Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Western grains 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 potential value of SCFs in managing price risk in grains production in Western Australia. While seasonal climate variability relates to production risk, uncertainty about production also accentuates price risks when it comes to farm-level planning. The key climate-sensitive decision identified by industry was what volume of potential grain production to forward sell in April when crops are sown. Importantly, the SCF is used to make a prediction in April of the potential total harvest volume, it does not adjust the proportion of crop forward sold, which is based on grain price in April. This decision assists growers to meet a prescribed forward selling strategy based on different forward selling prices in April. These selling strategies tend to be described as percentages of the final crop, with SCF potentially assisting to convert these percentages to volumes. Rainfall over the May to October growing season influences grain production and thus the volume forward sold according to the selling strategies. This case study investigates whether a skilful seasonal climate forecast issued in April is potentially valuable to help grain growers to meet forward selling strategies and lead to improved returns compared to if the decision was based on historical average rainfall amounts.

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 May–October rainfall received at Burracoppin over the period 1889 to 2016. Each year was classified as belonging to one of these climate states. Yields related to each of these climate states were obtained by classifying yearly outputs of wheat production data from the biophysical production model *APSIM*. These outputs were combined with wheat prices in April and November and results assessed economically to capture the links between climatic conditions, soil moisture and grain production. The analysis assessed potential profits of incorporating SCFs into forward selling decisions under a wide variety of scenarios.

A specific interest of this project was to understand how forecast and other important non-forecast decision variables interplay to influence forecast value. The use of a biophysical model allowed different levels of starting soil moisture in April to be captured and outcomes to be

explored in dry, average and wet states. Other key decision variables, including the level of April and November prices, help to represent the decision-making context prior to the consideration of a climate forecast.

In order to systematically assess the value of forecast skill, a hypothetical forecast system of dry, average and wet states was used. SCFs for 0% and 100% skill were assessed, with 0% representing climatology, or historically average conditions, and 100% skill reflecting a perfect forecast of one of the three climate states. The analysis was designed to establish an upper bound on forecast value.

Influence of non-forecast and forecast drivers on the volume forward sold

The volume of wheat forward sold under three selling strategies (aligned to prices in April sell – low 10%; medium 30%; high 50% of the final crop) and four different levels of soil moisture in April (25%, 50%, 75% and 100% of plant available water capacity (PAWC)) were assessed with and without a forecast. Using a perfect forecast led to small improvements (0.0–0.2 t/ha) in the volume of wheat forward sold relative to the desired selling strategy. This small increase in precision was traced back to the relatively reliable May–October rainfall at Burracoppin. The difference in rainfall between the dry and wet terciles was only 50 mm and this flowed through into only small yield differences between climate states.

The greatest improvement in alignment of the volume of wheat forward sold with the sell strategy occurred under low starting soil moisture conditions (25% and 50% of PAWC). However, these conditions only occurred for 13% of years, on average. Higher levels of soil moisture (75% and 100% of PAWC) occurred more frequently and buffered yields against potentially lower growing season rainfall.

Value of forecasts

The relatively small improvements in yield prediction offered by the use of SCFs were analysed in the context of wheat price volatility. These improvements led to mixed results in terms of changes to income. The critical driver of this outcome was that when the initial forward selling decision is made in April, wheat prices later in the season are volatile and unknown. As a consequence, movements in wheat prices during the season can result in growers being better or worse off under any given selling strategy that is fine-tuned with a climate forecast.

A skilful dry forecast lowers yield expectations and results in a smaller volume of grain being sold relative to the without-forecast scenario. With low April prices, this is advantageous as a lower amount is sold at the low April price. However, for high April prices, this increased certainty of the final yield was negative as a lower portion of yield was forward sold at higher prices and more was sold at lower prices later in the season.

A skilful wet forecast on the other hand raises yield expectation and results in a greater volume of grain being sold relative to the without-forecast scenario. With low April prices, this was a negative as a greater amount of grain is sold at a lower price than the without-forecast scenario. However, with high April prices, this is a benefit as a greater amount of grain is forward sold in April at the higher price. The maximum range of value of use of a perfect forecast, across all April and November price settings, was –$24.4/ha to +$18.5/ha.

Key findings

The main finding of this analysis is that while a skilful climate forecast provided marginally better yield estimates, and hence better alignment between planned and actual forward selling volumes, income effects were variable. The main driver of this variability is wheat price volatility that occurs after the forward selling decision is made in April. For this particular assessment and for some decision settings, the provision of better production information did not improve income as market settings overrode benefits of improved knowledge of production.

Contents

Glossary of terms

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

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

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

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

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

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

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

1 Introduction

1.1 Background

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

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

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

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

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

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

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

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

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

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

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

1.2 Project objectives

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

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

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

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

1.3 Case study approach

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

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

This report contains findings of the western 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. Identification of key decision points within the production system sensitive to SCF information.

[1] http://www.agriculture.gov.au/ag-farm-food/innovation/rural-research-development-for-profit/approved-projects

2. Biophysical modelling to represent the production system and the key decision point.
3. Economic modelling to evaluate the value of SCF to the decision point within the described production system.

Industry consultation was undertaken to capture important features of the production system and identify key decision points. A consistent approach was applied to all case studies following Cashen and Darbyshire (2017). A small group of industry experts and practitioners was invited to collaborate on the design of the case study. Invited participants were selected based on industry reputation and experience and differed depending on the case study. The group defined the production system that best reflected local conditions in the area. Subsequently, investigation of decision points within the system were explored. Each major decision point was further scrutinised to:

- identify which decisions were potentially sensitive to SCF information
- identify the key decision drivers including antecedent conditions (e.g. level of starting pasture) and SCF information
- investigate the relative sensitivities of the decision to the identified decision drivers.

The aim of the case studies was to provide some insights into the value of SCFs across a range of production systems and decision environments. They were not designed to be statistically representative and so cannot provide scalable results to indicate total potential value to each industry. Agricultural systems are inherently dynamic and the approach taken here attempts to strike a balance between highly specific farm-level analyses with very limited wider applicability and coarser level, more general analyses which can miss important features of production systems that may influence results.

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

2 Western grains production system

2.1 Industry overview

The wheat belt of Western Australia (WA) (Figure 1) is a key industry in the state, as demonstrated by the 2014–2015 grain exports, which contributed over $5.1 billion to the WA economy (DAFWA, 2016). Production of grains in WA is also significant to the wider Australian economy with WA accounting for 46% of Australian cereal exports over the past 10 years (WAAFFI, 2016). In recent years, WA has been the nation's largest grain producing state despite relatively infertile soils and low rainfall.

The total area of WA wheat-belt allocated to broadacre crops is 6 006 038 ha with 3442 businesses involved. On average, 84% of income is from farm business with another 11% from off-farm employment and 4% from other funding sources.

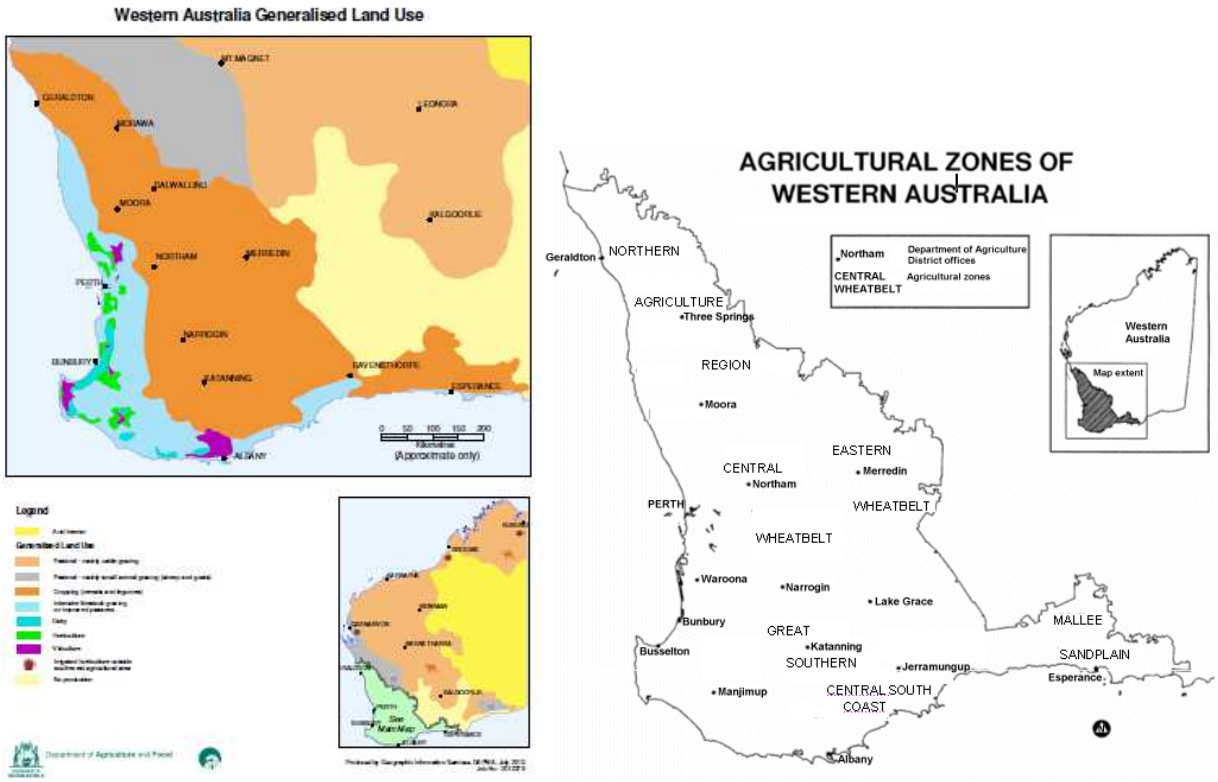


Figure 1 Agricultural zones of the wheat belt of south-west WA.

A variety of broadacre crops are grown in WA (Table 1). A survey for 2014–2015 (Planfarm Bankwest, 2015) found that the area of wheat has grown over the period 2004 to 2014 but so too has the average farm size, with the proportion of wheat grown on an individual farm consistently between 60% and 67% of the total farm area. The survey found that the pasture area has reduced to a 10-year low of 26% of arable area. Barley and canola have increased in area with improved varieties and pricing making these crops more profitable and attractive. However, wheat remains the predominant grain crop grown in WA.

Table 1 Broadacre crops – cereal crops, pulses and oilseeds in WA area (ha), number of businesses, production (t) and average yield (t/ha). *Pulses include lentils, navy beans, field peas for grain, faba beans, lupins and chickpeas.

	Wheat	Oats	Barley	Sorghum	Triticale	Pulses*	Canola
Area (ha)	5038134	233230	1308458	1453	17415	383515	1396952
No. businesses	3559	1875	2818	12	95	1212	2359
Production (t)	8824410	557595	3192452	3987	21774	515029	1640898
Yield (t/ha)	1.8	2.4	2.4	2.7	1.3	1.3	1.2

2.2 Managing the grains market

Reduction of exposure to price risk is important to many WA growers. Price risk exposure has increased following systematic deregulation of the sector and the dissolving of the single desk system in 2008. As such, Australian and WA growers operate under the realities of a global marketplace.

