



Department of
Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Southern grains case study



Published by the NSW Department of Primary Industries

Darbyshire R., Crean J., Anwar M. and Cashen M. (2018). Valuing seasonal climate forecasts in Australian agriculture: Southern grains case study. New South Wales Department of Primary Industries.

First published July 2018

More information

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Acknowledgments

This work was supported by funding from the Australian Government Department of Agriculture and Water Resources as part of its Rural R&D for Profit programme. Support from Birchip Cropping Group (BCG) and industry participation from Tim and Ian McClelland, Harm van Rees (Cropfacts), Hugh Keam and Deanne Ferrier and was greatly appreciated.

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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

The focus of this report is on the value of SCFs to the management of grains farms in the Grains Research and Development Corporation (GRDC) southern panel region. The key decision identified by industry was what winter crop mix to sow and to what area. Four crops were included in the analysis, canola, wheat, barley and field pea. Some constraints were placed on the area that could be sown to each crop to reflect rotational requirements. The timing of this decision was early April for a rainfall forecast for April to October. Rainfall over this period can have an important influence on crop production. A skilful seasonal climate forecast is potentially valuable if it helps farmers make a different winter cropping decision compared with the decision made based on historical average rainfall.

Methods

A probabilistic climate forecast system was adopted to assess the value of SCFs. Three discrete climate states (dry, average or wet) were identified based on the lower, middle and upper tercile of rainfall received at Birchip (April to October) over the period 1889 to 2015. Each year was classified as belonging to one of these climate states. Potential yield for each crop and for each of these climate states were calculated. These outputs were combined with crop production costs and built into an economic model to capture the links between climatic conditions and crop production. The economic model was used to select the most profitable cropping decision under a variety of scenarios.

A specific interest of this project was to understand how forecast and other important non-forecast decision variables interplay to influence forecast value. The use of a biophysical model allowed different amounts of soil moisture at sowing to be captured and outcomes to be explored in dry, average and wet climate states. Inclusion of crop price sensitivity helped to represent the decision-making context prior to the consideration of a climate forecast scenarios.

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

with 0% representing climatology (the historical average) and 100% skill reflecting a perfect forecast of the three climate states. Increasing forecast skill results in a higher probability of a particular climate state evolving, providing more certainty about future conditions.

Influence of non-forecast and forecast drivers on the cropping decision

Relative crop prices were found to have a strong influence on cropping decisions. When canola prices were high, with and without a forecast and across all tested stored soil moisture levels, canola was cropped in preference of wheat; when canola prices were low, wheat was sown in preference of canola.

Alternate crop decisions were selected based on forecasts of different climate states with medium canola prices. With a dry forecast, the cropping decision was to sow wheat under all stored soil moisture and price settings, while a wet forecast modified decisions to sow.

Value of forecasts

Forecasts of dry, average and wet climate states had different economic value. A climate forecast of average conditions was found to have no economic value under all decision settings. This is unsurprising as the without-forecast decision is based on long-term average rainfall over all years, which is normally close to conditions represented by average tercile rainfall. Dry forecasts were found to improve returns by up to \$20/ha for a single combination only (medium canola price and high stored soil moisture). The maximum value of a wet forecast improved returns by \$18/ha, with value only found for three of nine decision settings. Value was found when canola prices were medium, the median of the price data. This price setting is more likely to occur than the low or high prices tested (10th and 90th percentiles of the price data), therefore the forecast value found is also more likely to occur.

Improved forecast skill was naturally found to be positively related to forecast value, although the extent to which value related to incremental improvements was dependent on the decision environment settings.

Key findings

A general finding was that forecasts that led to decisions that run contrary to the direction of conditions provided the most value. For example, a wet forecast in combination with stored soil moisture 50% of plant available water capacity (PAWC) and medium canola price was valuable because it triggered a change from sowing wheat to canola. This finding has some parallels with observations of (Hirshleifer and Riley, 1992) that the 'news-worthiness' of information is a critical determinant of its value.

It is important to recognise that the decision investigated here represents only part of the risk grain growers manage. The case study necessarily only represented one site and one production system and other sites, systems and decisions may find different results. However, 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 grain growers more widely.

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Glossary of terms

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

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

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

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

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

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

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

1 Introduction

1.1 Background

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

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

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

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

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

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

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

Hansen (2002) provided a concise and application-oriented framework to assist in designing research for using SCFs in agricultural decision-making. In his assessment he identified that the value of SCFs lies in the intersection of climate predictability, system vulnerability and decision capacity. In considering this intersection, he noted five prerequisites for SCFs to provide value:

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

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

1.2 Project objectives

Given the estimated potential value of SCFs and the identified limitation of previous research in determining this value, a multi-agency project was funded by the Australian Government Department of Agriculture and Water Resources¹ with the aim to bridge the gap between seasonal climate forecasts and farm business decisions to improve productivity and profitability. The project had three aims:

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

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

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

1.3 Case study approach

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

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

This report contains findings of the southern grains 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 <http://www.agriculture.gov.au/ag-farm-food/innovation/rural-research-development-for-profit/approved-projects>

-
1. Identification of key decision points within the production system sensitive to SCF information.
 2. Biophysical modelling to represent the production system and the key decision point.
 3. Economic modelling to evaluate the value of SCF to the decision point within the described production system.

Industry consultation was undertaken to capture important features of the production system and identify key decision points. A consistent approach was applied to all case studies following Cashen and Darbyshire (2017). A small group of industry experts and practitioners was invited to describe the production system within which seasonal climate forecasts 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:

1. identify which decisions were potentially sensitive to SCF information
2. identify the key decision drivers including antecedent conditions (e.g. level of starting pasture) and SCF information
3. 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 seasonal climate forecasts across a range of production systems and decision environments. They were not designed to be statistically representative and so cannot provide scalable results to indicate total potential value to each industry. Agricultural systems are inherently dynamic and the approach taken here attempts to strike a balance between highly specific farm-level analyses with very limited wider applicability and coarser level, more general analyses which can miss important features of production systems that may influence results.

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

2 Southern grains production system

2.1 Industry overview

The value of Australian grains production was valued at \$12.5 billion in 2016/17 which represented 32% of the total Australian agriculture gross value (ABS, 2018). The range of crops and growing locations that combine to this significant value are diverse. Appreciating this diversity, the Grains Research and Development Corporation (GRDC) develop their priorities based on regional panels based on agroecological zone across northern, southern and western regions (Figure 1). Grains production in the southern region was the focus of this case study.

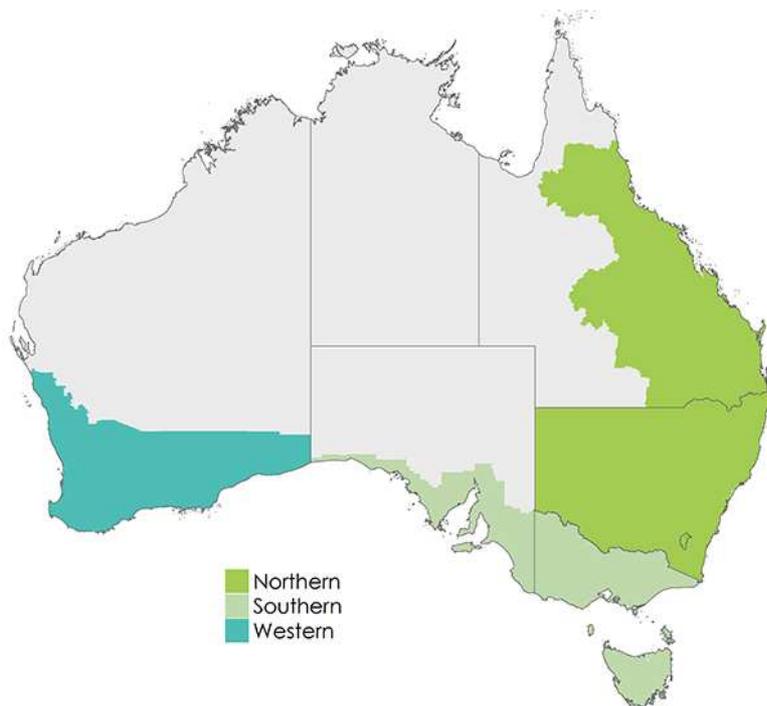


Figure 1 Regionalisation of GRDC research panels (ABARES, 2018)

The southern cropping region is characterised by a range of soils which are, in general, of low fertility (GRDC, 2018). Production systems typically focused on winter cropping, with many farms including both cropping and livestock (GRDC, 2018).

2.2 Description of production system and key decision point

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

The southern grains case study was focused on a winter cropping enterprise based in Birchip, Victoria (Figure 2). Through consultation, a typical farm in the region was described. This farm was a 5000-ha property with half the farm under a soil type suitable for cropping canola.

Cropping rotations were noted as important to follow with limited flexibility for deviation from rotational decisions. The typical rotation for the farm was:

canola – barley – wheat – pea

Key features of the cropping system in Birchip are shown in Figure 3.

