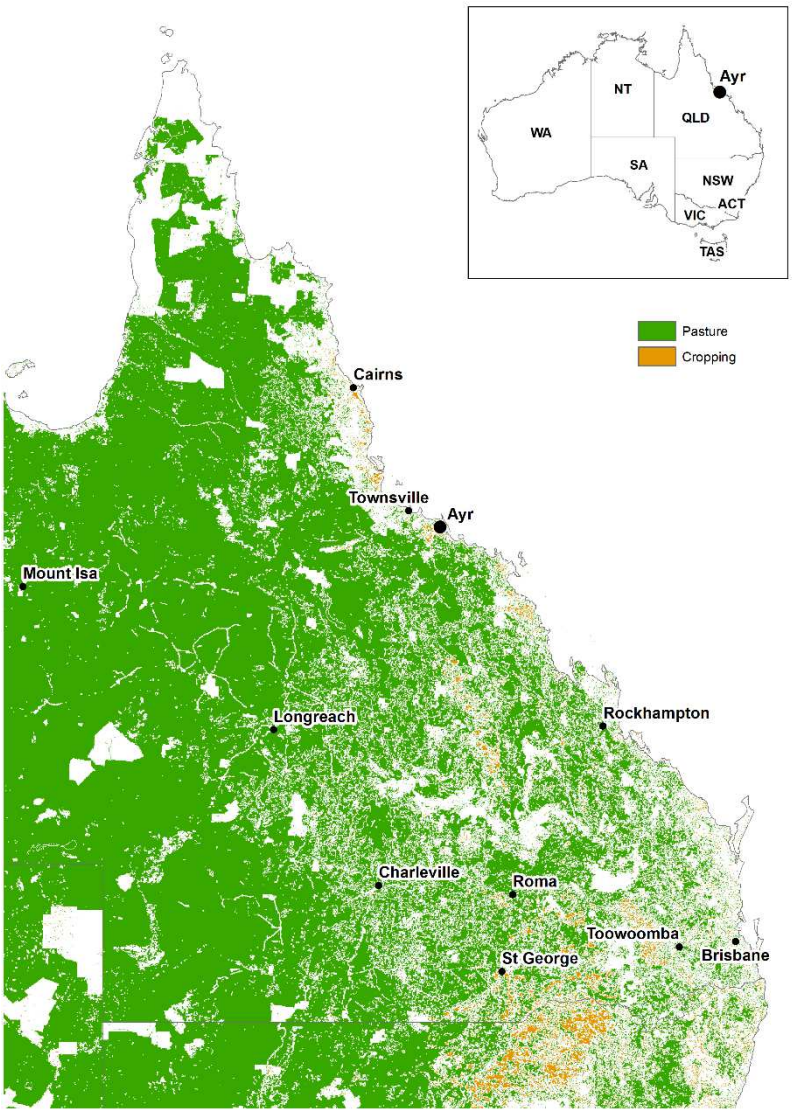
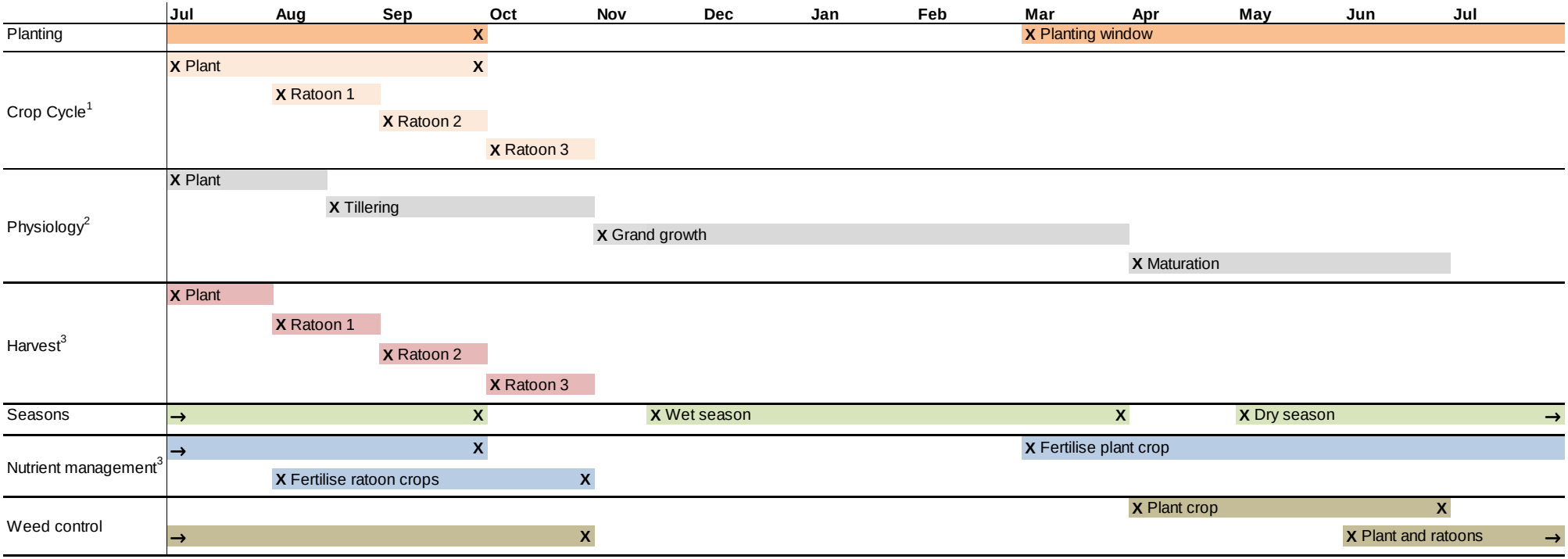


Figure 2 Map showing the location of Ayr, the case study site

Figure 3 Broad system characteristics of sugar case study



[1] planting timing is generally spread across the planting window. Ratoon emergence timing assumes July planting.
[2] for a plant crop (first year). This assumes a July planting. General sequencing the same for ratoon crop but later after harvest of the previous crop.
[3] dependent on timing of planting.

2.3.1 Decision point

The key decision point for this system was:

When will I harvest my ratoon 3 crop?

The harvest period extends from July through to October, from the dry season going into the wet season (Figure 3). The timing of harvesting ratoon 3 was selected for the case study as this is the latest crop to be harvested and most likely to be at risk of a wet harvest (Table 2).This decision occurs in September–October when the ratoon 3 crop matures (Table 1). Harvest must occur every year, so the primary driver for the harvest timing decision is the potential for wet weather during harvest.

Figure 4 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.