This price risk is demonstrated by the notable variation of grain prices throughout the growing season with little-to-no seasonal predictive capacity (Figure 2). These fluctuations are the result of global production, storage and other non-local affects with prices independent of local WA growing conditions (Grain Growers Limited, 2016).

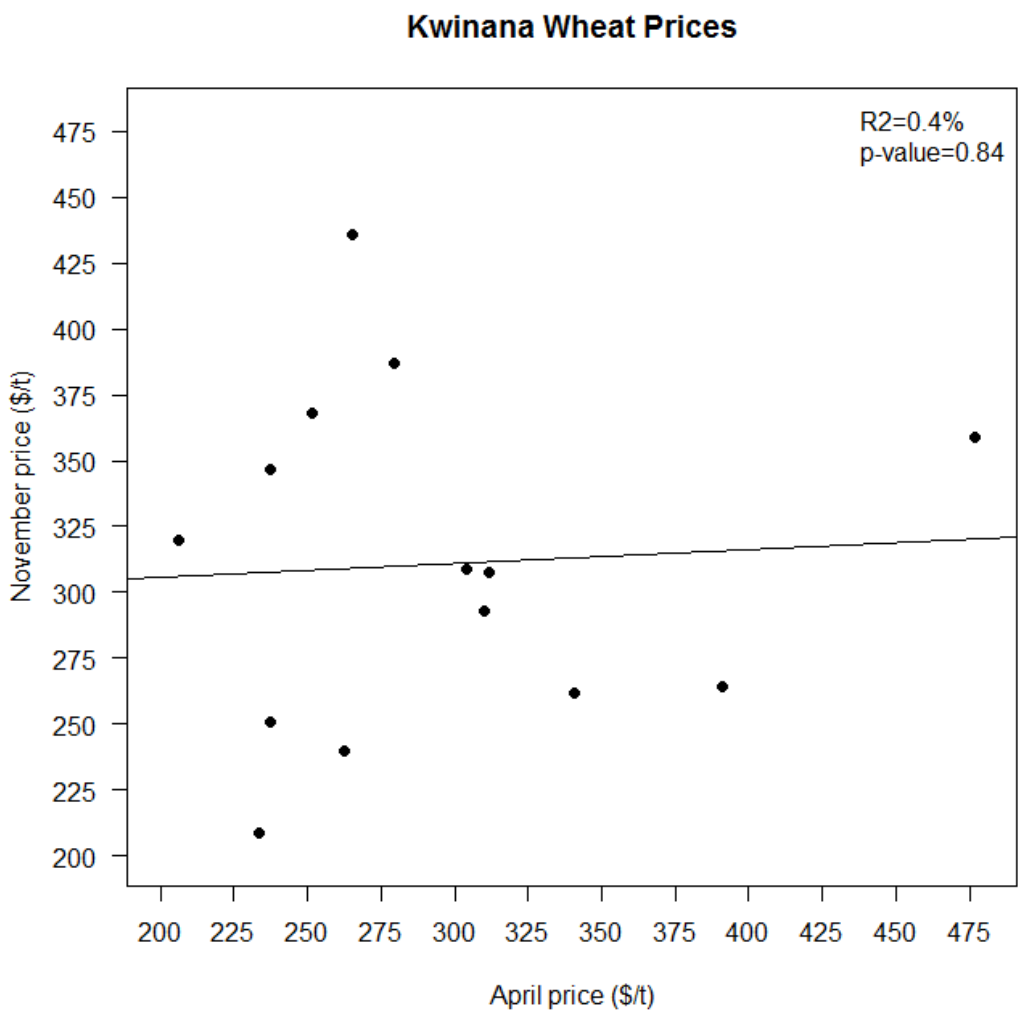


Figure 2 Relationship between wheat prices ($AU/t) in April and November for 2002–2015 (Profarmer, 2017). Line is the linear relationship between April and November prices highlighting poor correlation.

In response to this price volatility, several market mechanisms have been developed to provide price smoothing options for growers and security of supply for buyers. This marketing flexibility has allowed growers to potentially better manage market risk from price volatility. One commonly used market mechanism is to forward sell a portion of a crop prior to harvest to take advantage of current prices and minimise down side risk of price reductions at harvest. Hence, the benefits of forward selling lie in income smoothing and reducing exposure to potential price risk.

Forward selling, like many decisions in farming, is a personal choice driven by grower perception of risk and past history. Generally, WA growers tend to forward sell a percentage of their future crop before sowing and then another portion is sold in June–August once the global market is better known (pers. comm. Roderick Grieve, 13 October 2016).

There are many selling strategies that can be undertaken which can include a component of forward selling. A Grains Research and Development Corporation (GRDC) fact sheet, *Marketing versus Selling*[2] outlines several examples. One approach highlighted was a 33%:33%:33% strategy. This involves forward selling 33% of the crop, selling 33% at harvest and storing 33% to sell at a later time after harvest.

[2] https://grdc.com.au/__data/assets/pdf_file/0022/134338/8363-marketing-versus-selling-fs-pdf.pdf.pdf

A feature of forward selling strategies is selling a portion of the crop well before production is known. Hence, an estimation of the expected crop size at harvest must be made in order to, for instance, forward sell 33% of the final crop. Seasonal conditions will influence final yield and may assist in determining actual crop volume to sell to meet forward selling strategies.

2.3 Description of production system and key decision point

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

This case study was focused on a dryland cropping system on a 7000 ha farm based in Burracoppin WA (Figure 3). The farm described had three soil types and a crop rotation of fallow and liming – canola – barely –wheat. Wheat was the focus crop with 3000 ha typically cropped to wheat for any given year. The variety Mace was selected for analysis as it is the predominant variety cropped. Features of the system in Burracoppin, as related to the wheat rotation are shown in Figure 4.

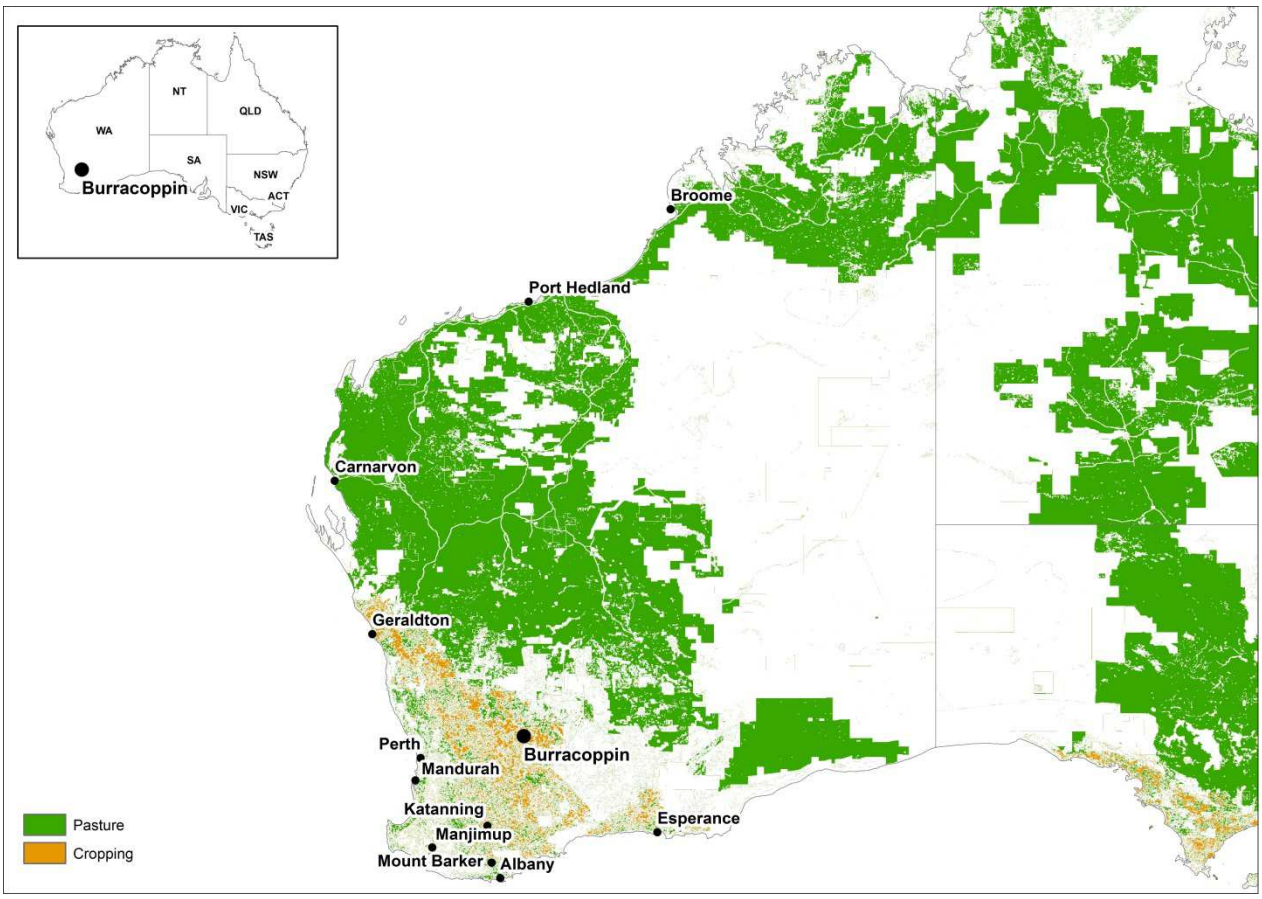
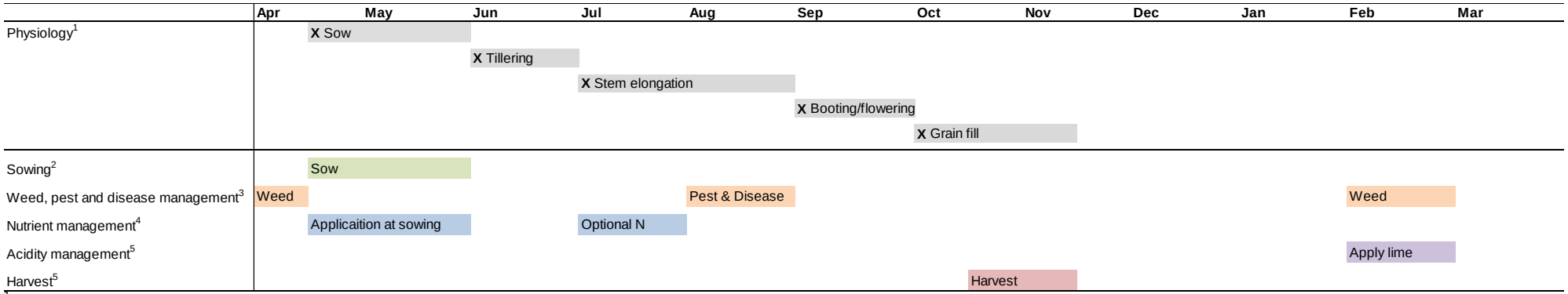


Figure 3 Map showing the location of Burracoppin, the case study site

Figure 4 Broad system characteristics of the western grains case study



[1]Various varieties are available (short, medium, long season). This is for Mace, short-mid season variety
[2]Sowing occurs all years, a proportion will be dry sown due to large program.
[3]Dependent on seasonal conditions as well as weed and pest and disease mix as to products used and number of activities.
[4]Rate and timing will vary according to soil type and estimate potential yield. Optimal top dressing may be dependent on seasonal conditions with N application varied from season-to-season.
[5]Applied to fallow paddocks ~20% of farm in any one year
[6]Harvest timing is dictated by plant development timing and logistical arrangements.