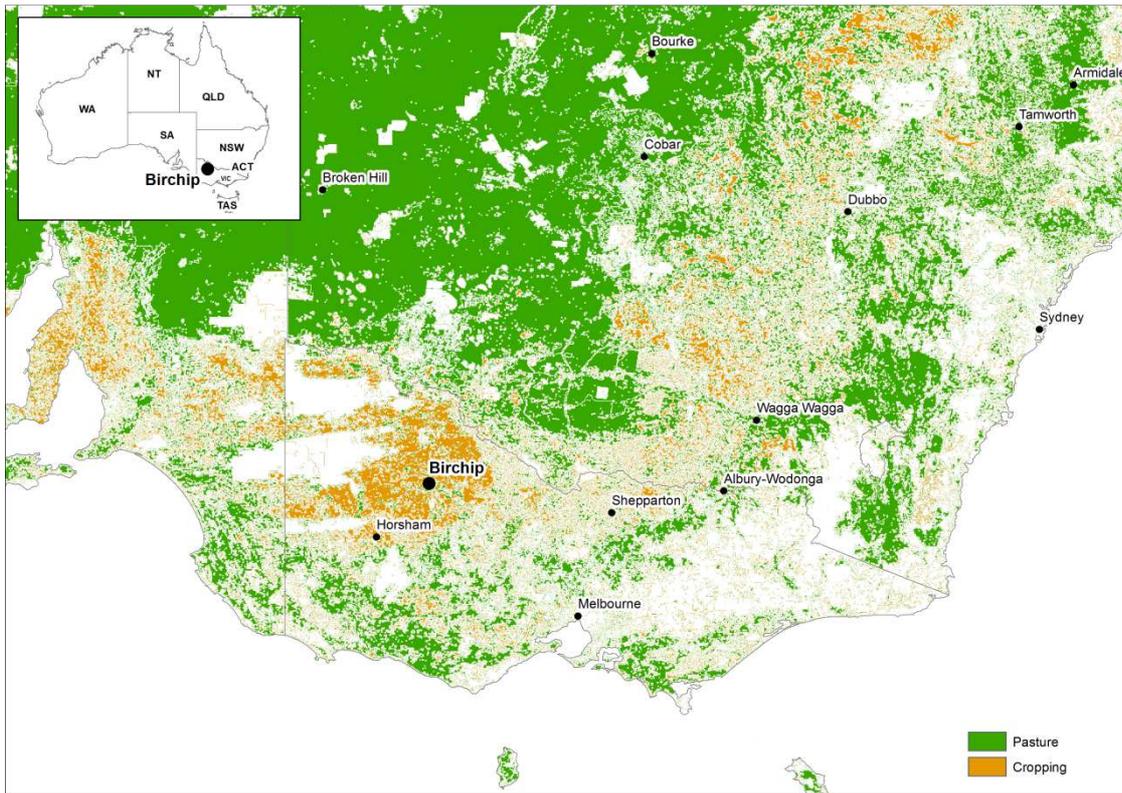
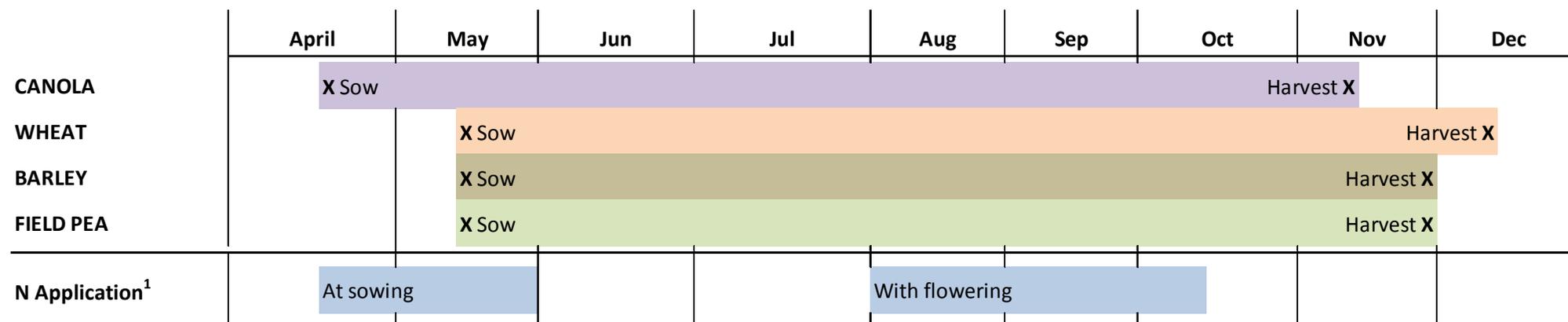


Figure 2 Map showing the location of Birchip, the case study site

Figure 3 Broad characteristics of the winter sowing decision for the southern grains case study



¹Nitrogen application in-season (rate and timing) will vary depending on crop, seasonal conditions and soil characteristics. Nitrogen maybe be applied several times on not at all.
 Note: These are estimated time of sowing and harvest, actual times will vary from season to season and with variety.

2.2.1 Decision point

The key decision point for this system was:

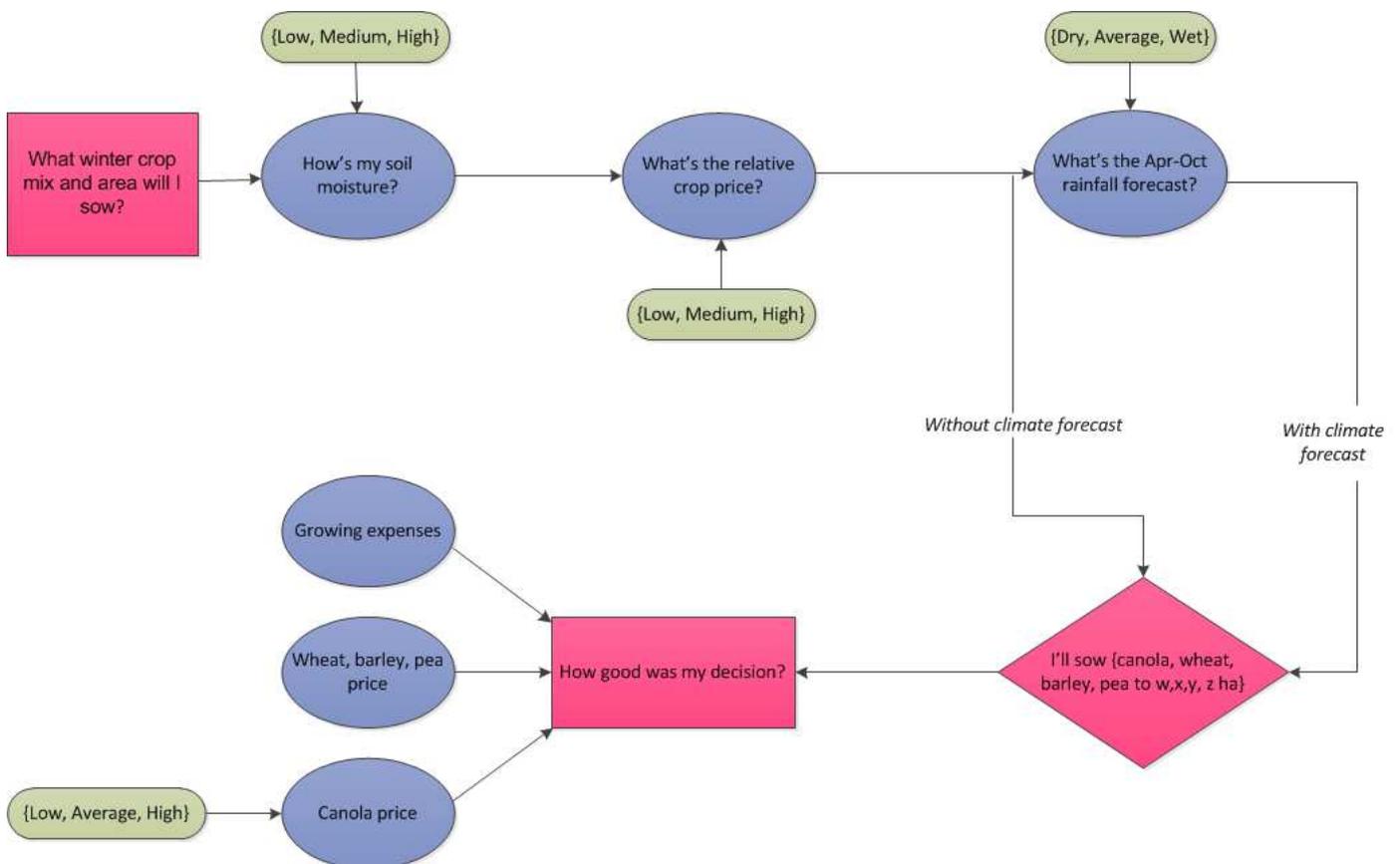
What winter crop mix and area will I sow?

The time of the decision was April and the options considered were canola, wheat, barley and field pea. In deciding between these options, four key decision drivers were identified:

1. Soil moisture at sowing: higher soil moisture levels are better suited to crops with higher moisture requirements, lower starting soil moisture favour crops with lower moisture requirements or fallowing.
2. Relative crop prices: an upward shift in relative price of one crop will favour sowing of that crop, a downward shift in relative price of one crop will favour sowing of an alternate crop.
3. Forecast of April to October rainfall: a wet outlook encourages sowing crops with higher in-crop moisture requirements, dry outlook encourages sowing crops with lower in-crop moisture requirements.