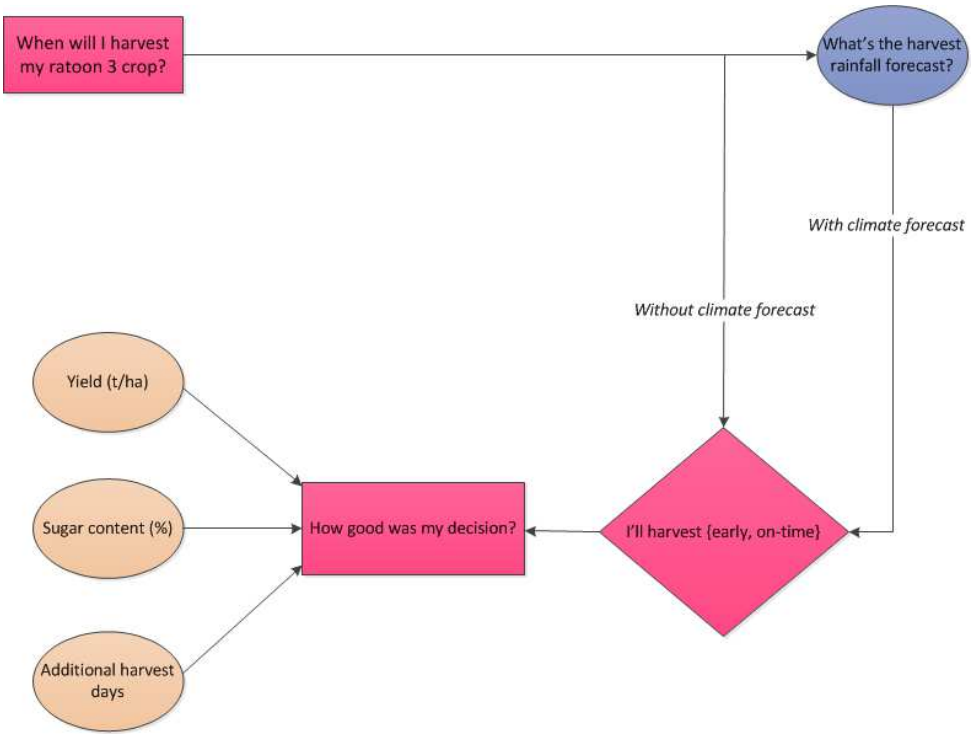


Figure 4 Decision pathway of when to harvest ratoon 3 sugarcane crop including an evaluation of the decision made

2.4 Previous studies of SCFs in sugar production systems

Inclusion of SCFs into decision-making processes within Australia's sugar industry may provide opportunities for growers to match decisions with expected seasonal conditions. Economically, this can provide benefit through reducing risk in poor future conditions (e.g. wet harvest conditions with poor outcomes) and by taking advantage of good future conditions (e.g. dry or average harvest conditions where crops are allowed to meet their potential).

To investigate the potential impact of wet harvesting on sugarcane grower profits, Antony et al. (2002) interviewed a small number of growers regarding the 1998 season, a particularly wet year. Impacts from that season included failed plantings, soil compaction, inability to harvest

cane and lower CCS. Using the information gathered through the interviews, it was estimated that perfect knowledge of rainfall in that season would have saved the sugar industry $19 million and a further $1.7 million could have been saved through improved management practices.

Limited studies have been conducted to quantitatively value SCFs for sugar farms. At the regional scale, Everingham et al. (2012) used a combination of grower records and synthetic data created from these records to obtain crop and harvest information for the Herbert region. Using this information, they generated a set of rules regarding the start of harvest for the whole crop (i.e. plant and ratoons). Using SOI phase, they modified harvest strategies, primarily for the start of harvest. The results indicated that use of the SOI phase forecast could improve profits for the region by between $0.1 million and $1.9 million per year. Savings were found in El Niño years, where harvesting later than the average due to drier conditions allowed for higher yields and CCS.

In a Master's thesis, Osborne (2011) investigated the potential benefit of a SOI three-phase forecast in modifying the start of harvest, for several areas and different soil types in the Herbert region. He found that forecast value differed with location and soil type. A maximum value of $23/ha was found for good soils in Bambaroo through to near zero value for poor soils at Macknade.

3 Methods

The potential value of SCFs was evaluated through maximising returns of the system by selecting an optimal harvest time under various system conditions. An overview of the methodology is outlined in Figure 5. 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.

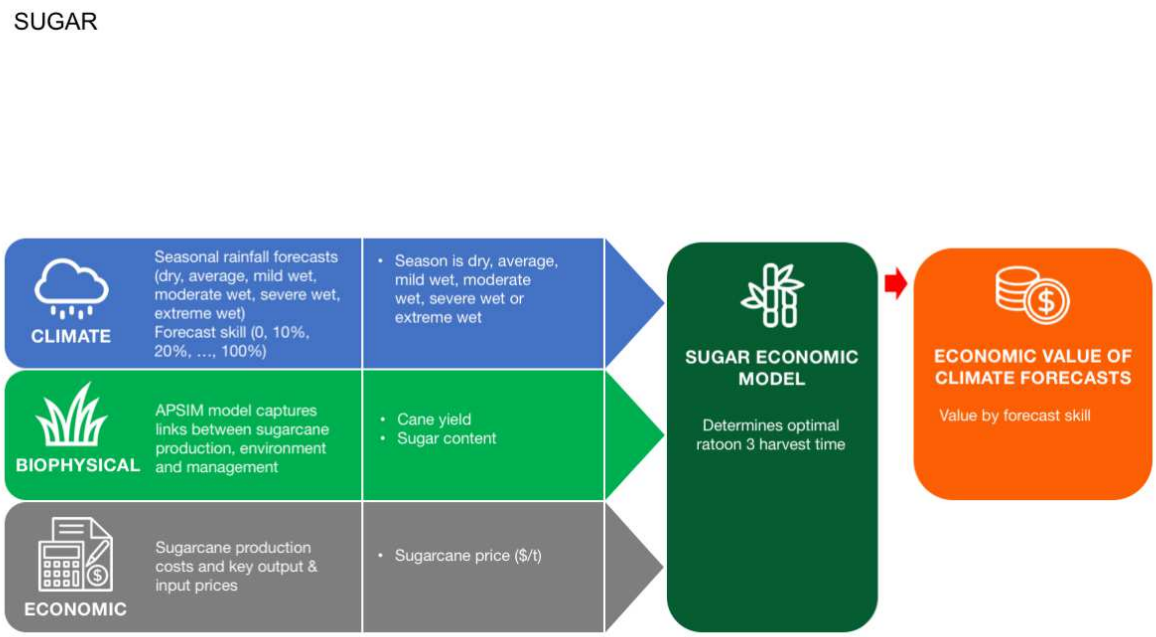


Figure 5 Methodological overview. Generation of biophysical data, sugar production costs, sugar price and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal harvest time based on maximising returns.

3.1 Sugar biophysical simulation model

The link between sugar yield and climatic conditions was captured through detailed biophysical modelling using the Agricultural Production Systems Simulator (*APSIM*) version 7.8 (Holzworth

et al., 2014). The *APSIM* model simulates crop yield for different climate attributes, plant varieties, soil types and management decisions. *APSIM* was configured with climate data sourced from SILO patched point dataset (Jeffrey et al., 2001) for station 33002 (Ayr DPI Research Station) for 1889 to 2017. A medium clay soil was selected, common in the Burdekin region. The modelling results were compared with sugar mill production statistics from the Burdekin region for the time period from 1942 to 2014 and found to be consistent.

A typical crop cycle for sugar includes one plant crop and three ratoon crops. The crop cycle for this simulation was set to 15 months for the plant crop and 13 months for the three ratoon crops. Each plant crop cycle was set to start at a fixed planting date (Table 1).

Table 1 Sugar cane crop cycle used in *APSIM* simulation

Crop cycle	Start of cycle	Harvest (following year)	Months
Plant	20-Apr	25 July	15
Ratoon 1	26-Jul	19 August	13
Ratoon 2	20-Aug	12 September	13
Ratoon 3	13-Sep	7 October	13

Analyses in this case study focused on ratoon 3, as the time of harvest for this portion of the crop (October) is most likely to be exposed to unseasonable rainfall (Figure 3 and Table 2). Slight increased likelihood of rainfall in August is interesting, as this may impact harvesting of ratoon 1; however, delaying harvest for ratoon 1 may be an option if unseasonable rainfall is received as September rainfall is, statistically, lower. The option to harvest later for ratoon 3 is not viable as risk of rainfall in November is much higher (Table 2).