2.3.1 Decision point

The key decision point for this system was:

What volume of wheat will I forward sell?

The time of the decision was the first forward sell opportunity, April, when farm plans have been determined. There are multiple selling opportunities throughout the season, however this was viewed as the most sensitive to SCFs as any future forward selling decisions will be dependent on the volume of crop initially sold.

In deciding what volume of the crop to forward sell, several aspects were considered. Three key decision drivers were identified:

1. Wheat grain price: high prices in April encourages a higher ***percentage*** of the crop to be forward sold, lower prices lower the ***percentage*** forward sold.
2. Starting soil moisture: higher soil moisture levels encourage a greater ***volume*** to be forward sold, lower starting soil moisture reduces the ***volume*** forward sold.
3. Growing season rainfall: a wet outlook encourages a greater ***volume*** to be forward sold, dry outlook reduces the ***volume*** forward sold.

To understand this decision, separation between the forward selling strategy and the forward selling volume must be made (Equ 1). The forward selling strategy sets the percentage of the final crop allocated to be forward sold. This only varies with April wheat prices. The volume forward sold is the forward sold percentage (determined by April wheat prices) of the final yield of the crop. In reality, final yields are unknown and are estimated. These estimations are dependent on starting soil conditions and seasonal climate.

$$f_{sold_g} = f(P_g)_g$$

$$V_{sold_g} = (100 - f_{sold}) \text{x} FY_g$$

$$FY_g = f(soil\ moisture, climate, management)_g \qquad \text{[Equ 1]}$$

Where f_{sold_g} is forward selling percentage, P_g is the price of wheat in April, V_{sold_g} is the volume forward sold and FY_g is the final, or predicted, yield.

As seen in Equ 1, it is the volume of grain rather than the percentage of the crop for which SCFs may prove useful in making forward selling decisions. That is, a SCF may assist in a more accurate estimate of yield allowing for better alignment of the volume forward sold (V_{sold}) with the forward selling strategy (f_{sold}).

Figure 5 illustrates this decision-making process, with an option to not include SCFs. This is necessary to evaluate the value of including SCF against decisions made without SCF information. Further details on the process of defining this decision point and the decision drivers are contained in Appendix 1.

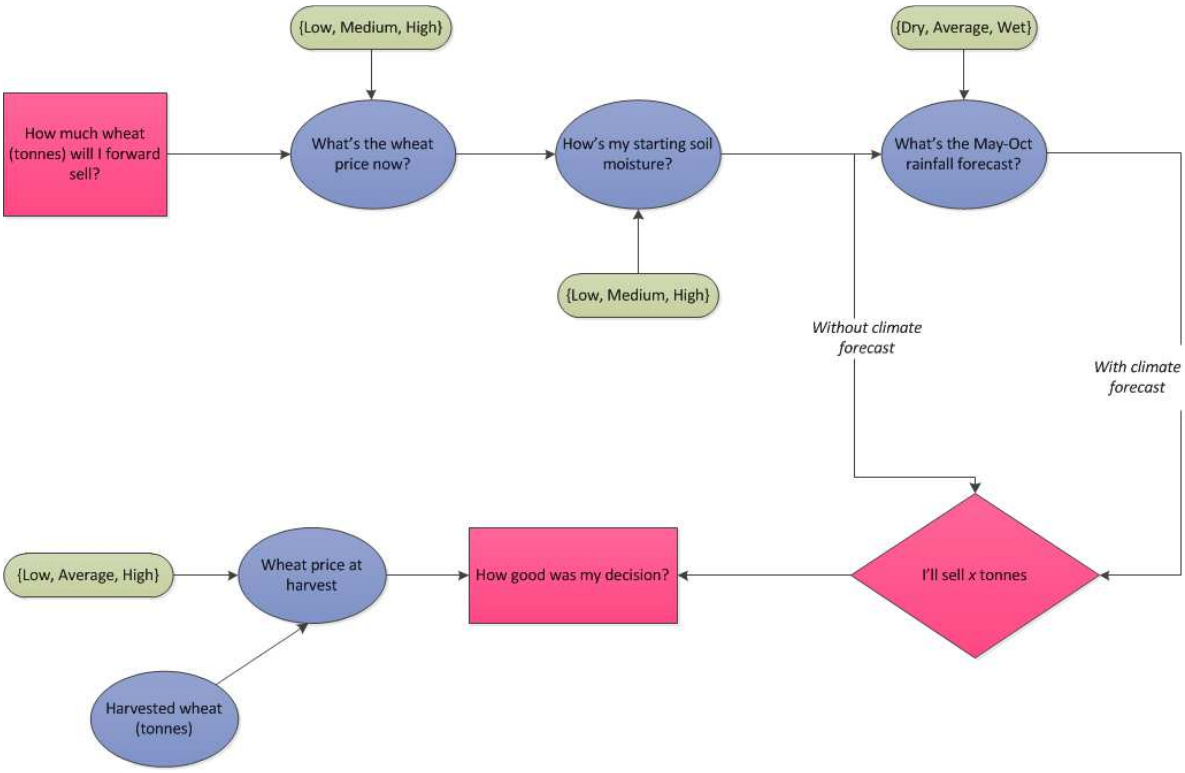


Figure 5 Decision pathway for volume of wheat forward sold in April including an evaluation of the decision made.

2.4Previous studies evaluating the value of SCFs to WA grain production systems

WA has been the focus of much research in the grains industries with studies considering the use and value of SCFs included. Typically, these studies have focused on the value of SCFs in improving on-farm management decisions. For instance, Petersen and Fraser (2001) aimed to improve the methodology for assessing the value of seasonal climate forecasting technology prior to its development, using the meteorological records in the Merredin agricultural region for the period 1907–1995 as an illustration. Results suggested that seasonal climate forecasting technologies that provide a 30% decrease in seasonal uncertainty could increase annual profits to growers in the Merredin region by approximately 5%, or $2 million.

Pannell (1994) considered herbicide strategies in wheat production for a perfect forecast of yield and evaluated different levels of risk aversion. He found a benefit of $6.1/ha for growers with high risk aversion. Moeller et al. (2008) evaluated the value of SCFs for various locations in WA for the decision on the amount of nitrogen fertiliser to apply when sowing wheat. For perfect rainfall forecasts, the value of the forecasts was found to be between $31/ha and $62/ha. Reducing the skill level to 40% resulted in a drop of the value to $15/ha at Merredin and $0/ha at Mingenew.

Several assessments of seasonal forecast value have been conducted using the Bureau of Meteorology POAMA dynamic model. McIntosh et al. (2010) and Asseng et al. (2012) considered the value of the 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. These studies are further explored by Parton and Crean (2016).

Limited studies in Australia have focused on the use of SCF to assist with marketing decisions. Early work (Meinke and Stone, 1997) suggested that seasonal production forecasts can assist producers in their marketing strategies. They suggested that if it is likely that wheat yields might

be suppressed (e.g. under El Niño conditions), growers will be more conservative when forward selling their crop, potentially saving them from over-hedging.

No research or case studies using SCFs for forward selling decisions were found.

3 Methods

The potential value of SCFs was evaluated by assessing the volume forward sold with and without a SCF and comparing these to the target forward selling strategies. Assessment was made in terms of how close the without and with SCF volumes met the target forward selling percentage. Evaluation was then conducted to assess the economic consequences of changing forward selling volumes with a SCF from the volumes forward sold without a forecast. This was assessed as differences in revenue only as costs were assumed to be constant and independent of selling strategies.

An overview of the overall methodology is outlined in Figure 6. Key production and price components are used for the economic analysis to evaluate the potential value of SCFs. Each of these components is described in the following sections.

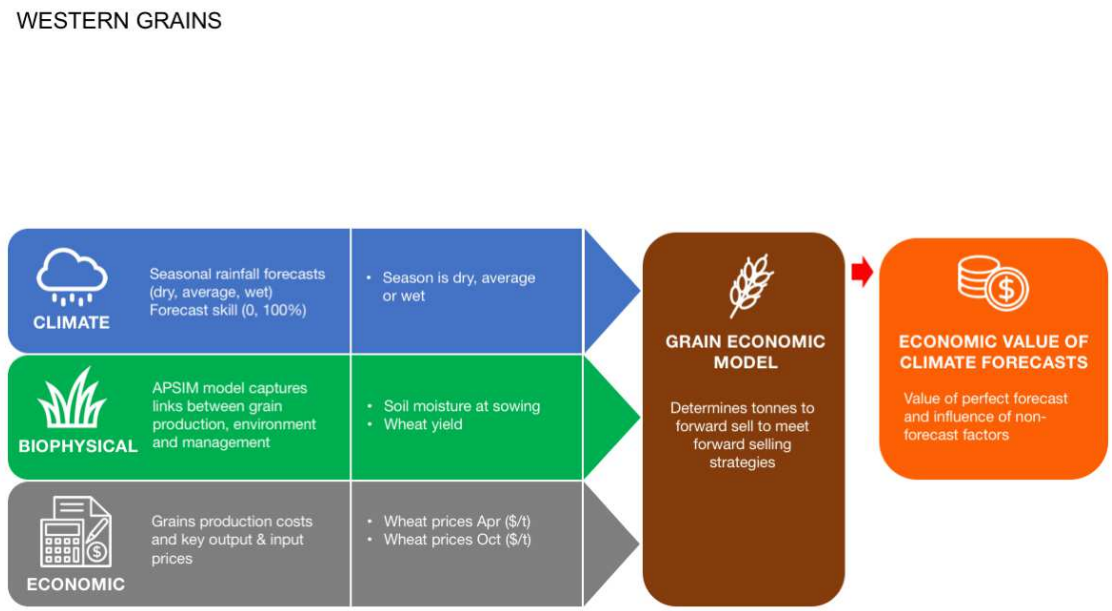


Figure 6 Methodological overview. Generation of biophysical data, wheat prices and climate state classification of historical data and forecasts are used in the economic analyses to select volume of wheat to forward sell to assess which criteria best meets the forward selling strategy and the economics consequences.

3.1 Wheat biophysical simulation model

The Agricultural Production Systems sIMulator (*APSIM*) version 7.8 (Holzworth et al., 2014) was used to produce the biophysical simulations of wheat yield. *APSIM* is a farming systems model that simulates key biophysical processes in a daily time step related to crop growth and wheat growth, water, carbon and nitrogen cycling in the soil-plant system under prescribed management strategies. Changes in soil water and soil nitrogen supply during the cropping season are included dynamically. *APSIM* has been tested extensively against field measurements of wheat in various growing conditions, including Mediterranean climatic regions of Western Australia (Anwar et al., 2015; Asseng et al., 2001; Oliver and Robertson, 2009).

Soils in the study region depict high spatial variation in terms of plant available water capacity (PAWC) due to differences in soil physical and chemical properties (Oliver et al., 2006). Three

soil types were considered as a representative of the area according to PAWC, based on local experts and previous studies (Oliver and Robertson, 2009; and APSoil https://www.apsim.info/Products/APSoil.aspx). They are listed in Table 2.

Table 2 Three soil types used in the simulation based on Isbell (1996). Soil characteristics were obtained from WA soil descriptions in Oliver and Robertson (2009). PAWC is plant available water capacity.