Note, this decision is subject to constraints due to rotational requirements.

Figure 4 illustrates this decision-making process, with an option to not include. 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.



2.3 Previous studies evaluating the value of SCFs to southern grain production systems

Many studies have investigated the potential value of SCFs in Australia's southern grains region. Across these studies, estimates of value of SCFs have centred on nitrogen application decisions, either at sowing, topdressing in the mid-season or both. Researchers have valued both operational and theoretical seasonal climate forecasts.

The value of the Southern Oscillation Index (SOI) phase based forecast system has been investigated by several researchers for value in nitrogen management decisions. McIntosh et al. (2007) considered the value of SOI phase forecasts in Birchip and estimated a value of between \$3 and \$65/ha. They also found that perfect knowledge of annual conditions (perfect weather forecast) provided a value of \$208/ha. Similarly, Wang et al. (2009a) evaluated the value of an SOI phase forecast at Wagga Wagga for nitrogen management decisions. They estimated value of between \$2 and \$34/ha for SOI phase forecasts and found value of \$54/ha for perfect climate forecast.

Wang et al. (2009b) assessed the value of a perfect forecast of climate conditions for 57 sites in the Murray–Darling Basin for nitrogen management decisions. They found value of \$26 to \$72/ha of a perfect forecast compared with decisions made according to climatology. Similarly, Yu et al. (2008) investigated nitrogen management for two sites in southern Australia. They found that, compared with nitrogen decisions based on climatology, inclusion of a perfect forecast of up-coming conditions had value of approximately \$65/ha for both sites. They noted that most value was found for forecasts of wet years at the drier site and dry years at the wetter site.

Several assessments of seasonal forecasts have valued the Bureau of Meteorology dynamic forecasts issued using the dynamic climate model, POAMA. Hayman et al. (2015) used POAMA to evaluate forecast value to fertiliser topdressing decisions. They obtained values between \$8/ha and \$23/ha at Hart, South Australia. In Western Australia, McIntosh et al. (2010) and Asseng et al. (2012) considered the value of the POAMA forecast for the amount of nitrogen applied at sowing. McIntosh et al. (2010) found the value of the forecast to growers to be \$60/ha while Asseng et al. (2012) found the value of the forecast to be up to \$50/ha.

3 Methods

The potential value of SCFs was evaluated through maximising returns of the system by selecting the optimal cropping decision 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, crop production costs, crop prices and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal cropping decision based on maximising returns.

3.1 Crop biophysical simulation model

The links between crop choice, climate conditions and yield were captured through biophysical modelling (French and Schultz, 1984; Sadras and Angus, 2006) (Equ 1).

Yield Potential = (Stored Soil Water + Growing Season Rainfall – Evaporation Coefficient) * water-use efficiency

$$\text{Crop yield potential} = (\text{SSW} + \text{GSR} - \text{EC}) * \text{WUE} \quad [\text{Equ 1}]$$

Where SSW is stored soil water, GSR is growing season rainfall, EC is evaporation coefficient, WUE is water-use efficiency. Evaporation coefficient and water-use efficiency are detailed in Table 1. Canola and wheat values were set according to (Sadras and Angus, 2006). It was assumed that barley WUE was the same as wheat and field pea WUE was 1.5 times canola (Sadras and McDonald, 2012).

Growing season rainfall was summed April to October rainfall using data from SILO (Jeffrey et al., 2001). The plant available water capacity (PAWC) from APSOIL No499-Generic² was 122 mm and this used to test various values of stored soil water. Four stored soil moisture levels were determined by calculating the 25th, 50th, 75th and 100th percentile of PAWC (122 mm).

Subsequently to calculating crop yield potential, nitrogen required to meet these yield values was calculated (Equ 2) (BCG and CSIRO, 2018):

$$\text{Nitrogen applied} = Y * \text{NUE} - \text{stN} - (0.15 * \text{OC} * \text{GSR}) \quad [\text{Equ 2}]$$

² <http://www.apsim.info/Products/APSoil.aspx>

Where Y is crop potential yield (Equ 1), NUE is nitrogen-use efficiency, stN is stored soil nitrogen, OC is soil organic content and GSR is growing season rainfall. Soil organic content was set to 1.8%, stored soil nitrogen to 50 kg/ha (Wallace et al., 2017) and crop nitrogen use efficiency varied (Table 1).

Table 1 Evaporation coefficient (EC) and water-use efficiency (WUE) (Sadras and Angus, 2006) and nitrogen-use efficiency (NUE) (BCG and CSIRO, 2018)

Crop	EC (mm)	WUE (%)	NUE (%)
Canola	60	10	80
Wheat	60	20	40
Barley	60	20	35
Field pea	60	15	0

3.2 Crop production costs

Crop production costs for winter cropping options in this study were based on the Southern Zone West (Appendix 2: Gross margin values) for the 2012 season. The budgets were sourced from NSW DPI³ and checked with Birchip Cropping Group for their relevance to the case study site. Some minor adjustments were made to the canola budget. Crop production costs were converted into 2014–15 dollars using the Consumer Price Index reported in ABARES (2017).

The budgets provide detailed information on management practices and input costs associated with sowing, managing crop nutrition, pests, weeds and disease throughout the growing season, and harvesting. These budgets were used as a basis to determine area- and yield-based costs which are combined with the crop simulation data to determine annual cropping returns.

3.3 Key output and input prices

Canola, wheat, barley and field pea prices were based on historical monthly crop prices over the 10-year period of 2005–06 to 2014–15 and were sourced from *The Land* newspaper via ABARES. Historical prices for all crops were converted from nominal to real values and expressed in 2014–15 dollars using the Consumer Price Index reported in ABARES (2017).

Prices for all crops were set to their median value (50th percentile) and were assumed to be known at the time of sowing (Table 2). The analysis assumes that median prices are a reasonable basis for planning, keeping the emphasis on the use of forecasts to manage production variability.

With crop prices identified as an important decision driver (Appendix 1: Industry engagement), a sensitivity analysis was undertaken on shifts in relative prices. The canola price was deemed to be of key influence, so low (10th percentile) and high (90th percentile) canola price scenarios were also assessed. Based on the 2005–06 to 2014–15 period, the 10th and 90th percentile values equated to canola prices of \$431/t and \$638/t, respectively, while the other crop prices were fixed at their median values shown in Table 2. The price of urea was set to \$560/t following nitrogen costs supplied in the gross margins used in the analysis (Appendix 2: Gross margin values).

Table 2 Crop prices used in economic analyses representing the median (50th percentile) of the price data

	Price
Canola (/t)	\$520
Wheat (/t)	\$261
Barley (/t)	\$235
Field pea (/t)	\$334

³ <https://www.dpi.nsw.gov.au/agriculture/budgets>

3.4 Seasonal climate forecasts

A probabilistic climate forecast system, in line with currently used operational forecast systems, was adopted to assess the value of SCFs. Three discrete climate states (dry, average, wet) were identified based on the lower, middle and upper tercile of April–October rainfall received at Birchip over the period 1889 to 2015. Each year was then classified as belonging to one of these climate states: dry was categorised by rainfall less than 210 mm, average as rainfall between 210 mm and 291 mm, and wet as rainfall in excess of 291 mm (Figure 6).

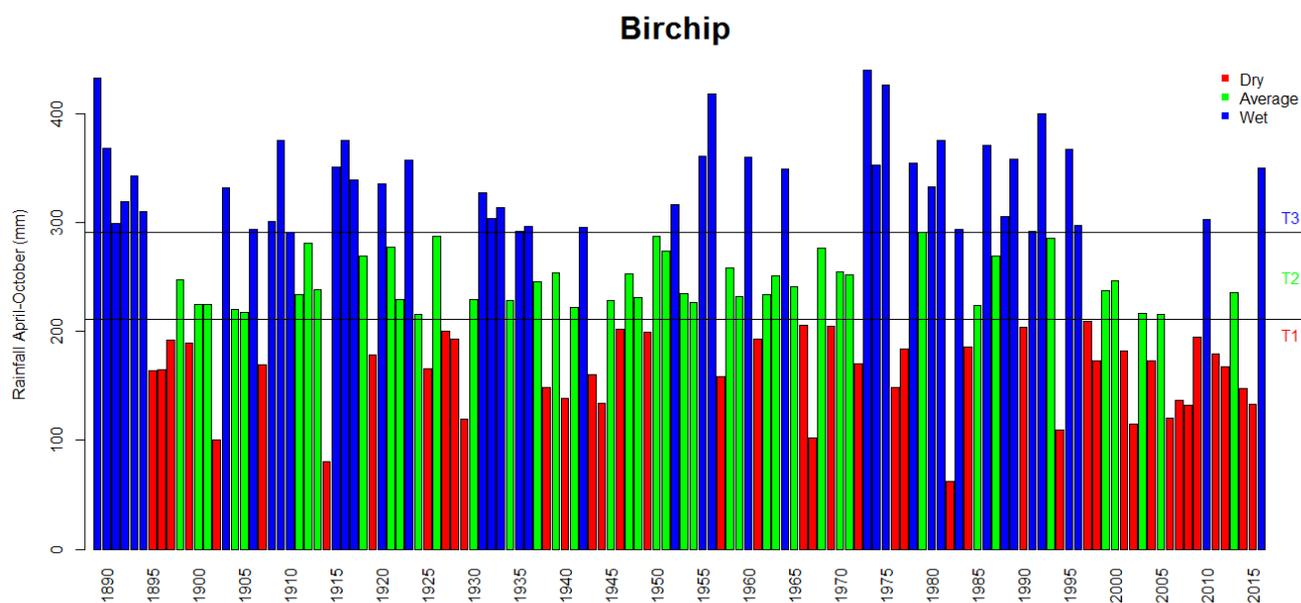


Figure 6 Total rainfall for April through October at Birchip for 1889–2015 sourced from SILO (Jeffrey et al., 2001). Dry, Average and Wet represent terciles 1, 2 and 3.