Table 2 Distribution of monthly rainfall (mm) for each harvest month in Ayr (1889–2017)

Month	10th percentile	50th percentile	90th percentile
July	0	5.4	49.1
August	0	2.8	53.5
September	0	2.4	44.9
October	0	7.2	59.7
November	1.7	20.7	104.9

3.2 Sugar production costs

Sugar production costs were obtained from the regional Farm Economic Analysis Tool (FEAT) (Queensland Department of Agriculture and Fisheries, 2015). The Department of Agriculture and Fisheries developed FEAT to assist Australian sugarcane growers to plan and measure progress and profitability. Scenarios within FEAT are developed in consultation with growers and industry advisors from each region, and are current for the year 2015. The operations, input costs and yields used in these scenarios reflect broad regional trends and are not reflective of any individual situation.

In this instance, production cost information from FEAT was used as a basis to determine area- and yield-based costs and were combined with *APSIM* crop simulation data to determine sugar returns.

Table 3 Sugar production costs and gross margin ($/ha) (Queensland Department of Agriculture and Fisheries, 2015)

Month	Plant	1st ratoon	2nd ratoon	3rd ratoon

A. Income	$5,766	$5,062	$4,663	$4,274
Growing costs	$1,663	$806	$806	$806
Harvesting costs	$1,024	$896	$825	$761
B. Total variable costs	$2,687	$1,702	$1,632	$1,568
C. Gross margin (A – B)	$3,079	$3,360	$3,032	$2,706

3.3 Key input costs

Sugar prices were obtained for the 2005–06 to 2014–15 period from IndexMundi[2]. These international sugar prices were converted into local cane sugar prices through the application of the standard cane price formula. The formula takes into account the sugar content of the cane (CCS) and the price of sugar on the international commodity market, and has been used extensively in the sugar industry by processors to establish benchmark prices. An example of its application is provided in Figure 6. The constant is a regionally specific amount and was set at $0.60/tonne cane in this instance.

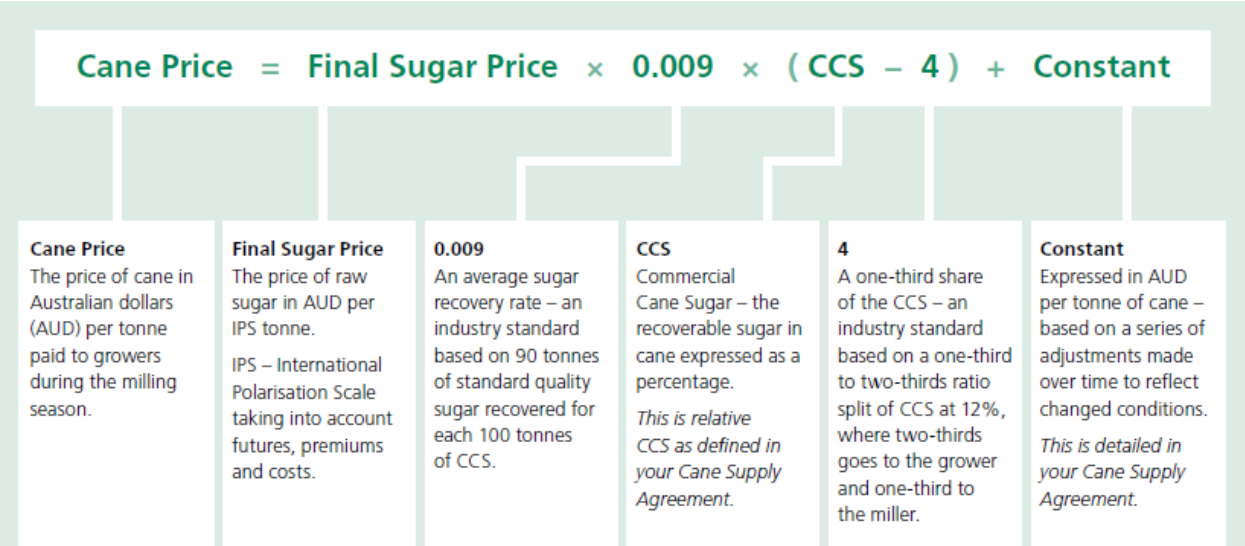


Figure 6 Application of Cane Price Formula (MSF, 2016)

3.4 Seasonal climate forecasts

A probabilistic climate forecast system was adopted to assess the value of SCFs. Six discrete climate states were identified based on the lower and middle tercile of rainfall (September and October) and splitting the upper tercile into four wet categories (Table 4). Each year in Ayr from 1893 to 2017 was then classified as belonging to one of these climate states (Figure 7).

Table 4 Rainfall categories used to assess the value of SCFs. Dry and average represent the first and second tercile and the four remaining categories splitting the upper tercile into four categories. Based on climate data at Ayr 1893–2017.

Rainfall category	Rainfall amount (mm)	Number years (n)	Probability (%)
Dry	0-8.2	41	33
Average	8.3-41.5	42	33
Mild Wet	41.6-53.6	11	8
Moderate Wet	53.7-74.9	11	8

[2] https://www.indexmundi.com/commodities/?commodity=sugar&months=240&currency=aud

Severe Wet	75.0-107.7	10	8
Extreme Wet	>107.7	10	8

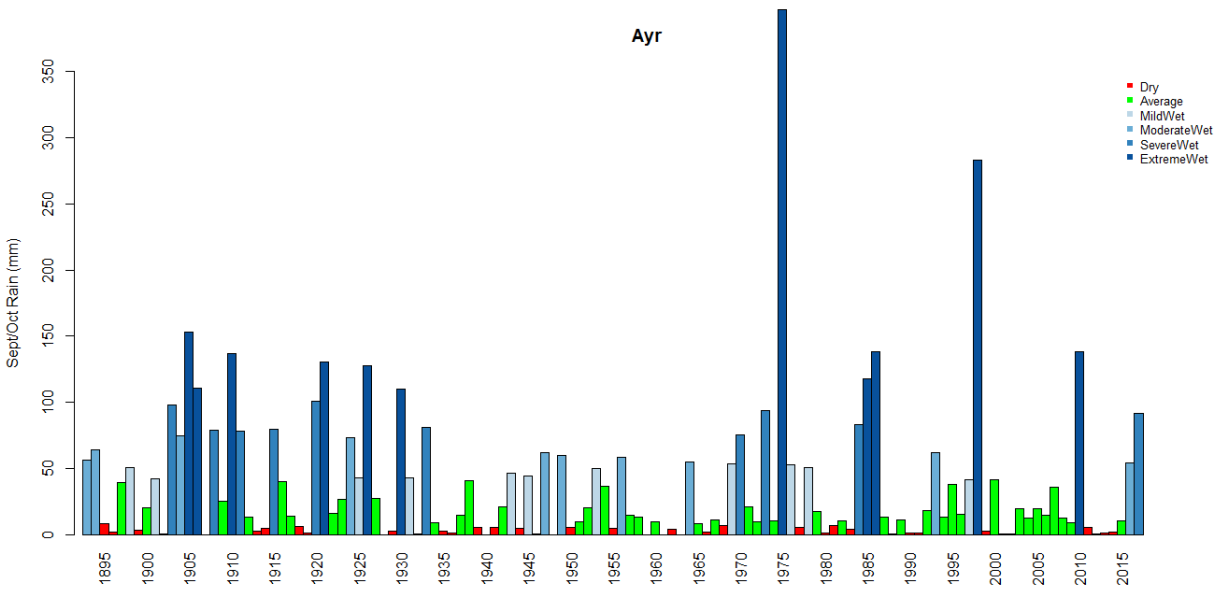


Figure 7 Total rainfall for September and October at Ayr for 1890–2017 sourced from SILO (Jeffrey et al., 2001).