	APSoil No.	Soil Type	PAWC (mm)
Soil 1	507	Sodosol and chromosols (shallow sandy duplex)	57
Soil 2	510	Sodosol and chromosols (deep loamy duplex)	90
Soil 3	512	Vertosol and dermosol (clay)	135

In the simulation experiment, each of the three soil types (Table 2) with four levels of starting soil water conditions (25%, 50%, 75% and 100% PAWC) at sowing were used to simulate potential wheat yield. The model was run using 128 years (1889–2016) of historical weather data obtained from the SILO patched point daily weather dataset (Jeffrey et al., 2001) sourced from station 10019 (Burracoppin).

Based on current agronomic practices, the wheat cultivar Mace was used and 25 April set as the sowing date each year. To avoid carry over effects of soil nutrients and water, the model was reset each year one day prior sowing (24 April) to initialise soil conditions including the PAWC levels tested. The amount of N-fertiliser applied at sowing was 14 and 30 kg N/ha as urea in soil-1 and soil-2, respectively. In soil-3 (higher PAWC (Table 2)), 13 kg N/ha was applied at sowing and subsequently top-dressed at floral initiation (about 70 days after sowing) based on a soil nitrogen deficit rule[3] which typically amounted to 30–41 kg N/ha.

3.2 Target forward selling strategies

Three forward selling strategies were defined after consultation with industry. The strategies were dependent on April wheat prices only and were reported in terms of percentage of the final crop forward sold (Table 3).

Table 3 Target forward selling percentages for low, medium and high April prices

April price	Low	Medium	High
Percentage forward sold	10%	30%	50%

The value of a SCF in meeting the target strategy was evaluated by assuming the remainder of the crop was sold in November (Equ 2).

$$Remainder\ \%_g = 100\% - forward\ sold\ April\%_{ig} \qquad \text{[Equ 2]}$$

Where ig is the forward sold percentage based on April prices (Table 3).

3.3 Key input and output costs

Historical free-in-store wheat prices for Kwinana (2002–2015) (Profarmer, 2017) were used to estimate low, medium and high prices. The data were for APW1 values where possible, with APW2 used where APW1 values were not available. Monthly April values were calculated as the monthly mean across weekly or daily data, dependent on data availability. The 10th, 50th and 90th percentiles of these April values were used to assess forward sell options for low, med and high April prices. The same prices were used to test potential November, or remainder of crop, sell price. This approach allowed for ease of interpretation of results.

[3] N was applied to meet a 40N target with the deficit calculated as 40 minus total N in the top three soil layers.

Sensitivity across all price options was evaluated (i.e. low, medium and high April prices for low, medium and high November prices) resulting in nine different price combinations being tested.

Table 4 Wheat prices evaluated, these were applied to both April and November prices. These were adjusted to real prices.

	Low	Medium	High
Wheat price	$234/t	$272/t	$376/t

3.4 Seasonal climate forecasts

Theoretical tercile forecasts were created using historical climate information (1889–2016) for the analysis. The SCF used for analysis was total May–October rainfall. Total rainfall for these six months was calculated for each year and classified into 'dry', 'average' and 'wet' climate states based on tercile values: dry was categorised by rainfall less than 192 mm, average as between 192 mm and 242 mm, and wet as rainfall in excess of 242 mm (Figure 8). Results using averages of these climate states were then used to evaluate SCFs of dry, average and wet climate state within the economic analyses.

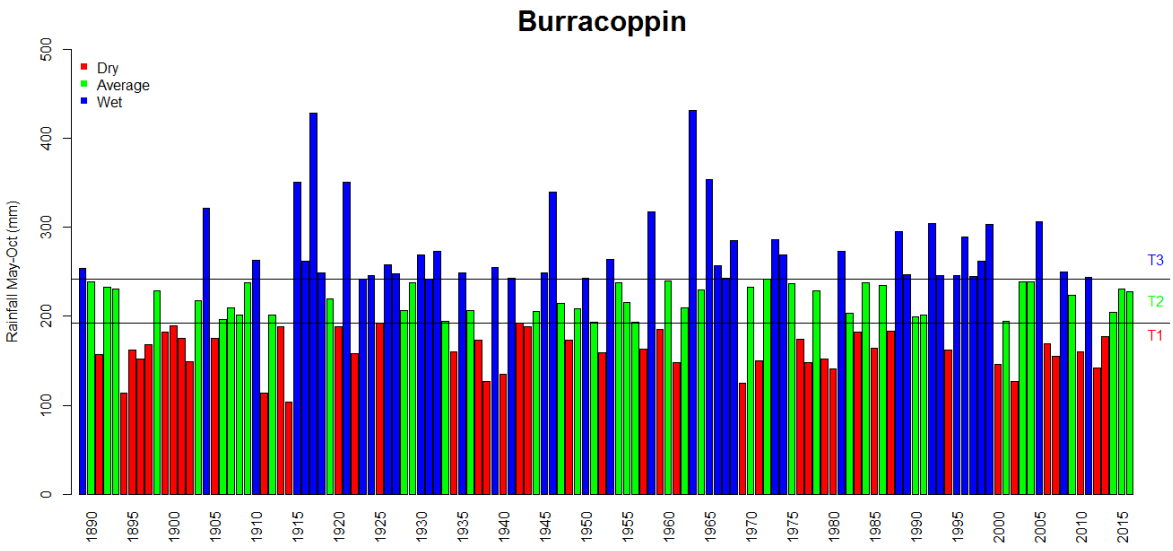


Figure 7 Total rainfall for May to October at Burracoppin for 1889–2016. Dry, Average and Wet represent tercile 1, 2 and 3.

Agricultural production levels representing dry, average and wet climate states were obtained by classifying yearly outputs of wheat yield from the biophysical production model (see section 3.1). Resulting yearly data for each state (42 years) were then averaged to represent each climate state within the economic model. This categorisation is a critical part of the approach because variations in production across climate states provide the necessary, but not sufficient, conditions for forecasts to offer value in decision-making.

Climate forecasts were evaluated 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, two probabilistic forecasts were created for each of the three climate states (dry, average, wet) representing forecast skill of 0% and 100%. These forecasts were incorporated

into the economic analysis 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 is as follows:

$$\sigma = \frac{\pi_{s|fg} - \pi_s}{1.0 - \pi_{sg}} \qquad \text{[Equ 3]}$$

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 was set to 1.0 for each climate state according to:

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

Using this definition of forecast skill, 0% skill equates to climatology where each state has a 33% chance of occurring, while perfect forecasts of dry, average and wet forecasts have 100% chance of occurring (Table 5).

Table 5 Example calculation of weightings of each climate state for 0% and 100% forecast skill

		Forecast skill			
	Forecast state	**0%**	**100%$_{dry}$**	**100%$_{ave}$**	**100%$_{wet}$**
Weighting (%)	Dry	33	100	0	0
	Avg	33	0	100	0
	Wet	33	0	0	100

3.5 Analyses

The case study site selected has variable soil types for which wheat yields were estimated (Table 2). The farm has different proportions of land cropped under each soil type: 21% to soil-1, 37% to soil-2 and 42% to soil-3. A total farm yield was estimated by weighting the yields obtained from *APSIM* for each soil type according to the percentage coverage of the farm.

The potential value of the theoretical SCFs was evaluated as the marginal benefit of the forecast. Specifically, the change in income using SCF information compared to the income obtained without a forecast. The value of the forecast was calculated in terms of $/ha.

The forecast value was assessed for several different decision environment settings, two levels of forecast skill and for each of the three climate state forecasts (dry, average, wet). This produced 216 results representing various decision environment settings, forecasts and forecast skill levels (Table 6).

Table 6 Variables and value levels assessed to evaluate forecast value

Variable	Values tested
April price	low, medium, high
Remaining crop price	low, medium, high
PAWC at sowing (%)	25, 50, 75, 100
Forecast state	dry, average, wet
Forecast skill (%)	0, 100

Initially, the without-forecast (0% skill) selling volume was reported for the different April prices for each PAWC value. Subsequently, the perfect-forecast (100% skill) selling volume for the three forecast states was similarly reported. The difference between the volume forward sold between the 0% and 100% skill forecasts was then investigated.

The potential value ($/ha) of the perfect forecast was calculated as the difference in income between perfect-forecast and without-forecast results. This represents largest potential value of each climate state forecast.

4 Results

4.1 Biophysical modelling

Initially, variability in starting soil moisture conditions was evaluated to assess how frequently the different categories of soil moisture eventuated. In this instance, starting soil moisture was not reset annually within *APSIM* and a wheat crop was grown and harvested each year. The percentage of years which fell into each PAWC category (25%, 50%, 75% and 100%) was found across 1900–2016 with the initialisation years 1889–1899 removed to ensure stabilisation of the soil conditions. This was conducted for each soil type. The allocation of years into each category was similar between the soil types (Table 7).

In most years, stored soil moisture at planting (25 April) was found to be 75% or more of PAWC (68% of the time) on average across the soil types. Less than 50% PAWC at planting was found for only 13% of years and less than 20% of years for individual soil types. These results will vary depending on management strategies (e.g. crop rotation, inclusion of fallow).

Table 7 Percentage of years for which soil moisture on 25 April fell within each quartile category (1900–2016) at Burracoppin by soil type.

	PAWC	<25%	25–49%	50–74%	75–99%	100%
Percentage of years	Soil 1	1	12	20	47	37
	Soil 2	8	7	20	45	37
	Soil 3	1	17	26	41	23
	Mean	**3**	**10**	**19**	**38**	**30**

Historical yields (1889–2016) weighted across the soil types were estimated for each stored soil moisture level (Figure 8). Lower yields with greater variability were found for lower stored soil moisture levels (25% and 50% PAWC) at sowing. Slightly higher and more reliable yields were found with 75% and 100% PAWC stored at sowing. Overall, there are small differences in mean yields between the different starting conditions (2.0–2.2 t/ha).

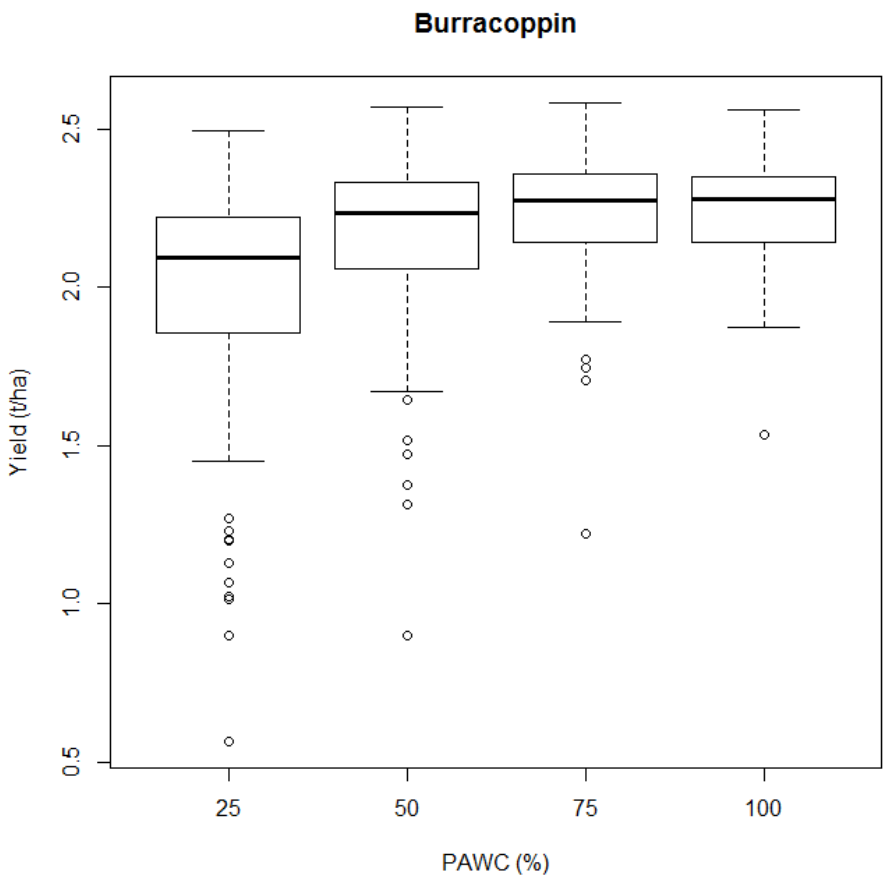


Figure 8 Total yields for 1889–2015 at Burracoppin, WA for four different PAWC (%) values at sowing in April. The results are proportional across three different soil types.