Agricultural production levels representing dry, average and wet climate states were obtained by classifying yearly outputs (1889 to 2015) of crop yields and fertiliser use (section 3.1). Resulting yearly data for each state (42 years) were then averaged to represent each climate state within the economic model. Variations in production across climate states provide the necessary, but not sufficient, conditions for forecasts to offer value in decision-making.

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

In this study, 11 probabilistic forecasts were created for each of the three climate states (dry, average, wet) each representing a different level of forecast skill (0 to 100%). These probabilistic forecasts are incorporated into the economic model by assigning a probability to the occurrence of each climate state based on forecast skill. The definition for forecast skill with reference to prior (without forecast) and posterior (with forecast) probabilities was as defined in Equ 3.

$$\sigma = \frac{\pi_S | f - \pi_S}{1.0 - \pi_S}$$

[Equ 3]

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

Forecast skill σ is set at pre-determined levels and is rearranged to provide posterior probabilities (Equ 4).

$$\pi_{s|f} = \sigma(1.0 - \pi_s) + \pi_s \quad [\text{Equ 4}]$$

Applying this equation to a forecast of a dry state with an assumed skill of 20% results in a weighting assigned to dry, average and wet states (Equ 5).

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

$$\text{Avg} = \text{Wet} = \frac{(1.00 - \pi_{dry|f})}{2} = \frac{(1.00 - 0.47)}{2} = 0.27 \quad [\text{Equ 5}]$$

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

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

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

3.5 Economic model

3.5.1 Overview

The economic model used key outputs from biophysical modelling to capture the links between climatic conditions and crop production. Combining these outputs with information on crop production costs and key output prices (crop prices) allows net returns to be estimated for each cropping option (i.e. wheat, canola, barley and field pea). The economic model evaluates the relative returns offered by each cropping option under dry, average and wet climate states and under varying levels of starting soil moisture at the start of the season.

The profitability of each cropping option was assessed under each forecast state (dry, average, wet). The economic model maximises returns by choosing the option that has the highest return weighted across the three climate states according to the prescribed forecast skill. The economic model takes the form of a discrete stochastic programming (DSP) problem which can be solved through adapting a conventional linear programming model and is represented in Equ 6 and 7.

$$\text{Max } E[Y] = \sum_{s=1}^S \pi_s y_s \quad [\text{Equ 6}]$$

$$y_s = \sum_{j=1}^J c_{1j} x_{1j} + \sum_{n=1}^N c_{2ns} x_{2ns} \quad [\text{Equ 7}]$$

In Equ 6, π_s is the probability of state s and y_s is the net return in state s .

The left-hand term of Equ 7 represents the total costs of growing selected crops. This is reflected in c_{1j} which is the per hectare cost of growing crop j and x_{1j} which is the area of crop j sown.

The right-hand term of Equ 7 is the net revenue realised from growing selected crops in each state. This is reflected in c_{2ns} the net revenue from activity n in state s (crop price less yield dependent costs related to harvest, levies and freight) and x_{2ns} which is the level of activity n chosen in state s in stage 2 (tonnes of grain harvested and sold). Structuring the model in this way reflects practical decisions to be made about harvesting and sale of crops, an important issue in dry years when yields can be very low.

Constraints on resources like available land, labour and capital can also be introduced as per conventional farm level linear programming models. In this application, labour and capital are not represented but constraints are introduced in the model to reflect the availability of cropping land (50% of total area – 2500 ha) and rotational constraints. To ensure that responses to climate forecasts are kept within rotational limits, the area of land allocated to field pea is fixed at 25% of the available crop area (625 ha), barley is allowed to vary between 15% and 25% (375–625 ha), while wheat and canola can be grown on the remaining 60% (1500 ha).

3.5.2 Rotational effects

Representing the relative profitability of cropping options under varying climatic conditions is a key focus of the economic modelling. An important consideration within this is to capture rotational effects given that break crops (e.g. canola and field pea) are well recognised for improving the returns of subsequent cereal crops (e.g. wheat and barley). Rotational benefits come in the form of disease control, nitrogen nutrition and soil water. In southern Australia, although much of the rotational benefit of break crops is attributed to the control of take-all disease in cereal crops (Kirkegaard et al., 1994; Kollmorgan et al., 1983) there are varying drivers and interactions that determine the benefits offered by break crops.

A large body of international literature supports substantial gains from break crops. Angus et al. (2015) undertook a comprehensive review of the extent of wheat yield increases related to break crops, drawing on more than 900 studies. Against the mean global wheat yield of 3.3 t/ha, the average wheat reported yield increase of 0.7 t/ha equated to a 21% gain from break crops. This followed an earlier study by Kirkegaard et al. (2008) who found similar effects with break crops improving mean cereal yields by up to 20% and more.

Australian-based studies also confirm important benefits from break crops. Particularly relevant to this case study are the findings of (Harris et al., 2002) who assessed the rotational benefits of break crops in Victoria and found that wheat yield increased by 12% after canola. Kirkegaard et al. (2014) assessed the productivity of Australian mixed farming systems and looked at trends and issues influencing cropping rotations. They provided a comparison of the profitability of various cropping options in southern Australia and assumed that, on average, wheat after all break crops provides a 0.4 t/ha yield gain (12.5% as a proportion of the stated average yield of 3.2 t/ha).

Rotational effects were addressed in the modelling for this case study in two ways. First, the area of field pea planted each year was fixed in the model at 25% of the total crop area as a core element of the rotation based on technical advice from Birchip Cropping. Second, canola was assumed to provide a benefit to winter cereals whenever it was selected. We attributed half of the 12.5% break crop benefit assumed by Kirkegaard et al. (2014) to canola, with the remaining half attributed to field pea which was already in the long-term crop mix.

3.5.3 Assessing a climate forecast

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

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

higher probability to a dry state, so the outcomes of a dry state are given more weight in the objective function of the model (see Table 3 for example). The change in weighting given to a dry state may lead to a change in the cropping decision and this creates economic value from forecast use.

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.

Greater information of the form of the economic model is contained in Appendix 3: Economic model.

3.6 Analyses

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

SCF value was assessed for several different decision settings (initial soil moisture, relative canola price) and for 11 levels of forecast skill for each of the three climate forecasts (dry, average, wet). This produced 396 results representing various decision environment settings, forecasts and forecast skill levels (Table 4).

Table 4 Variables and value levels assessed to evaluate forecast value

Variable	Values tested
Stored soil moisture	25 th , 50 th , 75 th , 100 th percentile
Relative canola crop price	low, medium, high
Forecast state	dry, average, wet
Forecast skill (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

Initially, the without-forecast (0% skill) cropping decision was reported for all variable values (initial soil moisture and relative canola price). Subsequently, the perfect-forecast (100% skill) cropping decision for the three forecast states was similarly reported. The potential value (\$/ha) of the perfect forecast was calculated as the difference between the with-forecast and without-forecast returns. This represents largest potential value of climate forecasts for each climate state. Finally, probabilistic forecast value (\$/ha) relative to the without-forecast decision were calculated for all decision environment settings.

4 Results

4.1 Biophysical modelling

Average crop yields were calculated for the three climate states (dry, average and wet) for 1889–2015 for each stored soil moisture level (Figure 7). Yield increases with stored soil moisture for all crops. Clear differences in yield according to climate state were seen for all crops, with lower yields in the dry climate state followed by average and wet states.