Agricultural production levels representing dry, average and wet (mild, moderate, severe, extreme) climate states were obtained by classifying yearly outputs (1893 to 2017) of yield and CCS production data from the *APSIM* production model (see section 3.1). Resulting yearly data for each state (Table 4) 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 six climate states 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.

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

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 0.3333 for dry and average states (4/12 or 1/3) and 0.0833 for each of the four wet climate states (calculated as 0.33/4 or 1/12) that comprise the wet tercile.

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

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

The application of Equ 2 can be best shown through an example. Applying Equ 2 to a forecast of a mild wet state with an assumed skill of 20% results in a modified weighting assigned to the forecasted state as shown below:

Mild Wet = $\pi_{mild\ wet|f} = \sigma(1.00 - \pi_{mild\ wet}) + \pi_{mild\ wet} = 0.20(1.0000 - 0.0833) + 0.0833 = 0.2667$

The residual probability of experiencing one of the non-forecasted states is evenly distributed in proportion to the prior probability of each state.

Using this definition of forecast skill, 0% skill equates to climatology where dry and average each has a 33.33% chance of occurring and the four wet states each have 8.33% chance. Table 5 provides an example of weighting between the climate states for the 11 skill levels for a mild wet forecast state.

Table 5 Example calculation of weightings of each climate state for a mild wet forecast state for skill levels 0% to 100%.

		Forecast skill										
	Climate state	**0%**	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Weighting (%)	Mild wet	8.3	17.5	26.7	36.0	45.0	54.2	63.3	72.5	81.7	90.8	100
	Moderate wet	8.3	7.5	6.7	5.8	5.0	4.2	3.3	2.5	1.7	0.8	0
	Severe wet	8.3	7.5	6.7	5.8	5.0	4.2	3.3	2.5	1.7	0.8	0
	Extreme wet	8.3	7.5	6.7	5.8	5.0	4.2	3.3	2.5	1.7	0.8	0
	Dry	33	30	26.7	23.3	20.0	16.7	13.3	10.0	6.7	3.3	0
	Ave	33	30	26.7	23.3	20.0	16.7	13.3	10.0	6.7	3.3	0

3.4.1 Sugar biophysical output adjustment

APSIM output data needed to be modified as the model does not currently account for yield or CCS penalties associated with excessive rainfall (Table 6). This is particularly clear in the results of the dry and extreme rainfall categories with these extreme opposite categories recording similar CCS and yield.

Table 6 *APSIM* results for yield and CCS for September–October rainfall categories for ratoon 3 harvested in October.

Rainfall category	CCS (%)	Yield (t/ha)
Dry	16.8	108.0
Average	16.7	109.1
Mild wet	16.8	109.4

Moderate wet	16.4	111.4
Severe wet	16.5	108.0
Extreme wet	16.3	111.1

The *APSIM* output data (yield and CCS) were adjusted based on industry consultation regarding the impact of different rainfall amounts (Table 7). No adjustment was made for the dry or average climate categories nor was any adjustment made for an early harvest option as the earlier harvest avoids these negative impacts. Additional costs in relation to longer harvest time also needed to be included into the economic analyses. These additional costs were similarly included following industry consultation (Table 7).

Table 7 Industry suggested yield and CCS penalties and additional harvest days required for four categories of September–October rainfall. Percentage represents percentage to be taken off the reported yield and CCS.

Rainfall category	Yield	CCS	Additional harvest days (ratoon 3 only)
Mild wet	–5.0%	–1.0%	0
Moderate wet	–7.5%	–2.0%	0.75
Severe wet	–10.0%	–5.0%	1.25
Extreme wet	–10.0%	–10.0%	1.75

3.5 Economic model

The economic model used key outputs from the *APSIM* production model to capture the links between climatic conditions and cane production. The economic model evaluated the changes in cane fresh weight and CCS for two harvest strategies (early or on time). This was achieved by applying a consistent set of prices and costs to the biophysical outputs, incorporating baseline information on sugar production costs and taking into consideration the costs of extra harvest days, where appropriate.

The profitability of the two harvest strategies was assessed under each forecast state (dry, average, mild wet, moderate wet, severe wet, extreme wet). The economic model maximises returns by choosing the harvest time that has the highest return weighted across the six 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 3.

$$Max\ E[Y] = \sum_{s=}^{s} \pi_s y_s \qquad \text{[Equ 3]}$$

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

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

Without a climate forecast, dry and average states have an equal chance of occurrence of 0.3333. The wet state also has the same 0.33 overall chance of occurrence, but it is disaggregated here into the finer scale wet states which have a 0.0833 probability. The weighted or expected return (*E[Y]*) is simply the sum of economic returns in each state (Y_{dry}, Y_{avg}, $Y_{mildwet}$, $Y_{moderatewet}$, $Y_{severewet}$, $Y_{extremewet}$) multiplied by the probability of each state occurring (π_{dry}, π_{avg}, π_{wet}, $\pi_{mildwet}$, $\pi_{moderatewet}$, $\pi_{severewet}$, $\pi_{extremewet}$). The optimal harvest strategy 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 one of the finer scale wet season states results in more weight being given to that state in the objective function of the

model (see Table 5 for example). The change in weighting given to the forecasted state may lead to a change in the harvest decision, creating economic value from forecast use.

Further detail of the economic modelling is contained in Appendix 2: 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. Value was calculated in terms of $/ha over the area of ratoon 3. The decision analysed was to harvest the crop at crop maturity (on time) which was 7 October according to *APSIM* or to harvest early, 12 September, in line with ratoon 2 harvest time (Table 1).

Value was assessed for 11 levels of forecast skill for each of the six climate forecasts (dry, average, mild wet, moderate wet, severe wet, extreme wet). A total of 132 results were produced representing the two harvest options and various forecasts and skill levels (Table 8).

Table 8 Variables and value levels assessed to evaluate forecast value

Variable	Values tested
Forecast state	dry, average, mild wet, moderate wet, severe wet, extreme wet
Forecast skill (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

Initially, the without-forecast (0% skill) harvest time decision was reported. Subsequently, the perfect-forecast (100% skill) harvest decision for the six forecast states was similarly reported. The potential value ($/ha) of the perfect forecast was calculated as the difference in returns between the with- and without-forecast returns. This represents the largest potential value of climate forecasts for each climate state. Probabilistic forecast value ($/ha) for each forecast skill level relative to the without-forecast decision was calculated.

Finally, the total forecast system value was calculated. This was assessed by weighing the reported forecast value by the relative likelihood of each forecast being issued, taken to be the same as the prior probability of each climate state (Table 4).

4 Results

4.1 Biophysical modelling

Average yield and CCS based on the climate state (dry, average, mild wet, moderate wet, severe wet and extreme wet) for both harvest times was calculated (Figure 8). For dry and average climate states, large differences in yield and CCS were found between the early and on-time harvests. This difference progressively reduced with increasing wet states. Yield and CCS was generally higher for on-time harvest than early harvest time for all climate states. The only exception was for the extreme wet category where CCS was higher for the early harvest date.