Further investigation into the variability in historical yields was conducted. For each stored soil moisture level at sowing, the yield distribution was found for the three climate states (dry, average and wet) (Figure 9). With lower soil moisture levels at sowing (25% and 50% PAWC), dry years cluster at lower yield values and wet and average rainfall seasons result in higher yields. With higher stored soil moisture conditions (75% and 100% PAWC), the separation of yields based on climate state is less clear. There are instances where dry years in Figure 9 resulted in relatively higher yields and in other circumstances wet years were among the lowest yields recorded.

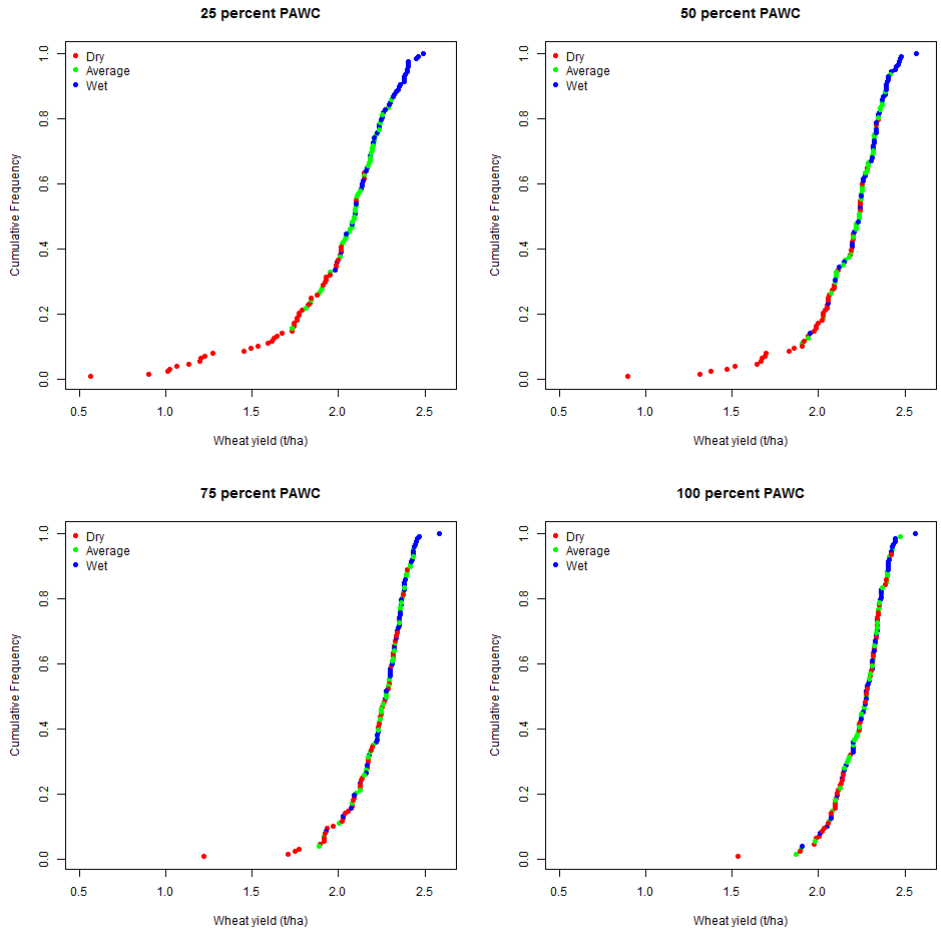


Figure 9 Distribution of historical yields for 25%, 50%, 75% and 100% PAWC at sowing. The colours indicate the different tercile allocations of the historical data with red for dry (lower tercile), green for average (middle tercile) and blue for wet (upper tercile). Climate states are for total May–October rainfall.

The combination of the high frequency of 75% PAWC or greater at sowing (Table 7) and the limited yield response to climate states with 75% and 100% PAWC at sowing (Figure 9) indicates a lower potential for value of SCFs. Nonetheless, investigations into the value of SCFs were conducted to quantify any potential value in relation to forward selling decisions.

4.2 Economic analyses

4.2.1 Without-forecast decision

To evaluate the potential value of SCFs, the optimal sell decision made without a forecast must be first be evaluated and subsequently compared with the decision made with a forecast.

The without-forecast forward selling volume was calculated using the historical yield mean (1889–2016) for each of the four stored soil moisture levels. A volume (t/ha) was derived for each of the three forward selling strategies (Table 3) with 10% forward sold if April prices are low, and 30% and 50% if April prices were medium and high, respectively (Table 8).

Table 8 Forward selling volumes (t/ha) without use of a climate forecast for each starting PAWC level and each forward selling strategy (i.e. different April prices for wheat).

PAWC (%)	Mean (t/ha)	Forward sold (t/ha)		
		Low April price	Medium April price	High April price
25	2.00	0.20	0.60	1.00
50	2.16	0.22	0.65	1.08
75	2.23	0.22	0.67	1.11
100	2.24	0.22	0.67	1.12

Using the without-forecast scenario there were minimal years for which a greater volume of grain was forward sold in April than was actually grown (i.e. in this case a grower would be required to source grain to meet the forward sell contract and incur significant economic losses). Across the analyses, this occurred at most for 3/128 years (2.3% of years) with 25% PAWC at sowing (3 years) and for 1/128 (0.8% of years) with 50% PAWC at sowing.

4.2.2 Perfect-forecast decision

The forward sell volume for perfect forecasts of dry, average and wet climate states (100% skill) were evaluated similarly to the without-forecast decision. Using mean historical yields for each of the climate states (dry, average, wet), forward selling volumes were estimated for each stored soil moisture level at sowing and for each price option in April (Table 9).

Table 9 Forecast forward selling volumes (t/ha) for each starting soil level, each climate state (dry, average, wet) and for low, medium and high April prices.

PAWC (%)	Climate state	Mean (t/ha)	Forward sold (t/ha)		
			Low April price	Medium April price	High April price
25	Wet	2.26	0.23	0.68	1.13
	Average	2.09	0.21	0.63	1.05
	Dry	1.65	0.17	0.50	0.83
50	Wet	2.32	0.23	0.69	1.16
	Average	2.23	0.22	0.67	1.12
	Dry	1.95	0.20	0.59	0.98
75	Wet	2.31	0.23	0.69	1.15
	Average	2.26	0.23	0.68	1.13
	Dry	2.12	0.21	0.64	1.06
100	Wet	2.29	0.23	0.69	1.14
	Average	2.25	0.23	0.68	1.13
	Dry	2.19	0.22	0.66	1.09

Using perfect SCFs, there was one year (0.8% years) at most for which a greater volume of grain was forward sold than grown. This was for a dry year and for when soil moisture was 25% or 50% at sowing.

Figure 10 contrasts the without-forecast and perfect-forecast forward sell volume for each April price and stored soil moisture level. In general, the dry climate forecast forward sells less grain than the without-forecast decision. Equally, the average and wet climate forecasts forward sell more than the without-forecast decision. These differences are small, particularly for low April prices (only 10% forward sold) and for high starting soil moisture conditions (75% and 100% PAWC). The greatest deviation from the without-forecast decision was for 25% PAWC and high April prices.

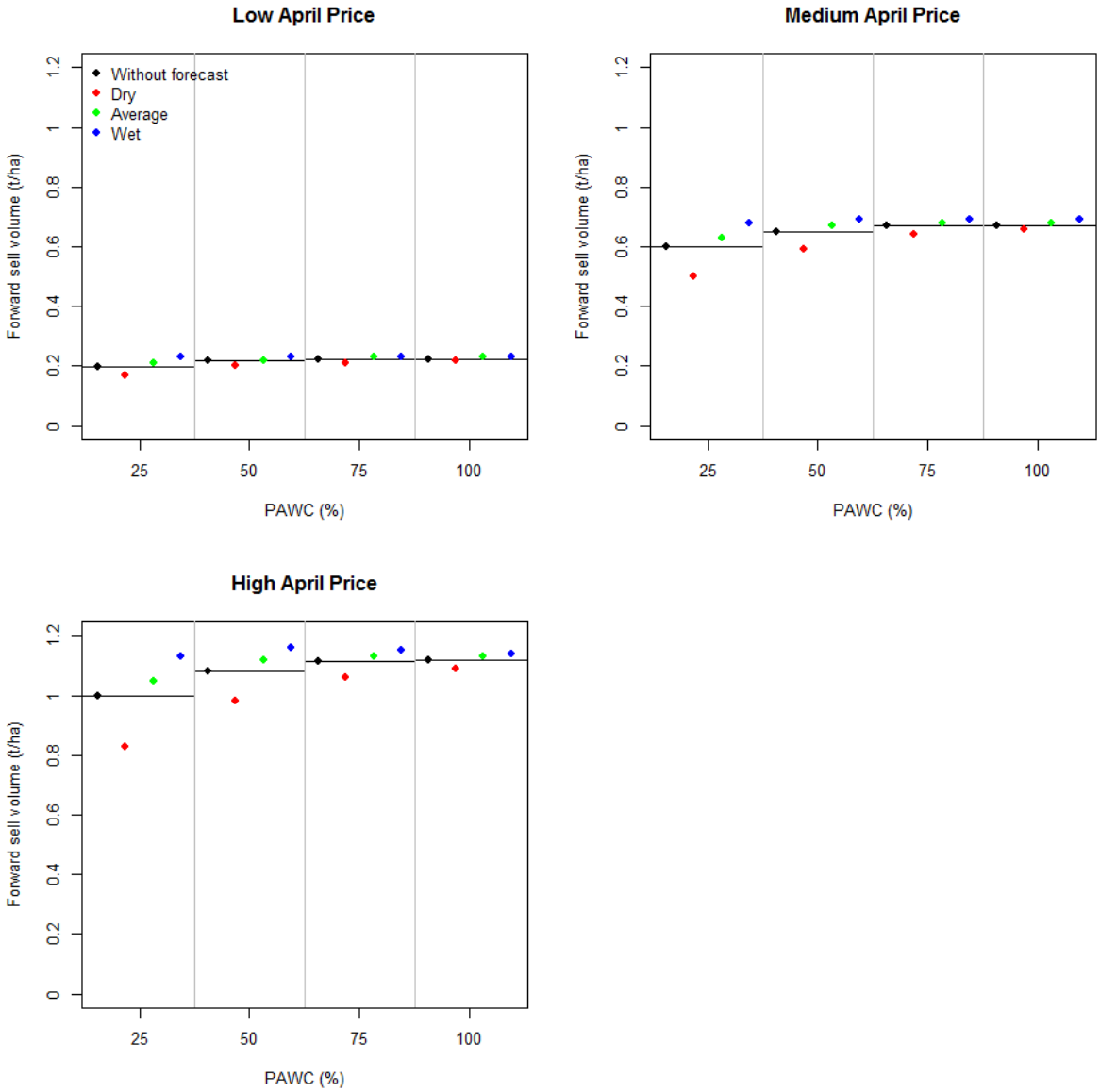


Figure 10 Forward sell volume for each April price for 25%, 50%, 75% and 100% PAWC using without-forecast and a perfect forecast of each of the climate states (dry, average and wet).