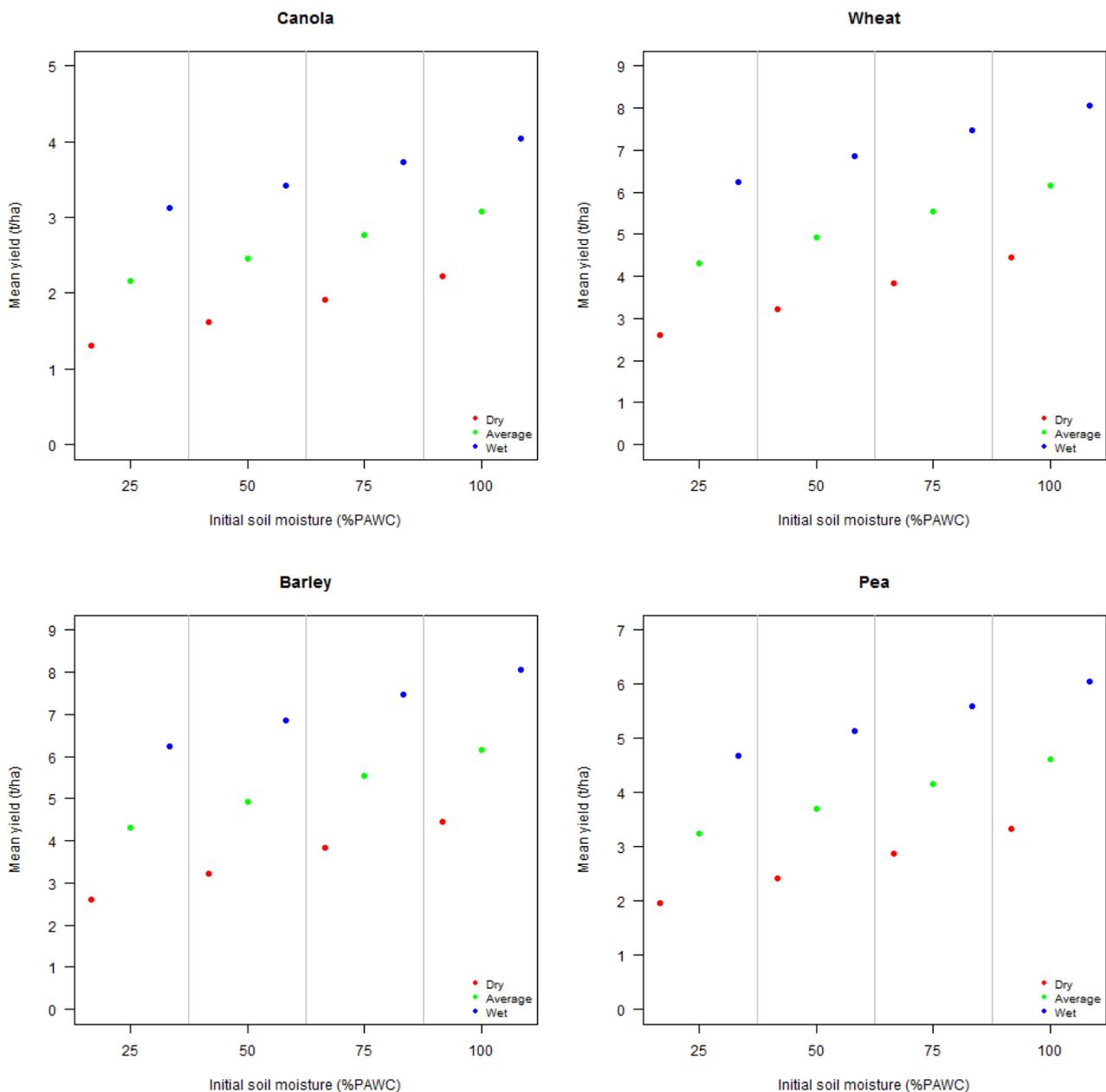


Figure 7 Average yields for each of the crops being assessed when sown at various stored soil moisture levels. The colours indicate the different tercile allocations of the historical data (1889–2015) with red for dry (lower tercile), green for average (middle tercile) and blue for wet (upper tercile). Climate states are for total rainfall April–October.

4.2 Economic analyses

4.2.1 Without-forecast decision

The optimal cropping decision without a forecast (0% skill) must be determined prior to calculating the potential value of SCFs. Figure 8 shows the optimal without-forecast cropping decision for each combination of the decision drivers (Table 4), noting that field pea area was fixed to 25% (not shown) under all scenarios. The relative price of canola was important in determining the cropping mix. If canola prices were high (90th percentile), canola was cropped to 60% of the area, 15% to barley and no wheat was planted for all stored soil moisture levels. If canola prices were low (10th percentile), the decision was to plant 60% of the area to wheat, 15% to barley and no canola across all stored soil moisture values. With medium canola prices, wheat was predominately sown, unless stored soil moisture was 100% of PAWC.

Cropping Decision Without Forecast

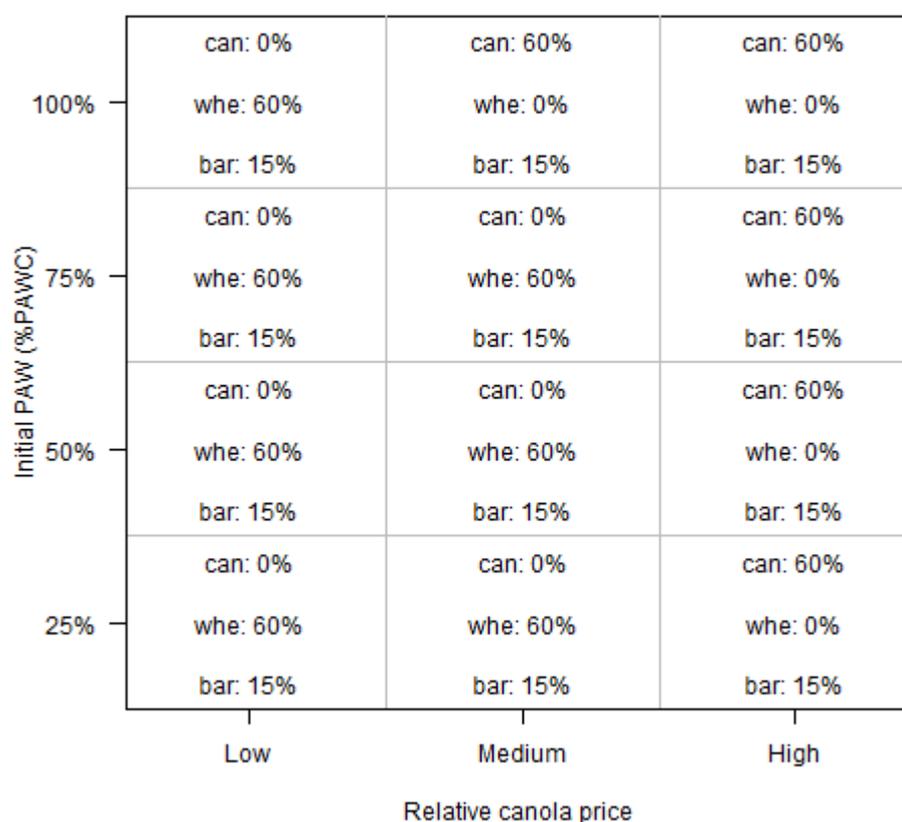


Figure 8 Optimal without forecast winter decision. Stored soil moisture is represented in the four rows and relative canola price (low, medium, high) is represented in the columns. Crop area is reported as a percentage of 2500 ha. can, whe and bar represent canola, wheat and barley, respectively. 25% of the crop area was set to field pea.

4.2.2 Perfect-forecast decision

The optimal cropping decisions for perfect forecasts of dry, average and wet climate states (100% skill) were evaluated for each combination of the decision drivers (Figure 9). For a dry climate state, the optimal decision was the same as the without-forecast decision, except when canola prices were medium and stored soil moisture was 100% of PAWC. Under this scenario, the area sown to canola (60%) was sown to wheat. For a wet climate state, the optimal decision changed when canola prices were medium. Under this price setting, canola was sown instead of wheat. For an average climate state, the optimal cropping decision was the same as the without-forecast choice for all relative price and stored soil moisture settings.

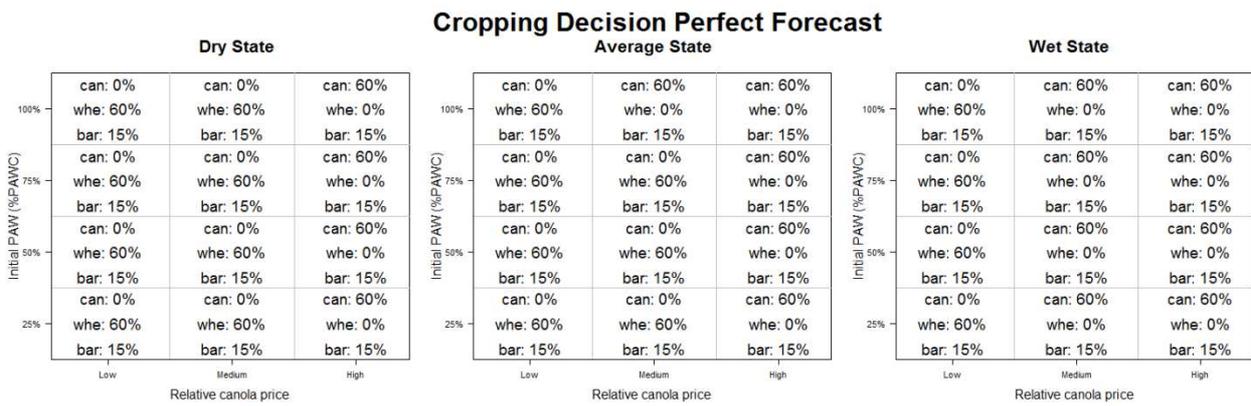


Figure 9 Optimal without-forecast winter cropping decision. The boxes contain the results for perfect forecasts of each climate state. Stored soil water is represented in the four internal rows and relative canola price (low, medium, high) is represented in the internal columns. Crop area is reported as a percentage of 2500 ha. can, whe and bar represent canola, wheat and barley, respectively. Note 25% of the crop area was set to field pea.