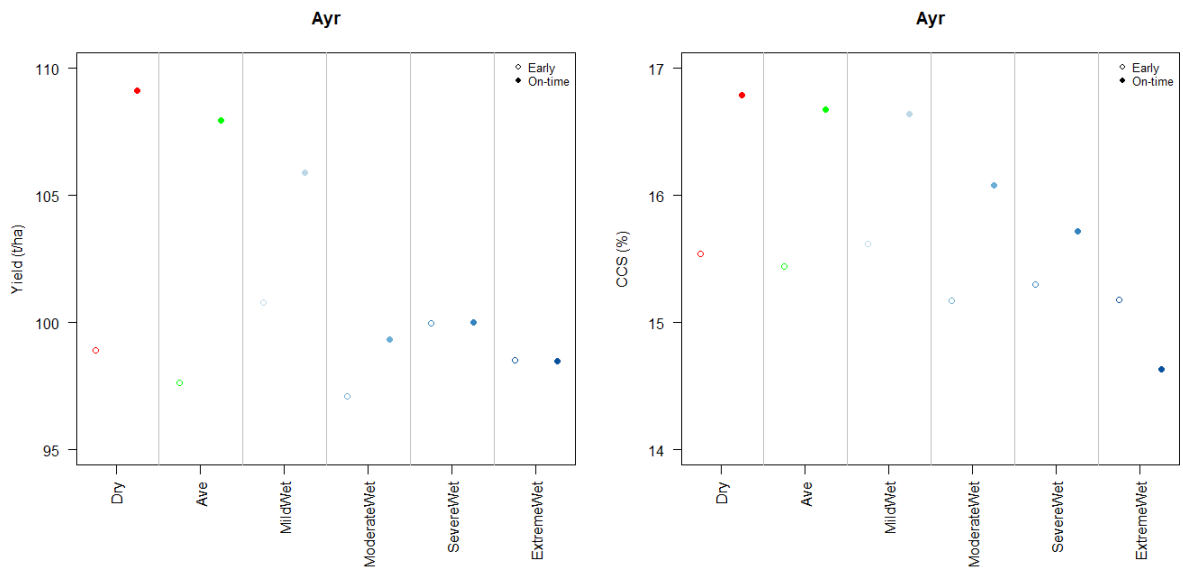


Figure 8 Average yield and CCS for each climate state forecast category. The colours indicate the different forecast allocations of the historical data (1893–2017) with red for dry, green for average and progressively darker blue for mild wet, moderate wet, severe wet and extreme wet. Climate states are for total rainfall September–October.

4.2 Economic analyses

4.2.1 Without forecast and perfect forecasts

The optimal harvest time decision without a forecast (0% skill) must be determined prior to calculating the potential value of SCFs. The without-forecast decision was to harvest on time. This was contrasted with the perfect-forecast decision for each of the six climate states (Table 9). The decision to harvest on time was unchanged with a dry, average or mild wet forecast. For a perfect moderate, severe or extreme wet forecast, the decision changed to harvest early (Table 9). This change in harvest time decision led to a forecast value of between $448/ha and $2,358/ha for these three forecast categories (Table 9).

Table 9 Without (0% skill) and perfect (100% skill) forecast harvest time decision and perfect-forecast value ($/ha) for each climate state

	Dry	Average	Mild wet	Moderate wet	Severe wet	Extreme wet
Without-forecast decision	on time	on time	on time	on time	on time	on time
Perfect-forecast decision	on time	on time	on time	early	early	early
Perfect-forecast value	$0/ha	$0/ha	$0/ha	$448/ha	$1359/ha	$2,358/ha

4.2.2 Imperfect-forecast value

The forecast value differed with forecast skill and for each climate forecast state (Figure 9). Forecast value was evident for moderate, severe and extreme wet categories and increased as forecast skill increased (Figure 9). The minimum skill required to yield value was 50%, 30% and 20% for moderate, severe and extreme wet categories, respectively.

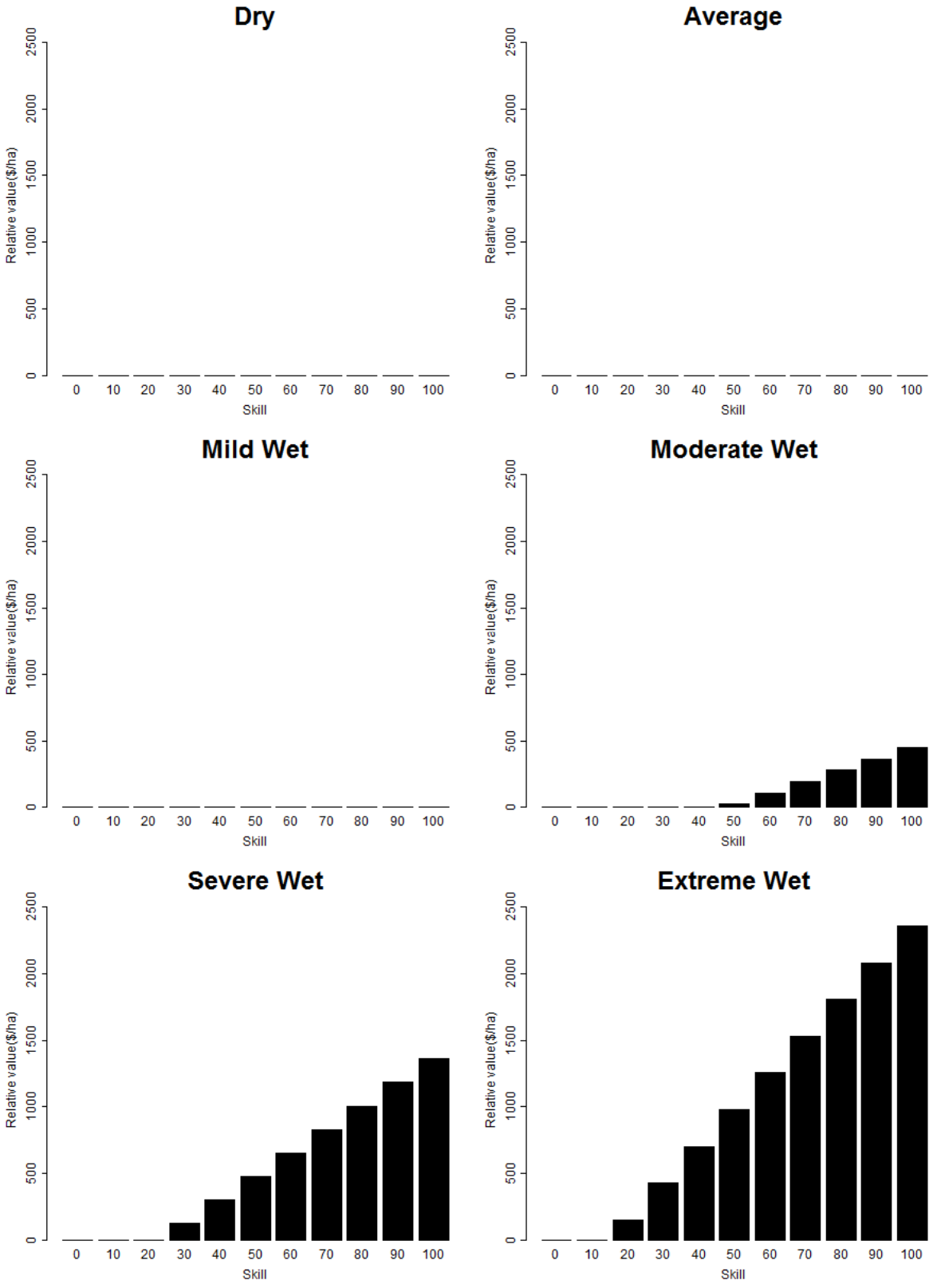


Figure 9 Imperfect forecast value for each climate state ($/ha). Skill (%) is represented on the x-axis as calculated in Table 5.