The difference between the volume forward sold with a perfect forecast compared to the without-forecast volume was calculated (Table 10). This quantifies the difference in Figure 10. In general, the differences were small with the largest deviation 0.17 t/ha (25% PAWC, dry climate state and high April price). Appendix 2: Historical deviation illustrates the deviation of individual years from the forward selling strategies without a forecast and for a perfect forecast.

Table 10 The difference in volume (t/ha) forward sold between a perfect and without forecast for each April price

PAWC (%)	Climate state	Low April price	Medium April price	High April price
25	Wet	0.03	0.08	0.13
	Average	0.01	0.03	0.05
	Dry	–0.03	–0.10	–0.17
50	Wet	0.01	0.04	0.08
	Average	0.00	0.02	0.04
	Dry	–0.02	–0.06	–0.10

75	Wet	0.01	0.02	0.04
	Average	0.01	0.01	0.02
	Dry	–0.01	–0.03	–0.05
100	Wet	0.01	0.02	0.02
	Average	0.01	0.01	0.01
	Dry	0.00	–0.01	–0.03

4.2.3 Perfect-forecast value

The volatile nature of grain prices means that prices in April have no bearing on prices obtained later in the season. Indeed, this is one the main reasons to implement a forward selling strategy that manages exposure to price volatility within the season. As such, evaluating the economic value of including a SCF is dependent on the price at which the remainder of the crop is sold, which is unknown at the time of making the decision to forward sell.

To explore how this expresses in this application of SCFs, two options were considered. Firstly, assume that the remainder of the crop was sold at a fixed price which was set to the medium price ($272/t). Secondly, evaluate a variable price for the remainder of the crop. The values tested were the same as the April prices ($234/t, $272/t, $376/t).

Assuming that the remainder of the crop was forward sold at the medium price ($272/t), the difference in the income the crop generated with a perfect forecast compared to without a forecast was calculated. These differences are the result of different volumes forward sold and are illustrated in Figure 11.

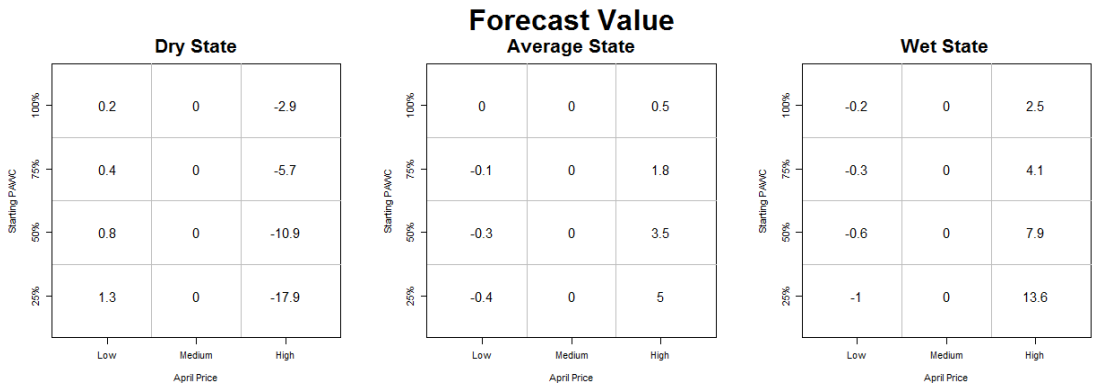


Figure 11 Difference in income between the forecast and no forecast strategy in $/ha. April prices for low medium and high were set to $234, $272 and $376, respectively. Remaining crop prices were assumed to be medium ($272/t).

Value varied with climate forecast state and price. The value found ranged from –$17.9/ha to $13.6/ha. Negative values indicate greater value was obtained using the without-forecast strategy, while positive numbers indicate value in using a perfect forecast. The zeroes are the result of the forward sell volume and the remainder of the crop volume all sold at a medium price ($272/t), hence different amounts for the forward sell volume between perfect-forecast and without-forecast had no impact.

For the dry state forecast, positive values are obtained for low April price as less grain was forward sold than the without-forecast scenario (Figure 10). Using the same logic, negative values are obtained for the high April price as less grain was forward sold (to meet 50% objective). This means a greater portion was sold at the medium price using a forecast, while the without-forecast scenario forward sold more grain at the high price (overestimated the 50% objective under dry conditions). This led to a negative value for the perfect-forecast scenario.

This pattern reverses for the average and wet state forecasts. For low April prices, more grain is forward sold than for the without-forecast scenario (Figure 10). Hence, a lower portion of the final yield was sold at the higher prices. Similarly, with high prices a greater proportion was forward sold in the average and wet climate state forecasts. As such, less was sold at the medium price than in the without-forecast scenario, resulting in positive value of the perfect forecast.

Figure 12 expands on Figure 11 and investigates the impact of variable prices for the remainder of the crop. These results highlight the difficulty in selecting a forward sell strategy to maximise income. As with Figure 11, the perfect dry forecast has positive value under different circumstances to the average and wet perfect forecasts. This reflects the dry forecast allocating a lower volume of grain than the without-forecast strategy, while the average and wet forecast scenarios forward sell a greater volume than the without-forecast strategy (Figure 10).

Greater values (positive and negative) were found when April prices were high. This reflects the greater forward sell strategy applied at high April prices (50%). As such, the forecast forward sell volumes have a greater net deviation from the without-forecast decision (Figure **15**).

The value of the forecast, negative and positive, increased with decreasing starting soil moisture. For instance, the value of a wet forecast, with high April prices and low November prices, was $18.5/ha at 25% PAWC. This decreased to $3.3/ha at 100% PAWC. Similarly, the value of a dry climate forecast, with high April prices and low November prices, was –$24.4/ha at 25% PAWC. This reduced to –$3.9/ha at 100% PAWC.

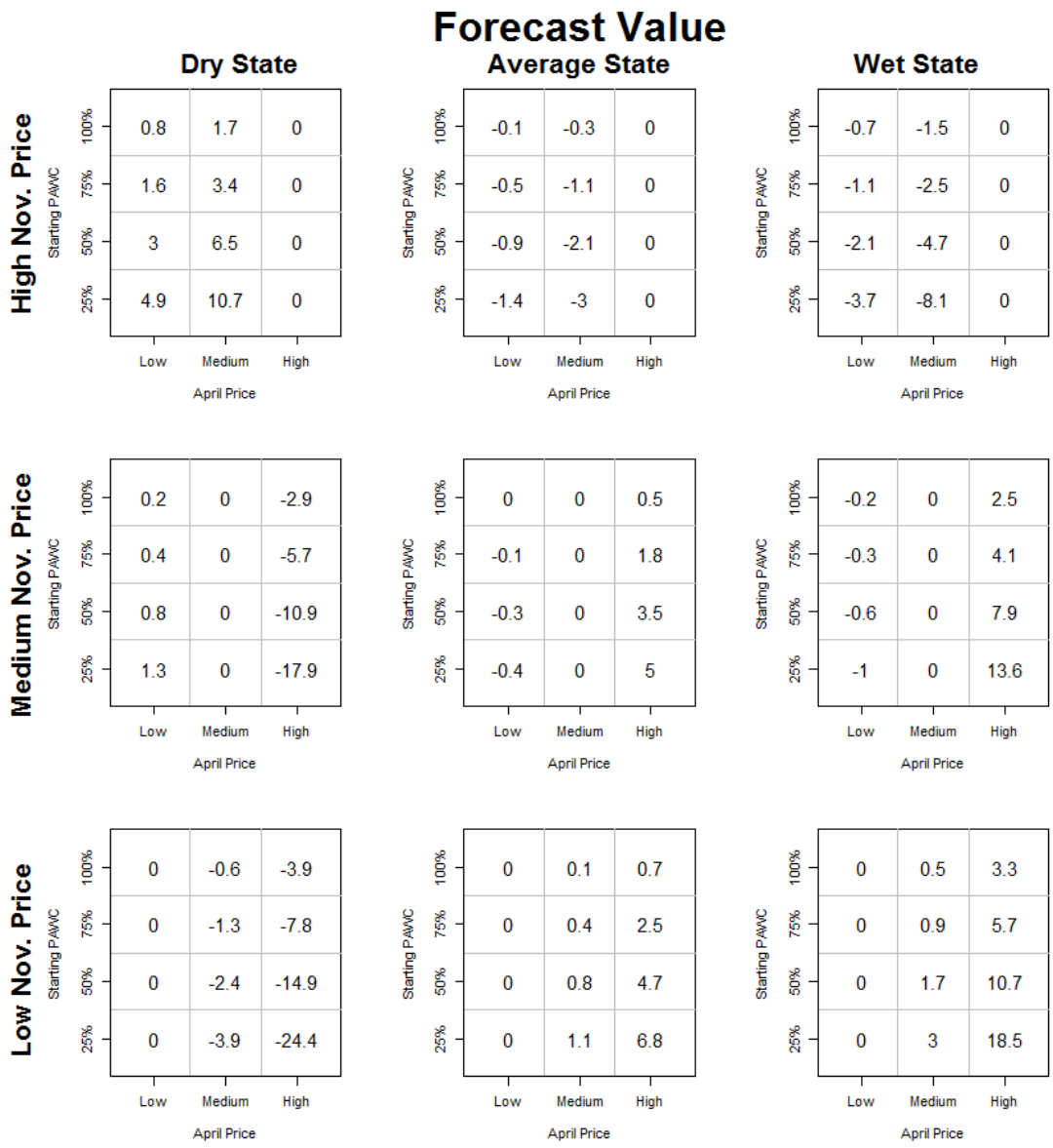


Figure 12 Difference in income between perfect forecasts and without-forecast strategies ($/ha). Both April price and remaining crop price values (Nov. price) were set to $234, $272 and $376 for low, medium and high prices, respectively.

5 Discussion

The key decision that is potentially sensitive to SCFs identified by industry was around forward selling decisions. This decision is related to risk management of price volatility and is not directly related to production. This aspect is a point of difference of this case study. In exploring the forward selling decision, the role of SCFs was identified as assisting in allocating the volume of grain to forward sell to match a pre-determined forward selling strategy, not to set the forward selling strategy. Forward selling strategies are driven by wheat prices at the time of the decision and are discussed in terms of the percentage of the final crop to forward sell. In order to meet the strategy, the final yield must be known. As yields can fluctuate with seasonal conditions, the potential value of a SCF was assessed in converting the selling strategy percentage into a volume.