4.2.3 Perfect-forecast value

The range in the value of a perfect forecast (100% skilful) across the three climate states was \$0 to \$20/ha. The results highlighted the importance of the decision driver settings (Figure 10). Price was the major determinant of forecast value, more so than stored soil moisture conditions.

The results for a dry forecast show that only one combination of the decision drivers led to forecast value (\$20/ha). This value was obtained through changing from sowing canola to wheat. Value was found more often for a wet forecast, with three of the 12 decision settings yielding value. Forecast value was only obtained when canola prices were medium. Under these conditions, the area cropped shifted to wheat from canola.

No value was found for an average forecast as the planting decision did not change from the without-forecast decision.

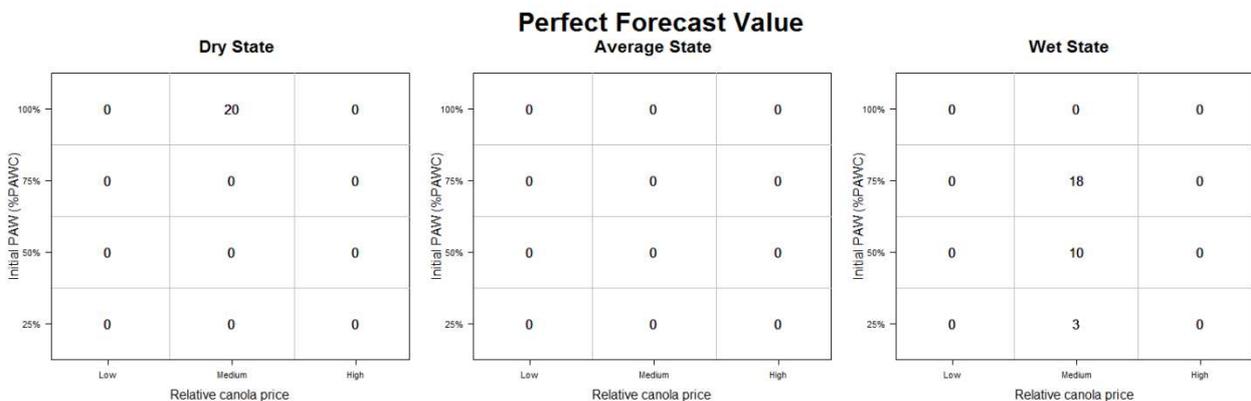


Figure 10 Perfect-forecast value (\$/ha). Dry, average and wet states in the three boxes, stored soil water is represented in the four internal rows are represented and relative canola price (low, medium, high) is represented in the internal columns.

4.2.4 Imperfect-forecast value

Forecast value differed with forecast skill for the decision driver combination settings for which value was found (Figure 11). These plots provide greater detail of the results in Figure 10, illustrating the value of forecasts with various skill levels. Forecast value increased as forecast skill increased (Figure 11). The lack of value when canola prices were low or high is clear in this figure. The minimum skill required to yield value ranged from 20% to 60%.

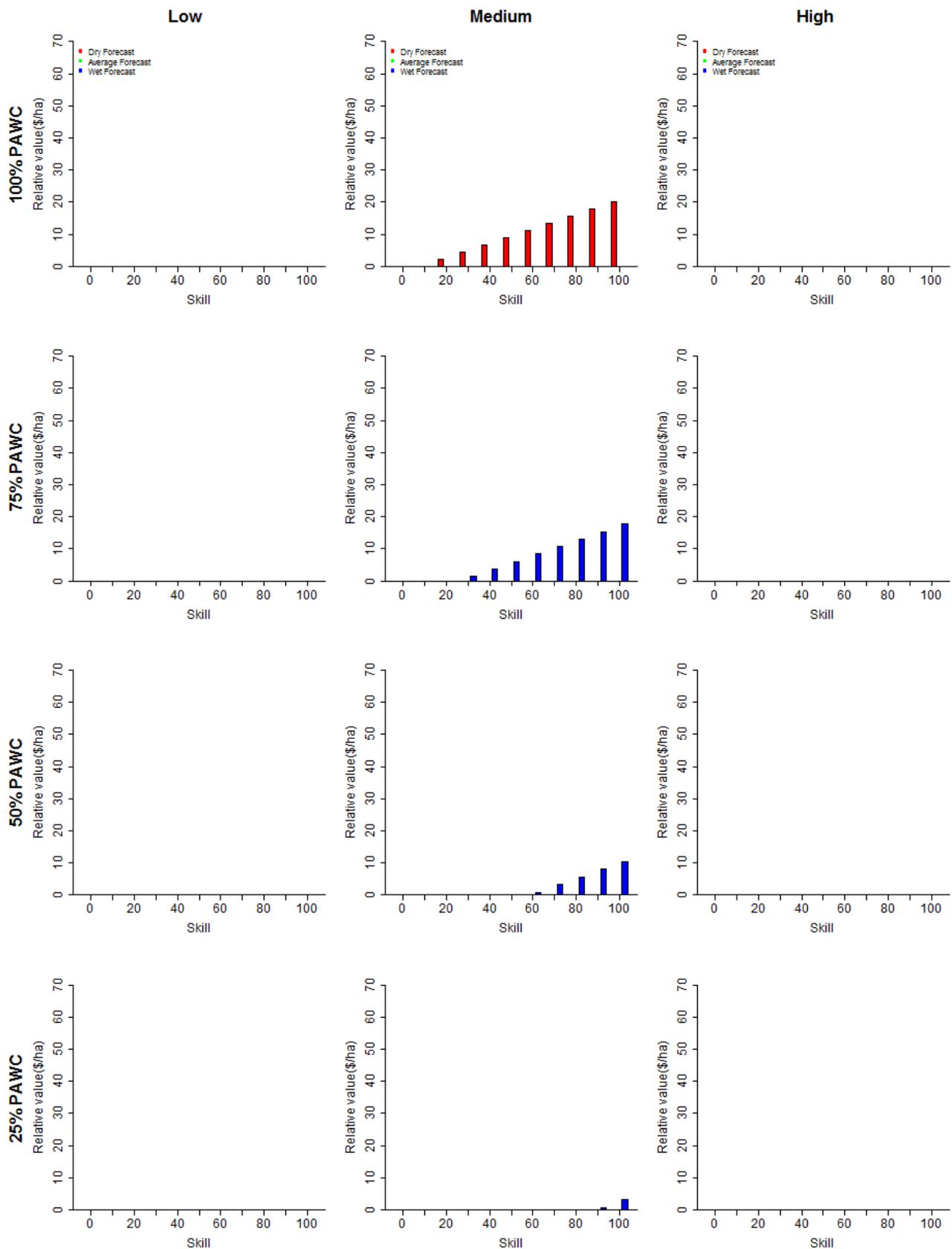


Figure 11 Imperfect-forecast value (\$/ha). Stored soil water is represented in the four rows and relative canola price (low, medium, high) is represented in the columns. Skill (%) is represented on the x-axis as calculated in Table 3.

5 Discussion

The key production decision sensitive to SCFs identified by industry was choosing the winter crop mix. The decision was constrained by practical rotational requirements, reflected in the modelling by imposing area-based constraints. Of the available crop area, 25% was fixed to field pea, between 15% and 25% to barley and the remaining area was available for wheat and/or canola. Using these constraints, the decision model assessed the performance of the crops under different decision settings.

5.1 Cropping decision made without seasonal climate forecasts

The relative crop price (in this case, canola price was varied) had the largest influence on the cropping decision in the absence of a forecast. If canola price was low, the decision across all stored soil moisture settings was to crop 60% of the area to wheat, 15% to barley, 25% to field pea and no canola (Figure 8). Conversely, if canola prices were high, the cropping decision was to sow canola in preference of wheat. For medium canola prices, 60% of the area was cropped to wheat if stored soil moisture was 25–75% PAWC, while canola was selected at 100% PAWC.

5.2 Cropping decision made with seasonal climate forecasts

A climate forecast of an average climate state was found to be of no economic value for all decision settings. The lack of value of an average forecast state is a reflection of the limited change in climate conditions compared to the without the forecast decision, which is based on climatology. As climatology is the mean of the climate, the limited and small forecast value of a forecast of the average forecast state (middle tercile of climate data) is unsurprising.

Inclusion of perfect (100% skilful) forecasts of dry and wet climate states led to different crop choices to the without-forecast choice for a few of the decision settings. A perfect wet forecast was found to have a value between \$0 and \$18/ha. This value was only obtained when canola prices were medium. Under these circumstances, the decision was to crop canola with no area sown to wheat for all stored soil moisture levels. A perfect dry forecast was found to have a value from \$0 to \$20/ha. A single combination of decision drivers (medium canola price and stored soil moisture of 100% of PAWC) led to forecast value as a result of exchanging sowing canola for wheat.

The above discussion highlights the maximum possible value of SCFs under different scenarios through a perfect or 100% skilful forecast. However, in reality SCFs are imperfect and different levels of skill were analysed to assess the value of improvements. To realise value in a SCF, forecast skill needed to be at least 20% (Figure 11).