4.2.3 Weighted-forecast value

The forecast states evaluated had uneven probabilities. Forecasts of wet states, which were of particular interest for this case study, each represented an 8.33% likelihood of occurrence, while the dry and average states had 33.33% chance. When considering the value of a forecast system, the value obtained for each forecast needs to be weighted according the likelihood of that forecast being issued. Weighted-forecast value by skill is shown in Figure 10. The perfect value of the forecast system weighted across climate states was $347/ha, notably lower than the maximum perfect forecast for the extreme wet forecast of $2358/ha (Table 9).

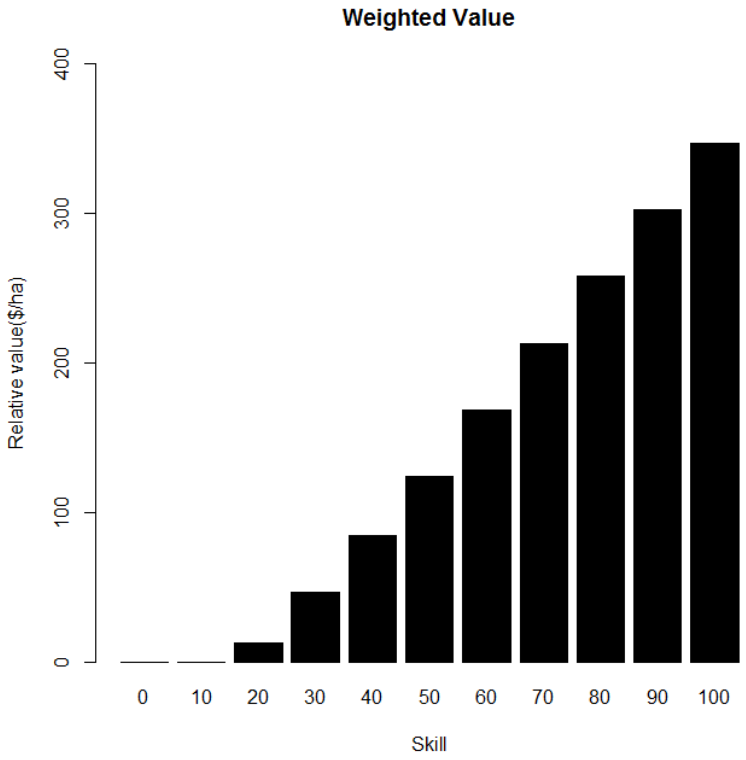


Figure 10 Weighted imperfect forecast value across all climate states ($/ha). Skill (%) is represented on the x-axis as calculated in Table 5.

5 Discussion

The key production decision sensitive to SCFs identified by industry and evaluated here was when to harvest to minimise wet harvest impacts. This decision is a trade-off between harvesting earlier at potentially lower yield and CCS, and harvesting later with risk of wet harvest which lowers yield, CCS and incurs additional harvest costs.

5.1 Optimal decisions made with and without seasonal climate forecasts

The optimal without-forecast decision, which assumes the long-term rainfall received, was to harvest on time. This result reflects that for two-thirds of the climate dataset (i.e. dry and average climate states), there is no penalty for on-time harvest (yield, CCS or additional harvest days) and therefore, in the absence of forecast information, this is the best strategy.

Introducing a perfect (100% skilful) climate state forecast modified the optimal decision for the three wetter climate states (moderate wet, severe wet and extreme wet). Under perfect forecast information, the decision was to harvest earlier. This decision to harvest earlier was largely reflecting additional harvest costs (machinery and labour) associated with a wet harvest. The on-time harvest strategy in these wetter years, including yield and CCS penalties for rainfall, still led to higher yield and CCS than if the crop was harvested earlier (Figure 8). However, with a

perfect forecast, this decision was modified to harvest early, with harvest costs out-weighing the benefits of additional yield and higher CCS of waiting to harvest on time.

No value was obtained for perfect forecasts of dry, average or mild wet climate states. Under these circumstances, the without-forecast decision to harvest on time remains the most profitable. Notably for these strategies, no additional harvest days are required, with no additional costs associated with harvesting.

5.2 Imperfect-forecast value

There was value for three out of four wet forecast states (moderate, severe and extreme wet), and this value increased with skill (Figure 9). Positive value was found at skill levels of 50%, 30% and 20% for moderate, severe and extreme wet forecast categories, respectively. At these skill levels and above, the optimal decision changed to harvest early.

The extent of value varied according to the forecasted state. Substantial forecast value was found for the extreme wet climate state (up to $2358/ha). The extent of this forecast value is driven by a range of factors. Firstly, the probability of the extreme wet category occurring is 8% or 1 in 12 years. Thus, even with a skilful forecast, this value could only be realised 8% of the time. In order to balance forecast value by the likelihood of climate state occurrence, weighted forecast value was calculated (Figure 10). These results calculated the potential value of the forecast system as a whole, rather than the value of a single, irregular, climate state. Notably, the maximum value of the forecast system was $347/ha, much lower than the individual forecast state value of $2358/ha. Secondly, for the extreme wet forecast, this is the highest impact category. Thus, great value was found for this particular category due to the deviation from average conditions. The mild wet forecast, with the same occurrence probability as the extreme category, was not found valuable as this rainfall category was closer to average conditions. Nonetheless, the results highlight that a skilful forecast of irregular events can be of considerable value.

5.3 Comparison to previous findings

Limited studies have been conducted to assess the value of SCFs on Australian sugar farms. Two studies using SOI phase forecasts have been conducted, both considering harvesting decisions. Using this operational forecast, a regional value of between $0.1 million and $1.9 million per year was found (Everingham et al., 2012). A Master's thesis found an on-farm value up to $23/ha through the inclusion of a SOI phase forecast (Osborne, 2011).

In this study we find a large variation in value from $0 to $2358/ha. The difference in results between this study and previous research stems from key differences in methodological approaches. These include the form of the harvest decision, and a focus here on a skilful theoretical rather than operational forecast systems like the SOI phase system (Stone and Auliciems, 1992) or Bureau of Meteorology POAMA model (Wang et al., 2004). The methodology outlined here does provide a robust framework for further analyses of operational forecast systems.

5.4 Limitations and assumptions

The case study design used particular parameter settings both within the *APSIM* production model and the economic model. *APSIM* has been used to investigate sugarcane production systems previously (Kingston, 2011; Osborne, 2011; Thorburn et al., 2010). Limitations of the *APSIM* model have been previously outlined (Angus and Van Herwaarden, 2001; Chauhan et al., 2017; Hanan and Hearn, 2003; Robertson et al., 2000). For the *APSIM* settings used here, the farm characteristics were developed in consultation with industry to provide a representative farm. These characteristics will vary from one farm to the next in terms of planting times and soil types. This case study is best considered as an example of the potential value of SCFs, not a comprehensive assessment for all possible sugar enterprise arrangements.