The without and perfect forecasts were used to set a volume to forward sell, aligning with the forward selling strategies determined by prices in April (Table 3), noting that the perfect forecasts were perfect tercile forecasts, not for any particular year. Using perfect forecasts led to

only small changes (0.0–0.17 t/ha) in the volume of wheat forward sold compared with the without-forecast scenario (Table 10).

This small difference in target forward sell volume between the perfect and without-forecast scenarios is the result of relatively reliable May–October rainfall at Burracoppin (Figure 7). The difference between the dry and wet terciles was only 50 mm. The value of SCFs tends to be reduced for climates that are relatively stable, given they have lower production variability. Again, it is important to note this analysis considered perfect tercile forecasts, not perfect forecasts of any particular year. As such, the low sensitivity is related to the forecast characteristics. Indeed, more accurate forecasts, quintiles or deciles, may result in greater sensitivity to SCF information. Operational forecasts issued by the Bureau of Meteorology are for two climate states (above or below medium), which is of lower accuracy than the theoretical forecasts used here. For this particular application of SCFs in this region of WA, higher accuracy forecasts may be more valuable in the forward selling decision.

The greatest change in the volumes forward sold from the without-forecast scenario were for starting soil moisture conditions of 25% and 50%. However, these circumstances were evaluated to only occur for 13% of years, on average. This further reduces the potential value of SCFs in this application. The Burracoppin region tends to store soil moisture at 75% PAWC or more prior to sowing. This provides some buffering against potentially poor growing conditions as storage soil water can be used by the plants in the absence of good rains.

Although small improvements in aligning forward selling volumes with the forward selling strategies could be obtained by using perfect forecasts (Appendix 2: Historical deviation), this did not necessarily translate to improved income. Due to the uncertainty in the market, it cannot be known what prices will be available when the remainder of the crop is sold. Thus, under some price circumstances, use of a SCF to anticipate forward selling volumes decreased income (Figure 11 and Figure 12). For example, using a perfect dry forecast, a lower volume of grain is forward sold compared to the without-forecast volume, as it is know that the final yield will be lower (Table 10). With low April prices, this is advantageous as a lower amount is sold at the low April price. However, for high April prices, this increased accuracy of final yield was negative as a lower portion of yield is forward sold at higher prices; or more is sold at lower prices later in the season (Figure 11 and Figure 12).
Conversely, this was reversed for wet forecasts. Using perfect wet forecasts, a greater volume of grain is forward sold as it is known that a higher yield will occur (Table 10). For low April prices, this is a negative as a greater amount of grain is sold at a lower price than the without-forecast scenario. However, with high April prices this is a benefit as a greater amount of grain is forward sold in April at the higher price (Figure 11 and Figure 12).

The maximum range of value of use of a perfect forecast, across all April and November price settings, was –$24.4/ha to +$18.5/ha. As approximately 3000 ha of the case study farm is sown to wheat for any one year, this range is equivalent to a change in income of –$73 200 to +$55 500. It must be noted many other possible settings resulted in values much lower than these two extremes.

Reduction in income variability is desired by growers who employ forward selling strategies. As such, the different standard deviation between the perfect and without-forecast scenarios was calculated (across forecast states, PAWC, April prices and remainder of crop prices). Near zero differences were found: the maximum difference was 1.8×10^{-14} (data not shown). Hence, the results of the perfect forecast were not found to reduce income variability more so than the without-forecast scenario.

This analysis only considered the potential value of perfect tercile forecasts. Further analyses using imperfect or probabilistic forecasts, which better reflect operational forecasts, were not conducted. This was deliberate as inconsistent value in the forward selling decision was found with perfect forecasts, and probabilistic forecasts would serve to further reduce any value from the without forecast selling options. The mixed results in terms of income from using a perfect

forecast were due to market volatility. Probabilistic forecasts would produce similar mixed results. Finally, the few scenarios that showed notable value (negative and positive) were for 25% and, to a lesser extent, 50% PAWC stored soil moisture at sowing. 25% or 50% PAWC at sowing are not commonly experienced (Table 7) and hence the number of seasons for which a small change in volume forward sold from the without-forecast volume would eventuate are few.

This case study has highlighted the importance of local conditions, both stored soil moisture at sowing and seasonal variability, for SCFs to have potential value. Other wheat growing areas with greater variability in growing season rainfall would likely demonstrate greater differences in forward selling volumes between the without and perfect forecasts. However, the mixed results in income when using SCFs will remain. This highlights the difficulty in choosing optimal marketing strategies for wheat growers.

Other forward selling opportunities throughout the season are available to growers. In particular, a within-season decision (e.g. around August) provides an opportunity to further reduce price risk and is at a time in the season when potential yield may be better understood. The value of SCFs for this decision could be assessed, however, again, the volatility in prices means meeting the selling strategy may not result in greater income.

An important feature for wheat growers in Burracoppin that this analysis has highlighted that forward selling strategies, when determined as percentages, need only to consider the current grain price. When converting the desired percentage of the crop into a volume, this analysis has indicated that using long-term historical yields is no more or less valuable than incorporating SCF information. This reduces the need to include additional, potentially confusing, SCF information into the decision which will reduce the complexity of the decision to market factors only.

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Appendix 1: Industry engagement

Engagement for the WA grains case study was conducted in consultation with key WA grains industry members, following advice from Dr Mike Ewing, Deputy Chair GRDC western panel (1 July 2016), who suggested target regions to investigate (Merredin and Tambellup). Primary engagement was conducted by Meredith Guthrie (DAFWA) supported by Rebecca Darbyshire (NSW DPI).

Several targeted consultations were undertaken. Specifically, Dr Ross Kingwell, Chief Economist, AEGIC (16 May 2016 and 13 October 2016); Doug McGinnis, MADFIG chair (21 July 2016); Tony Murfit, farm manager (21 July 2016); Nigel and Garry Sheriden, growers (22 July 2016); Roderick Grieve, Farm Management Consultant, Arbitrage (13 October 2016); Greg Kirk, Managing Director, Planfarm, Geraldton (24 October 2016); Kim Povey, Director, Market Ag, Independent Commodity Advisers (24 October 2016); Greg Shea, Development Officer, DAFWA (24 October 2016).

1 Identifying climate-sensitive decision points

Discussions with participants centred on a typical farm management cycle based in Merredin and in Tambellup. In Merredin, the example rotation system for a larger, corporate farm was canola – wheat – barely – oats – long fallow with cover crop. In Tambellup, systems tended to include sheep as well as grains, with an example split of 70% grains and 30% grazing. In this system, the rotation discussed was canola – wheat – barely – canola/oats or include a clover rotation with sheep.

Using these typical systems, several management decisions were identified as potentially sensitive to seasonal climate information. These included decisions for nitrogen management prior to sowing and later in July. There was also some discussion regarding area planted and cropping mix, which may alter with different conditions (e.g. switch canola for wheat in dry starts).

A consistent and common topic for discussion centred on forward selling decisions. Typically, growers will make forward selling decisions in April, prior to sowing and/or later in August when the crop is part-way finished. Anticipating potential yield in combination with market prices and movements are key factors in making this decision.

Given these discussions, it was decided that the focus of this case study will be on wheat forward selling decisions. This decision point was selected for three reasons: (1) a body of research has already been completed investigating use of seasonal climate forecasts for nitrogen management and tools are already operational (e.g. http://www.yieldprophet.com.au/yplite/), (2) decisions to plant canola or wheat will be considered in the southern grains case study with duplication in WA unlikely to add meaningful additional information and (3) forward selling is becoming a common income management strategy and no work to date has focused on use of seasonal climate forecasts in WA to assist with this decision.

1.1 Decision point

To investigate the forward selling decision, a case study farm based in Burracoppin, close to Merredin was used. This farm is 7000 ha with three soil types and a rotation of fallow and liming – canola – barely – wheat. Typically, 3000 ha will be cropped to wheat for any given year.

Decision point:

What volume of wheat will I forward sell?

Through discussions with participants, April and August were identified as important for forward selling. April represents the beginning of the season, with larger uncertainty in crop performance.

August represents a time closer to harvest with potentially more certainty in crop performance but still some uncertainty in the finish. A rainfall forecast could provide an estimate of yield potential, assisting to decide the volume of grains to forward sell. It was noted that other weather factors also influence yield, including yield-limiting events such as frosts or early season heat waves.

For both of these decision points, several drivers influence the selling decision.

The key drivers for the April forward selling decision point are:

1. Grain price: higher prices would encourage selling, lower prices may discourage selling
2. Starting soil moisture: higher soil moisture levels encourage selling, lower starting soil moisture may discourage selling.
3. Seasonal rainfall outlook: a wet outlook would encourage selling, dry outlook discourage selling.

The rainfall forecast period is for the growing season, May–October. Figure 13 illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including seasonal climate forecast information against decisions made without this information.

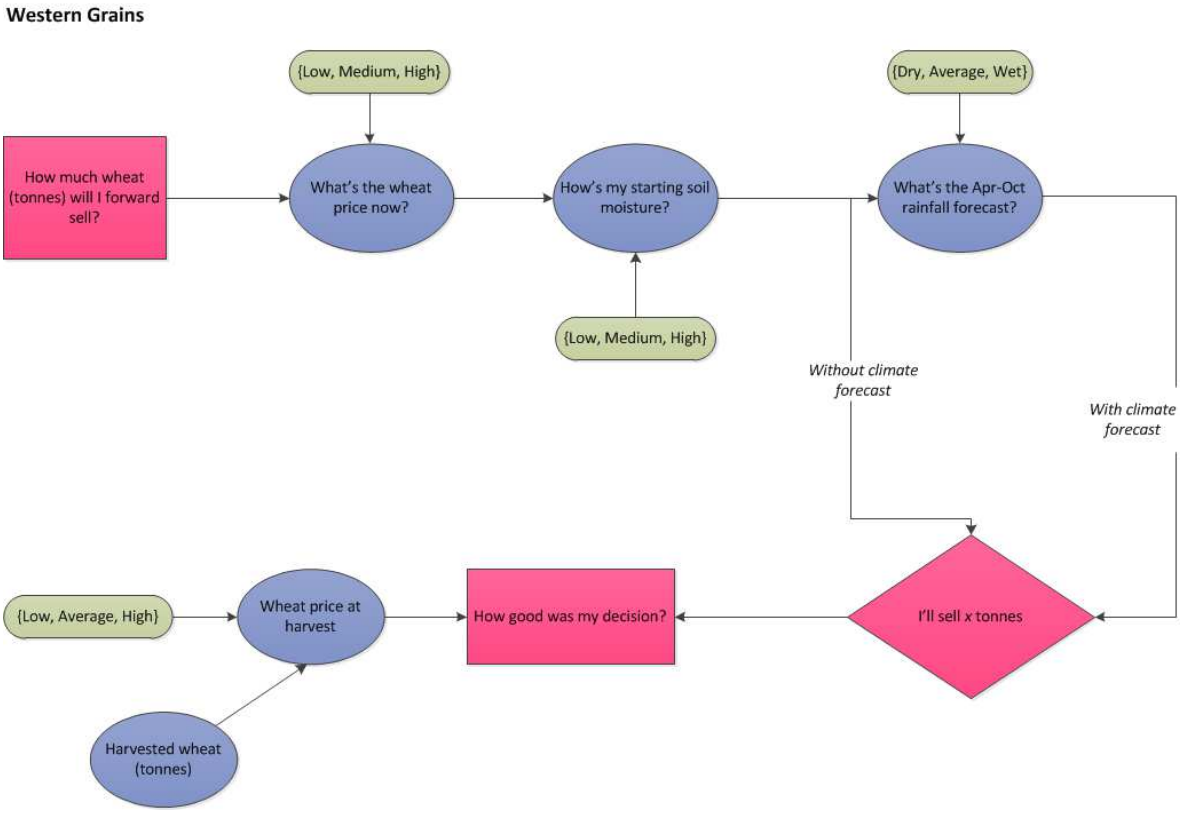

Figure 13 Decision pathway for deciding the amount of wheat to forward sell in April

The key drivers for the August forward selling decision point are:

1. Current grain price: higher prices would encourage selling, lower prices may discourage selling
2. Current soil moisture: higher soil moisture levels encourage selling, lower starting soil moisture may discourage selling.