5.3 Comparison to previous findings

The majority of previous research valuing SCFs to southern cropping systems has focused on nitrogen application decisions, predominately for wheat and often using operational forecasts. These studies have found a wide range in value. For example, McIntosh et al. (2007) found value of \$208/ha for a perfect weather forecast while Wang et al. (2009b) found value of a perfect forecast of up to \$72/ha. The decision evaluated here centred on crop choice and crop area, constrained by rotational effects. The maximum value of a perfect climate forecast was \$20/ha. The value found was much lower than McIntosh et al. (2007) but comparable to other studies of the value of SCFs to nutrient management decisions (Asseng et al., 2012; Wang et al., 2009a; Wang et al., 2009b).

A study investigating the opportunistic inclusion of canola based on different rainfall years (Sadras et al., 2003), without evaluating the value of a forecast system, does provide a comparison to this analysis. They compared two planting strategies, a conservative strategy with no canola in the mix and a risky strategy with 20% of the crop area allocated to canola. They found that the risky strategy was more profitable in wet years and maintaining the conservative strategy in dry years was the best option. The results found in this study are consistent with their conclusions.

5.4 Limitations and assumptions

The analyses showed that forecast value was found to be sensitive to a range of parameters important to the relative profitability of wheat and canola. A significant shift in canola prices (using the 10th or 90th percentile price) for example clearly resulted in a large shift in land use (interchanging wheat and canola). Different settings of relative crop prices provided a different baseline of land use which could then be either more or less responsive to forecast information. Similarly, changes in the relative productivity of cropping options through different assumptions of water efficiencies (i.e. 20 kg/mm for wheat and 10 kg/mm for canola), would also affect the relative profitability of wheat and canola. These changes could influence optimal crop choices with and without a climate forecast and ultimately change forecast value. The same comment applies to other settings, including soil moisture. For example, higher water holding soils may lead to canola being selected as the optimum crop under a greater range of canola prices and potentially climate states. Equally, soils with low water holding capacity would select wheat more often across relative price and climate states.

During the industry consultation process, receiving sowing rains prior to sowing canola was identified as an additional decision setting to determine the cropping decision. Analysis of historical likelihood of receiving sowing rains, defined as 10 mm rainfall during the week centred on 15 April, was conducted. With results of the analysis showing that sowing rains was only received in 18% of years (1889–2015), a separate analysis of forecast value was not undertaken. Notwithstanding, receiving sowing rains would likely influence the establishment of canola and inclusion of this variable into analyses may exert some influence on the value of forecasts.

This case was study designed using particular parameter settings within both the yield and economic models. Potential yield was estimated from French and Schultz (1984), an approach that has been used widely to investigate cropping systems in Australia (Hoogmoed et al., 2018; Sadras and McDonald, 2012; Sadras et al., 2003; Sadras and Angus, 2006). The potential yield model does not include the influence of the timing of rain within the growing season or other climate variables (e.g. temperature, solar radiation). Nevertheless, the approach has broad industry acceptance in the Birchip region through Yield Prophet^{®4} and was chosen here in preference to alternative crop modelling systems like *APSIM* (Holzworth et al., 2014) that require greater parameterisation, particularly for non-cereal crops including canola and field pea. These modelling settings and farm characteristics will vary between individual farms, with this case study providing an example of the potential value of SCFs rather than a comprehensive assessment for all possible enterprise arrangements.

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

Like operational forecasts, the theoretical forecasts used in this analysis provided an indication of the likely climate state (dry, average or wet) not the precise evolution of weather conditions. The value of a higher resolution forecast, such as a decile forecast, may be greater. This sets a challenge to the forecasting community. For instance, the Bureau of Meteorology currently operates on a two-state climate forecast (above or below median). Current percent consistent values for the Birchip region for April to June rainfall is 50–55%, equating to a skill score used here of 0–10%.

⁴ Yield Prophet[®] is an on-line crop production model designed to present grain growers and consultants with real-time information about their crops, providing integrated production risk advice and monitoring decision support relevant to farm management.

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Appendix 1: Industry engagement

Valuing the Forecast: Southern Grains Workshop

18 October 2016

BCG, Birchip, Victoria

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Overview

As part of the project 'Improved Use of Seasonal Forecasting to Increase Farmer Profitability', a case study approach is being used to assess the potential value of seasonal climate forecasts when incorporated into key farm management decisions. Within the grains industry a southern, northern and western case study will be evaluated based on the current GRDC boundaries (<https://grdc.com.au/About-Us/GRDC-Regional-Panels>). This workshop was held to explore the southern grains case study.

Representative farm

Discussions were centred on a representative operation based in Marlbed with a farm size of 5000 ha with 70% equity available. Three predominant soil types are present: 20% sandy loam, 50% JilJil (good), 30% JilJil (bad). Canola is only cropped on sandy loams within a wheat, barley, pea, canola rotation.

Decision points

Two decision points which may be sensitive to seasonal climate information were identified:

1. Decisions around the planting of and subsequent area of canola
2. In-season nitrogen application on winter cropping program

Of these two decisions, those around canola were selected for full biophysical and economic modelling. This decision was made as substantial effort has already been directed into assisting farmers with topdressing applications with good applied tools currently available (YieldProphetLITE).

Canola

The decision is:

“Will I sow canola and if so, how much?”

This could include nil and an expansion of area within the limits of paddock rotational history. If canola is not sown, or a smaller area is sown, a cereal can be sown instead (mid-season variety).

Forecast time for decision = beginning of April

Forecast = rainfall (April, May, Jun, Jul, Aug, Sep, Oct, Nov)

Key decision drivers:

1. Starting soil moisture
2. Sowing rains
3. Seasonal forecast

Through discussion the following decision matrix was completed.

Interpolated	Sowing rain	Soil moisture	Climate forecast	Decision	Comment
	Yes	Med	Equal chance	sow planned area	
	No	Med	Equal chance	Don't sow	
	Yes	Low	Dry	Don't sow	
*	Yes	Low	Equal chance	smaller area (~1 paddock)	
	Yes	Low	Wet	smaller area (~1 paddock), or sow planned	maybe more if price was high would sway
	Yes	High	Dry	smaller area (~1 paddock), or sow planned	maybe more if price was high would sway
*	Yes	High	Equal chance	sow planned area	
	Yes	High	Wet	sow additional area	especially if prices were good
*	No	Low	Dry	Don't sow	
	No	Low	Equal chance	Don't sow	
*	No	Low	Wet	Don't sow	
*	No	High	Dry	Don't sow/ sow smaller amount	maybe more if price was high would sway
*	No	High	Equal chance	Don't sow/ sow smaller amount	maybe more if price was high would sway
	No	High	Wet	Don't sow/ sow smaller amount	maybe more if price was high would sway

Key assumptions:

Starting soil moisture; low = <10 mm; medium = 50 mm; high = >50 mm

Sowing rains defined as 10 mm within 3 days

Area sown:

- Planned area sown = 25% of 'good' soils (625 ha) for any one year
- Smaller area sown = 375 ha
- Additional area sown = 875 ha

Price of canola does not generally have a major impact on decisions (there will be individual exceptions and exceptional high prices may have some sway).

Nitrogen application

Information from this decision point will not be subjected to biophysical and economical modelling. However, skill testing of various forecasting models will be investigated for this decision point.

“How much N will I spread?”

Forecast time for decision = beginning of July

Forecast = rainfall (Jul, Aug, Sep, Oct, Nov)

Key decision drivers:

1. Cash flow
2. Current soil N
3. Current soil moisture
4. Seasonal forecast

Through discussion the following decision matrix was defined. Note this will not form part of the case study.

Interpolated	Cash Flow	Soil N	Soil Moisture	Climate Forecast	Application decision
	High	Med	Med	Equal Chance	L
	Low	Med	Med	Equal Chance	L
*	High	High	High	Dry	L
	High	High	High	Equal Chance	M
	High	High	High	Wet	H
	High	High	Low	Dry	Nil
	High	High	Low	Equal Chance	L
*	High	High	Low	Wet	M
*	High	Low	High	Dry	L
	High	Low	High	Equal Chance	M
	High	Low	High	Wet	H
	High	Low	Low	Dry	Nil
*	High	Low	Low	Equal Chance	L
	High	Low	Low	Wet	H
*	Low	High	High	Dry	Nil
	Low	High	High	Equal Chance	L
	Low	High	High	Wet	M
	Low	High	Low	Dry	Nil
*	Low	High	Low	Equal Chance	Nil
	Low	High	Low	Wet	Nil
*	Low	Low	High	Dry	L
	Low	Low	High	Equal Chance	L
	Low	Low	High	Wet	M
	Low	Low	Low	Dry	Nil
*	Low	Low	Low	Equal Chance	L
	Low	Low	Low	Wet	M

Key assumptions:

Fertiliser is spreading urea, not liquid fertiliser

Starting soil moisture: low = <10 mm; medium = 50 mm; high = >50 mm

Soil N: low = < 40 KgN; medium = 60 KgN, high = 80 kgN

Application rates: nil = 0; L = 15 N/ha; M = 25 N/ha; H = 40 N/ha

Appendix 2: Gross margin values

Crop production costs for winter cropping options in this study were based on the Southern Zone West (Figure 12). The budgets were sourced from NSW DPI and checked with Birchip Cropping Group (<https://www.dpi.nsw.gov.au/agriculture/budgets>) for their relevance to the case study site. Some minor adjustments were made to the canola budget.