In this analysis, total September–October rainfall was used to represent different climate states. The impacts associated with rainfall at harvest may differ depending on how rainfall is received for the same total rainfall value. For example, a single 80 mm event will likely have a greater impact that 80 mm received evenly across the time period. Additionally, soil wetness prior to rainfall will modify the potential impact. As most farms are irrigated, it can be assumed that additional soil wetness from rainfall prior to the September–October forecast period may amplify the impact of subsequent rainfall. This soil-rainfall-management interaction was not solvable within the *APSIM* model but is important when considering operational use of SCFs.

The *APSIM* model does not adequately account for yield and CCS reductions under high rainfall conditions. As such, industry was consulted to estimate reductions in yield and CCS (Table 7). Alternate reduction values may influence the results. For example, more severe reductions may make on-time harvest less profitable and the optimal decision to harvest early may be selected more often. Ideally, *APSIM* would be updated to include impacts on yield and CCS of wet conditions. This would require data collection of field observations of yield and CCS changes under different conditions and incorporation of processes into the model platform.

Modification to additional harvest days would likely have a greater impact than different yield and CCS penalties under wet conditions. In the economic model, harvesting represented a large component of the costs associated with sugar production. Additional harvest days associated with wet conditions were sourced from industry advice. This study used industry advice to set these wet harvest penalties. In the absence of scientific studies determining these relationships, the use of expert opinion was deemed suitable. Nonetheless, further research to better understand these relationships is warranted.

Modification of additional harvest day values would influence the forecast value. If growers are able to minimise additional harvest days cost, forecast value will reduce. However, if additional harvest days increase notably, the form of forecast value may change. If these costs are substantial, the without-forecast optimal decision may change to harvesting early to avoid these costs. As such, value would then be associated with dry and average forecasts which would change to harvesting on time. Supporting this possibility, Everingham et al. (2012) found that forecast value was associated with El Niño type conditions (i.e. dry) as harvest could occur later. The flow on influences to subsequent seasons would need to be incorporated if harvest was allowed to occur later, as this later harvest will then shift maturity for the following ratoon crop later in the year, further into the wet season.

Like operational forecasts, the theoretical forecasts used in this analysis provided an indication of the likely climate state (dry, average, mild wet, moderate wet, severe wet or extreme wet) not the precise evolution of weather conditions. The value of a precise forecast may be greater. The analysis conducted here sets a challenge to the forecasting community. The wet forecasts represent states that each had a 8.33% chance of occurring (1/12 of the full climatic distribution). This is a much finer resolution than currently available through the Bureau of Meteorology, for example, which issues probabilistic climate forecasts on a two-state basis (above or below median; 50th percentile).

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Appendix 1: Industry engagement

Engagement with the industry for development of a case study for the sugarcane industry was conducted following a meeting with Ms Felice Driver, Program Manager at the Sugar Research Council (4 April 2016). Climate risk workshops were held in Gordonvale, Tully, Proserpine, Childers, Mossman, Babinda, Mareeba and Mackay with farmers, extension officers and other business operators associated with the sugarcane industry. In total, there were 172 participants in the workshops. These discussions identified the timing of the annual management calendar, key decision points, planting operation, harvest management, milling operations and marketing options, and the key climate-sensitive decision points.

1 Identifying climate-sensitive decision points in the sugarcane industry

The sugarcane industry consists of an integrated value chain including growing, harvesting and transport, milling, marketing and shipping sectors. Climate impacts across each of these sectors. The timing of when harvesting takes place can impact significantly across the whole value chain. In northern Australia, sugarcane harvest begins during the drier months of the year from May–June through to October–November, before the onset of the tropical wet season. A key climate-sensitive decision is for the harvesting season to start early enough so that all the sugarcane is harvested before the rainy season commences, but late enough to capitalise on the higher sugar content in the cane stalk, which forms the basis of industry payment. Advanced knowledge about the risk of extreme rainfall and other severe weather events during the harvest season can be very useful in supporting decisions about the order to which to harvest blocks, adjusting the start of milling operations and investment in harvesting equipment.

Forecasts need to provide cane growers with the confidence and capability to plan for an optimal start and season length to harvest and to maximise economic returns from sugarcane production. During the industry engagement, it was evident that the following weather and climate information would be useful to improve decision-making:

- Accuracy and lead-time of May-Nov rainfall
- Skill testing of GCMs at seasonal scale
- Testing of multi-year forecast systems
- Cyclone forecast systems
- Forecasts of unseasonal rain during the harvesting season
- Seasonal and multi-year forecasts, and
- Tools and support for making key economic and environmental decisions

The most important key decision point for the sugar industry is:

When to harvest?

Figure 11 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 SCFs.

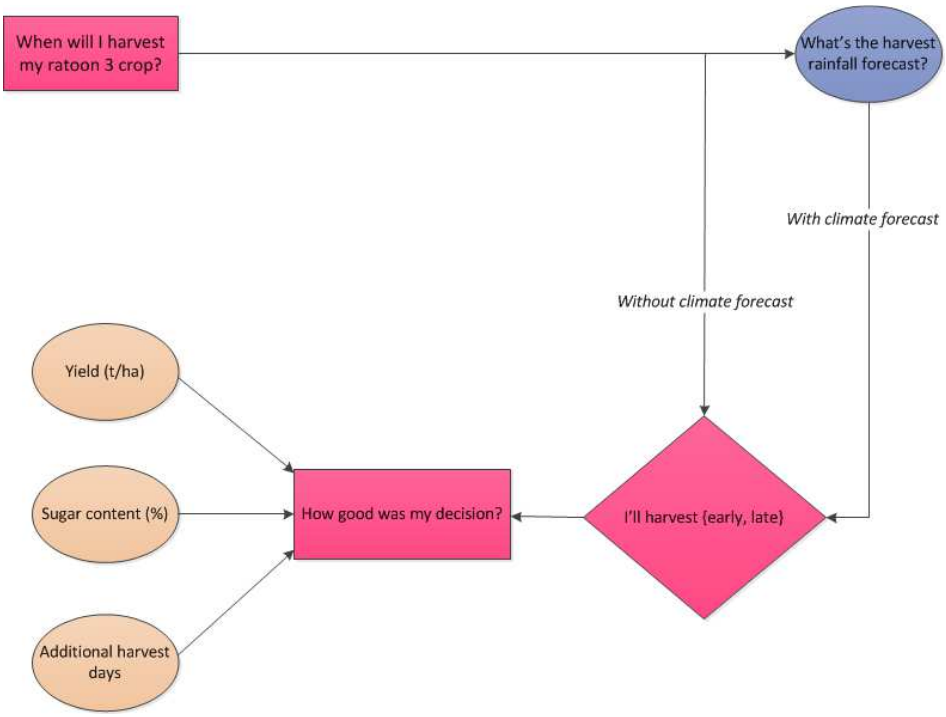

Figure 11 Decision pathway of when to harvest ratoon 3 sugarcane crop including an evaluation of the decision made