3. Remaining seasonal rainfall outlook: a wet outlook would encourage selling, dry outlook discourage selling.

The rainfall forecast period is for the remaining of the growing season, August-October. Figure 14 illustrates this decision-making process.

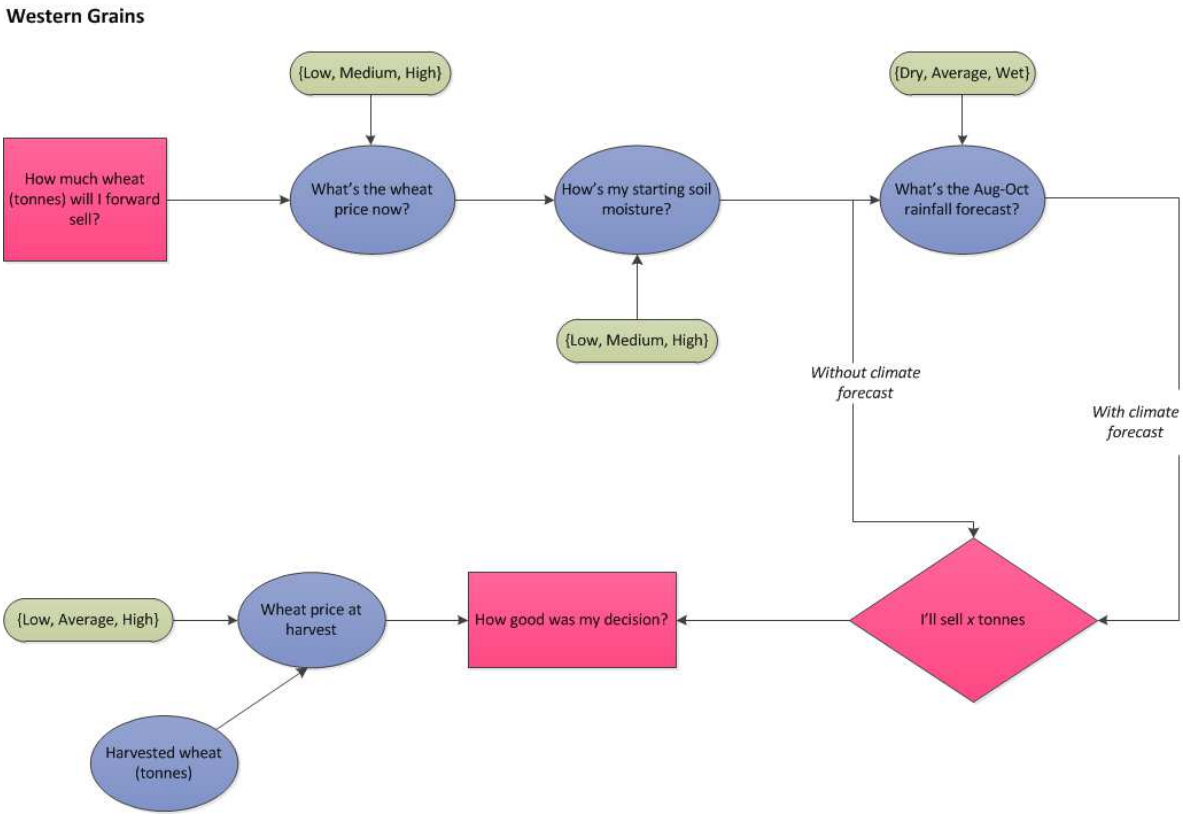

Figure 14 Decision pathway for deciding the amount of wheat to forward sell in August.

Table 11 illustrates how the three drivers can combine to influence a grower's decision to forward sell at the two decision points (April, August) based on discussions held with industry.

Table 11 Forward selling decision (percentage of grain sold) at April and August with low (<$200/t), medium ($250/t), high (>$300/t) grain price, starting soil moisture and seasonal rain forecast for the growing season (April) or Aug–Oct (August).

Grain price in April	Soil moisture at sowing	May–Oct forecast	Forward selling (%)		Comments
			April	August	
	Low	Dry	0	0	Worse position
	Medium	Dry	0	0	
	High	Dry	0	0	Sensitivity worse position to summer rainfall
Low	Low	Equal chance	0	0	
	Medium	Equal chance	10	15	
	High	Equal chance	10	15	
	Low	Wet	10	15	Sensitivity of worse position to forecast

	Medium	Wet	10	15	
	High	Wet	10	15	
Medium	Low	Dry	0	0	
	Medium	Dry	0	0	
	High	Dry	10	15	
	Low	Equal chance	10	15	
	Medium	Equal chance	30	20	Baseline decision
	High	Equal chance	30	25	
	Low	Wet	10	15	
	Medium	Wet	30	20	
	High	Wet	30	25	
High	Low	Dry	0	0	Price sensitivity in poor environmental position
	Medium	Dry	0	0	
	High	Dry	10	15	Best position sensitivity to forecast
	Low	Equal chance	10	15	
	Medium	Equal chance	10	15	
	High	Equal chance	30	25	
	Low	Wet	10	15	Best position sensitivity to summer rainfall
	Medium	Wet	30	30	
	High	Wet	30	50	Best position

Appendix 2: Historical deviation

The forward sell volumes calculated for the without-forecast (Table 8) and perfect-forecast (Table 9) scenarios were estimated using the historical mean (1889–2015) and the mean of the years in each tercile grouping, respectively. Figure **15** illustrates the deviation of the target forward sell volume (10%, 30% or 50% of yield) for individual years in the historical data for the without- and perfect-forecast scenarios.

For a low April price, there is very limited deviation in the dataset from the mean target forward selling volume for both the without- and perfect-forecast scenarios. For a medium April price, greater deviations are apparent, particularly for lower stored soil moisture levels. Small differences can be seen between the without-forecast and perfect-forecast scenarios, with average and wet perfect forecasts showing slightly better accuracy at the lower starting soil moisture levels. With high April prices, year-to-year variability increases for the without-forecast and perfect-forecast scenarios. Note that the without-forecast does not perform notably worse than the perfect forecasts. The perfect average climate state forecast performs best across all April prices and starting soil moisture levels in terms of lowest year-to-year variability.

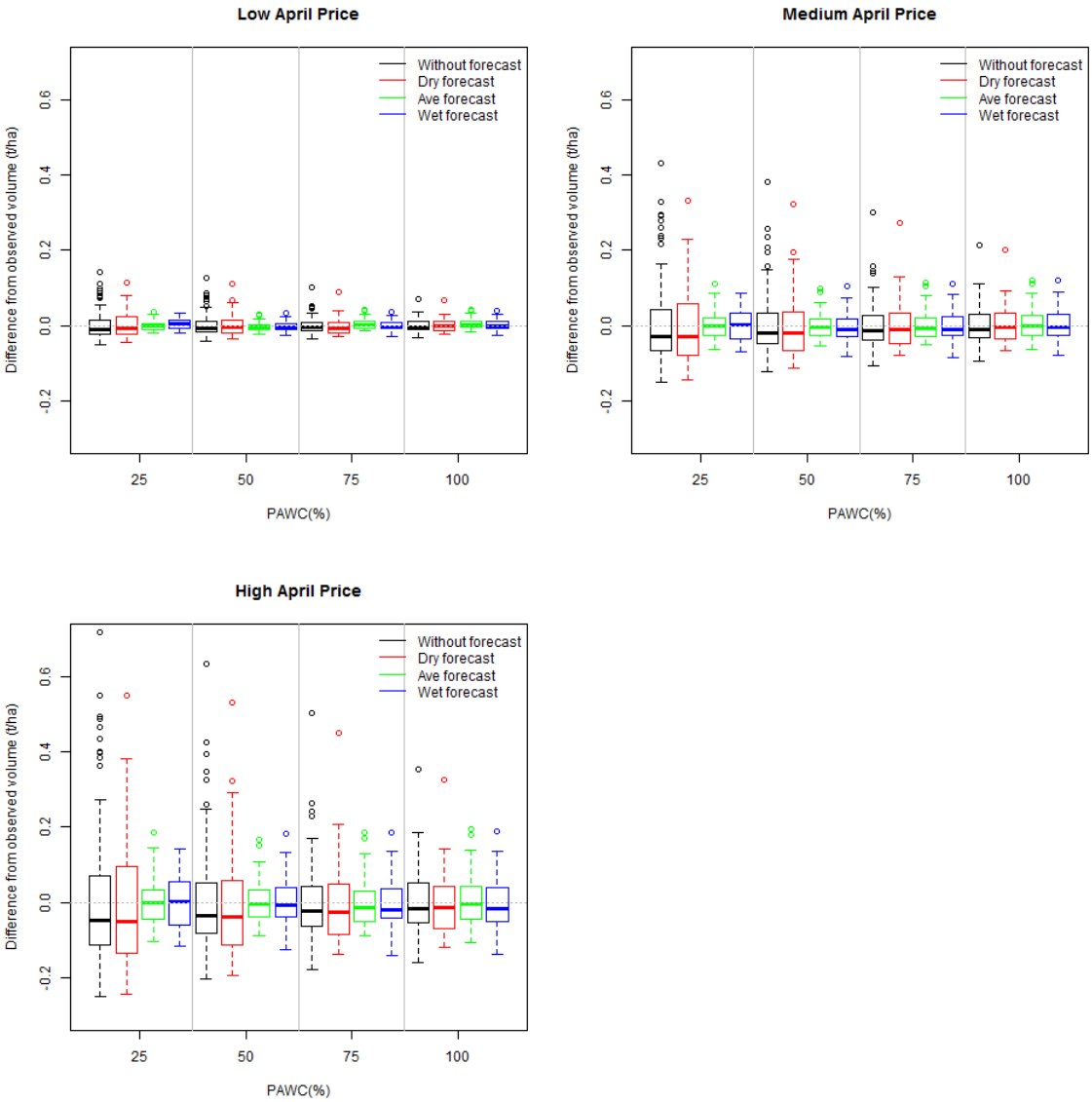

Figure 15 Year-to-year deviation in meeting forward selling target for without forecast and perfect forecast scenarios (dry, average, wet). 0 indicates no difference from the target forward sell volume. The box indicates the 25th and 75th percentiles and the line in the box is the median of the data.