The budgets provide detailed information on management practices and input costs associated with sowing, managing crop nutrition, pests, weeds and disease throughout the growing season, and harvesting. These budgets were used as a basis to determine area and yield based costs which are combined with the crop simulation data to determine annual cropping returns. A summary of crop gross margins is provided in Table 5.

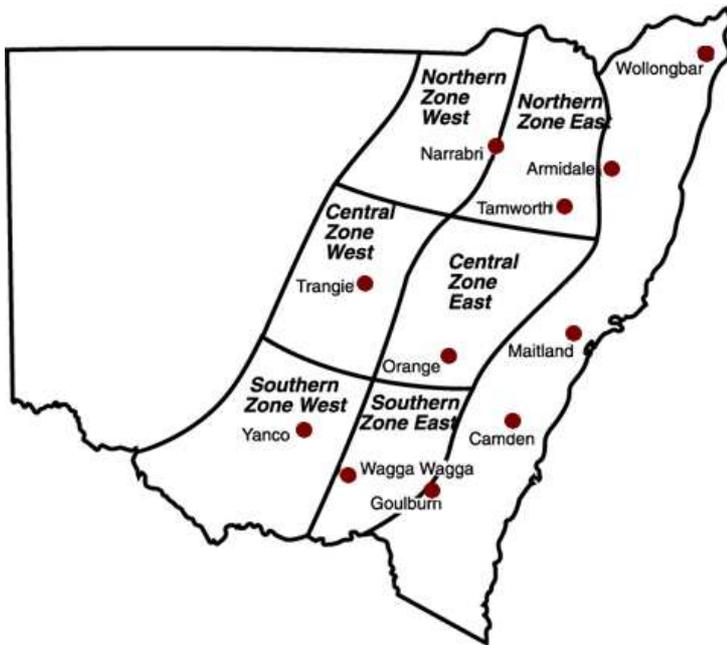


Figure 12 Crop production zones in NSW

Table 5 Gross Margin Summary – Southern Zone West

	CANOLA (LF)	WHEAT (SF)	BARLEY	FIELD PEA
	DPI 2012; Canola: Long Fallow; Southern Zone - West	DPI 2012; WHEAT: Short Fallow (ASW/APW/AH): No till - Southern Zone - West	DPI 2012; BARLEY: Short Fallow: No-till - Southern Zone - West	DPI 2012; FIELD PEA: After Cereal - No till - Southern Zone - West
A. INCOME	per ha	per ha		
Yield 1	1.5	2.5	2.2	1.5
Price 1 (on-farm price)	520	200	150	220
sub total	780	500	330	330
B. VARIABLE COSTS				
area based - within season	per ha	per ha	per ha	per ha
- cultivation	\$34.00	\$0.00	\$0.00	\$12.00
- sowing	\$44.00	\$24.00	\$24.00	\$145.00
- fertiliser & application	\$141.00	\$72.00	\$53.00	\$61.00
- herbicide & application	\$38.00	\$49.00	\$53.00	\$43.00
- insecticide & application	\$13.00	\$0.00	\$0.00	\$19.00
sub total	\$270.00	\$145.00	\$130.00	\$280.00
area based - harvest	per ha	per ha	per ha	per ha
- windrowing	\$50.00			
- harvesting	\$54.36	\$64.00	\$37.00	\$49.00
sub total	\$104.36	\$64.00	\$37.00	\$49.00
yield based	per ha	per ha	per ha	per ha
- Insurance	\$30.00	11.00	\$7.34	\$13.00
- Other levies	\$10.00	\$5.00	\$6.65	\$3.00
sub total	\$40.00	\$16.00	\$13.99	\$16.00
Total	\$414.00	\$225.00	\$181.00	\$346.00
C. GROSS MARGIN	\$366.00	\$275.00	\$149.00	-\$16.00

These standard gross margins were used as a basis for enterprise costs in the model. Some adaptations were made to reflect more localised conditions or to address budget inconsistencies.

Appendix 3: Economic model

1 Overview of the modelling approach

SOUTHERN GRAINS



2 Economic model description

The economic model used key outputs from the potential yield modelling to capture the links between climatic conditions and crop production. Combining these outputs with information on crop production costs and key output prices (crop prices) allows net returns to be estimated for each cropping option (i.e. wheat, canola, barley and field pea). The economic model evaluates the relative returns offered by each cropping option under dry, average and wet climate states and under varying levels of stored soil moisture at the start of the season.

A two-stage discrete stochastic programming (DSP) model was developed for the southern cropping 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 (crop options – wheat, canola, barley and field pea – in April), s is the state of nature (tercile rainfall – dry, avg and wet) and $x_2 (s, x_1)$ represents Stage 2 decisions (tonnes of grain harvested). These Stage 2 decisions are contingent upon earlier Stage 1 decisions and the state of nature that occurs. The farm-planning problem is to choose the optimal crop mix in April to maximise the expected level of return across climatic states. In algebraic terms, the main elements of the model are as follows.

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

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

subject to:

Land, labour and capital constraints

$$\sum_{j=1}^J a_{1ij} x_{1j} + \sum_{n=1}^N a_{2ns} x_{2ns} \leq b_i \quad \text{for all } i, s \quad [\text{Equ 3}]$$

Use of crop outputs

$$\sum_{j=1}^J a_{1mjs} x_{1j} + \sum_{n=1}^N a_{2mns} x_{2ns} \leq 0 \quad \text{for all } m, s \quad [\text{Equ 4}]$$

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 or bales/ha)

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

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 planted in Stage 1

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

The objective function (Equ 1) maximises the expected net return from activities across three climatic states. The expected return takes into account the level of return in each state and the probability of each state occurring. The expected net return is maximised subject to constraints on the overall number of steers available for sale. The DSP model was solved using the What's Best!® 14.0 add-in to Microsoft Excel®.

The two-stage decision process is reflected in returns for each state (Equ 2). The left-hand term of Equ 2 indicates a commitment of input costs (variable costs of growing winter crops) 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 crops). 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. crop prices) were assumed to be independent of climatic conditions. With a high proportion of most Australian crops sold into international markets, this was considered a reasonable assumption.

Constraints in the economic model are reflected in Equ 3 and 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, labour and capital are not represented but constraints are introduced in the model to reflect the availability of cropping land (50% of total area – 2500 ha) and rotational constraints. To

ensure that responses to climate forecasts are kept within rotational limits, the area of land allocated to field pea is fixed at 25% of the available crop area (625 ha), barley is allowed to vary between 15% and 25% (375–625 ha), while wheat and canola can be grown on the remaining 60% (1500 ha).

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 grow a winter crop in Stage 1, combined with the intervening rainfall state, leads to crop 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 crops up to the amount physically produced. Importantly in some sowing combinations (e.g. low stored soil moisture at sowing) that result in low yields, it may be uneconomic to proceed with harvest in a dry state because the cost of harvest, levies and cartage (i.e. yield dependent costs) may actually exceed the crop price on a per tonne basis. The model will not harvest in this instance and therefore avoids compounding losses of a dry season.

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

The introduction of a climate forecast with skill greater than 0% leads to a revision of the probabilities in line with the extent of forecast skill. For example, a skilful forecast of a dry season results in the assignment of a higher probability to a dry state so the outcomes of a dry state are given more weight in the objective function of the model. For a forecast to have economic value, the change in weighting must lead to a change in the cropping decision relative to the without-forecast scenario. Model restrictions ensure that the overall probability of the occurrence of each climatic state is the same as its historical probability of occurrence (i.e. the prior probability π_s). This restriction ensures that the model is valuing improved knowledge about the occurrence of each state.

The value of the forecast system is derived from optimal decisions taken with and without the forecast. Expected 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 1) and the hypothetical forecast system described elsewhere, the value of a specific forecast f within this system was defined as:

$$V_f = \sum_{s=1}^3 \pi_{sf} y_{sf}^* - \sum_{s=1}^3 \pi_s y_{so}^* \quad [\text{Equ 5}]$$

where:

- y_{sf}^* denotes the net return in state s resulting from implementing the optimal crop choice x_{sf}^* based on forecast f , and
- y_{so}^* denotes net return in state s resulting from implementing the optimal crop 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 the without-forecast decision is the same). The estimated value of a particular forecast accounts for both the decisions made in Stage 1 (May) and the state-contingent tactical adjustments made in Stage 2 (November).

The value of a forecast system is obtained by weighting the value of each forecast within the system by the frequency with which each forecast occurs. If \mathbf{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:

$$V_{\mathbf{F}} = \sum_{f=1}^3 q_f V_f \quad [\text{Equ 6}]$$

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 three rainfall states ($f = f_{dry}, f_{avg}, f_{wet}$) and eleven skill levels ($\sigma = 0, 10\%, 20\%, \dots, 100\%$), the DSP model is solved 33 times in order to value the hypothetical forecast system for a given set of conditions (initial soil moisture and crop price scenarios).