Appendix 2: Economic model

1 Overview of the modelling approach

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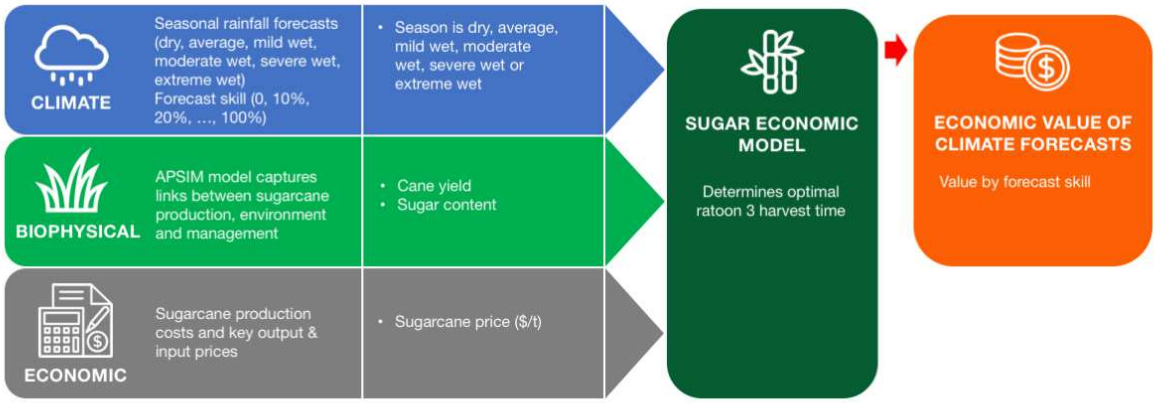

2 Economic model description

The economic model used key outputs from the *APSIM* production model to capture the links between climatic conditions and cane production. The economic model evaluated the changes in cane fresh weight and CCS for two harvest strategies (early or on time). This was achieved by applying a consistent set of prices and costs to the biophysical outputs, incorporating baseline information on sugar production costs and taking into consideration the costs of extra harvest days, where appropriate.

The profitability of the two harvest strategies was assessed under each forecast state (dry, average, mild wet, moderate wet, severe wet, extreme wet). The economic model maximises returns by choosing the harvest time that has the highest return weighted across the six climate states according to the prescribed forecast skill.

A two-stage discrete stochastic programming (DSP) model was developed for the sugar 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 (harvest early or on time), s is the state of nature (rainfall – dry, avg, mild wet, moderate wet, severe wet, extreme wet).) and $x_2\ (s, x_1)$ represents Stage 2 decisions (tonnes of sugar harvested). The 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 harvest strategy to maximise the expected level of return across climatic states. In algebraic terms, the main elements of the model are as follows.

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

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

subject to:

Land, labour and capital constraints

$$\sum_{j=}^{J} a_{\ ij} x_{\ j} + \sum_{n=}^{N} a_{2ns} x_{2ns} \leq b_i \quad \text{for all } i, s \qquad \text{[Equ 3]}$$

Use of crop outputs

$$\sum_{j=}^{J} a_{\ mjs} x_{\ j} + \sum_{n=}^{N} a_{2mns} x_{2ns} \leq 0 \quad \text{for all } m, s \qquad \text{[Equ 4]}$$

Where model parameters are:

π_s probability of state *s*

c_{1j} the costs of growing crop *j* in Stage 1 ($/ha)

a_{1ij} the quantity of resource *i* required by crop *j* in Stage 1 (units/ha)

a_{1mjs} the quantity of output *m* produced by crop *j* in state *s* (t/ha)

c_{2ns} the net revenue or cost from activity *n* in state *s* (crop price less yield dependent costs related to harvest, levies)

a_{2ins} the quantity of resource *i* required by activity *n* in state *s*

a_{2mns} the quantity of output *m* required by activity *n* in state *s* (tonnes)

b_i the availability of resource *i*

and the model variables are:

y_s the net return in state *s*

x_{1j} the area of crop *j* harvested either early or on time in Stage 1

x_{2ns} the level of activity *n* chosen in state *s* in Stage 2 (tonnes of sugar harvested and sold)

The objective function (Equ 1) maximises the expected net return from activities across six 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). The left-hand term of Equ 2 indicates a commitment of input costs (variable costs of growing sugar) based on the selection of Stage 1 activities (x_{1j}), while the right-hand term reflects state-contingent revenue derived from Stage 2 activities (x_{2ns}) (harvest and sale of sugar). The inputs committed through Stage 1 decisions are the same in every state of nature, while outputs 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. sugar price) were assumed to be independent of climatic

conditions. With a high proportion of Australian crop production sold into international markets, this was considered a reasonable assumption.

Constraints in the economic model are reflected in Equ 3 and Equ 4. Equ 3 constrains the choice of crops to available land, labour and capital as per conventional farm level linear programming models. In this application, the only constraint introduced in the model is the area of land available for sugar ratoon 3 (14 ha for our case study farm).

Linkages between decisions taken in Stage 1, and state-contingent outputs in Stage 2, are captured in Equ 4. For example, the commitment of inputs to maintain sugar ratoon 3 in Stage 1, combined with the intervening rainfall state, leads to a sugar output in state *s*, represented by a_{1mjs}. This output forms a resource that can be utilised by Stage 2 activities (x_{2ns}) which is simply an opportunity to harvest and sell sugar up to the amount physically produced. Importantly, in really adverse harvesting conditions it may be uneconomic to proceed with harvest because the cost of harvest may actually exceed the crop price on a per tonne basis. The model will not harvest in this instance and therefore avoids compounding losses.

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 crop decisions in each state. This is an important feature when considering the value of imperfect forecasts. Second, the modelling reflects the ability of farmers to consider state-contingent responses, something readily observed in practice. Third, with operational forecasts being probabilistic in nature, rational farmers will interpret probabilistic forecasts as a shift in the odds. This can be readily reflected in a DSP model through the assignment of posterior probabilities to each state based on forecast skill.

2.1 Valuing the forecast system

Without a climate forecast, dry and average states have an equal chance of occurrence of 0.3333. The wet state also has the same 0.33 overall chance of occurrence, but it is disaggregated here into the finer scale wet states which have a 0.0833 probability. The weighted or expected return (*E[Y]*) is simply the sum of economic returns in each state (Y_{dry}, Y_{avg}, $Y_{mildwet}$, $Y_{moderatewet}$, $Y_{severewet}$, $Y_{extremewet}$) multiplied by the probability of each state occurring (π_{dry}, π_{avg}, π_{wet}, $\pi_{mildwet}$, $\pi_{moderatewet}$, $\pi_{severewet}$, $\pi_{extremewet}$). The optimal harvest strategy 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 one of the finer scale wet season states results in more weight being given to that state in the objective function of the model. The change in weighting given to the forecasted state may lead to a change in the harvest decision, creating economic value from forecast use. 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 returns 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 5) and the hypothetical forecast system described elsewhere, the value of a specific forecast *f* within this system was defined as:

$$V_f = \sum_{s=}^{6} \pi_{s|f} y_{sf}^{*} - \sum_{s=}^{6} \pi_s y_{s0}^{*} \qquad \text{[Equ 5]}$$

where:

y^*_{sf} notes the net return in state *s* resulting from implementing the optimal harvest choice x^*_{sf} based on forecast *f*; and

y^*_{so} denotes net return in state *s* resulting from implementing the optimal harvest choice 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 without-forecast decision is the same). The estimated value of a particular forecast accounts for both the decisions made in Stage 1 and the state-contingent tactical adjustments made in Stage 2.

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 six possible forecasts can be defined as:

$$V_F = \sum_{f=}^{6} q_f V_f \qquad \text{[Equ 6]}$$

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 six rainfall states ($f = f_{dry}$, f_{avg}, $f_{mildwet}$, $f_{moderatewet}$, $f_{severewet}$, $f_{extremewet}$) and 11 skill levels (σ = 0, 10%, 20%, …,100%), the DSP model is solved 66 times in order to value the hypothetical forecast system.