Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Rice case study

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Executive summary

Importance of climate variability and forecasts

There are many sources of uncertainty in agricultural production systems. Of these, it is agriculture's basic dependence on climatically sensitive biological systems that often exerts the most influence on the sector from one year to the next. Seasonal climate forecasts (SCFs) provide opportunities for farmers to better match farm decisions to pending climatic conditions. Using SCFs, farmers can select crop types, varieties, stocking rates and nutrient inputs that are better suited to expected seasonal climatic conditions. SCFs offer economic value by moving farmers towards a position of greater certainty about the real state of nature at the time decisions are made.

Objective of the project

Insufficient evidence about the value of SCFs has been considered to be a major factor limiting their adoption in Australia and other countries. Hansen (2002) identified that the value of SCFs lies in the intersection of climate predictability, system vulnerability and decision capacity. This project aimed to develop a better understanding of this intersection and assess where, when and how SCFs offer value in agricultural production systems by undertaking a range of case studies. It is important to recognise that case studies provide an example of the potential value of a forecast based on a particular production system, at a specific time of year and at a specific location with its own historical climate variability. While the case studies reflect climate-sensitive management decisions identified by engagement with industries, they were not designed to be statistically representative or assess the potential value of SCFs to a sector as a whole.

Objective of this report

This report focuses on the value of SCFs to the management of rice production. The key decision identified by industry was when to drain rice fields. The weather conditions at drainage influence rice wholegrain percentage, which is marker of quality and attracts a price premium. The decision is a trade-off between draining early with lower wholegrain percentage and reducing water costs and draining later at a higher wholegrain percentage with potentially higher water costs. Evapotranspiration (ETo) from late February to late May influence both wholegrain percentage and water requirements (through evaporation). A skilful daily ETo forecast issued in late February is potentially valuable if it helps rice producers make a different drainage-timing decision compared with the decision made based on historical ETo amounts.

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 drainage times to be captured and outcomes to be explored in the context of water costs associated with earlier or later drainage. In order to systematically assess the value of forecast skill, a hypothetical forecast system was used. Forecasts with 0% and 100% skill were assessed, with 0% representing climatology (or historically average conditions) and 100% skill reflecting a perfect forecast of ETo evolution for each of the historical years analysed.

Methods

Historical ETo data (1889–2016) was used for the assessment. Wholegrain percentages for each year and each drainage date were obtained from outputs of a wholegrain model based on previous research (Clampett et al., 2004). Variations in wholegrain percentage were valued by applying the industry standard premium/discount. This information was combined with an estimate of water costs related to drainage time. Results were assessed to capture the links between climatic conditions, water price and wholegrain percentage. The analysis assessed potential profits of including ETo forecasts under a variety of scenarios.

Influence of non-forecast and forecast drivers on drainage date

Water prices were found to have a substantial influence of the drainage date decision across all years. With medium water prices, the without-forecast drainage decision was to drain late in the season. For high water prices, the optimal decision was to drain early with and without a forecast. The cost of water associated with delaying drainage outweighs any premium benefit from higher wholegrain percentages. Conversely, low water prices offer greater returns from draining later in the season due to premiums associated with a higher wholegrain percentage.

Value of forecasts

For medium water prices, a range of optimal drainage dates were obtained. At this water price point, changing drainage dates to balance seasons with higher ETo rates (earlier drainage) and lower ETo rates (later drainage) proved most valuable. The range in value for perfect ETo forecasts across the years investigated ranged from $0 to $120/ha. Less value was found for low and high water prices.

Key findings

A key finding was that the decision setting that leads to trade-offs between expenses (water) and income (wholegrain percentage) provides the most scope for value. Greater investigation to the use of forecasts for this purpose by growers requires additional research into the wholegrain percentage model as well as the provision of probabilistic daily ETo forecasts.

Contents

Glossary of terms

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

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

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

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

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

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

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

1 Introduction

1.1 Background

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

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

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

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

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

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

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

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

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

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

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

1.2 Project objectives

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

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

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

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

1.3 Case study approach

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

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

This report contains findings of the rice case study.

A key aspect of the case studies was the intentional and explicit focus on farm decision environments and the potential value of SCFs within these systems. A common approach was used for each of the nine case studies, consisting of three key steps:

1. Identification of key decision points within the production system sensitive to SCF information.

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

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

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

2.1 Industry overview

Rice production in Australia is dependent on irrigation water and as such production varies with irrigation water availability. For instance, due to limited water availability in 2008 rice production was only 17 600 tonnes while in 2013, with greater water availability, production increased to 161 100 tonnes (ABS, 2016a). In step with this variability in production, the value of the industry also fluctuates seasonally. For the 2015–16 season, rice production was valued at $114.8 million (ABS, 2016b).

Rice production in Australia is concentrated in New South Wales within the Murray and Murrumbidgee valleys, with a small amount of production in northern Victoria (Figure 1).

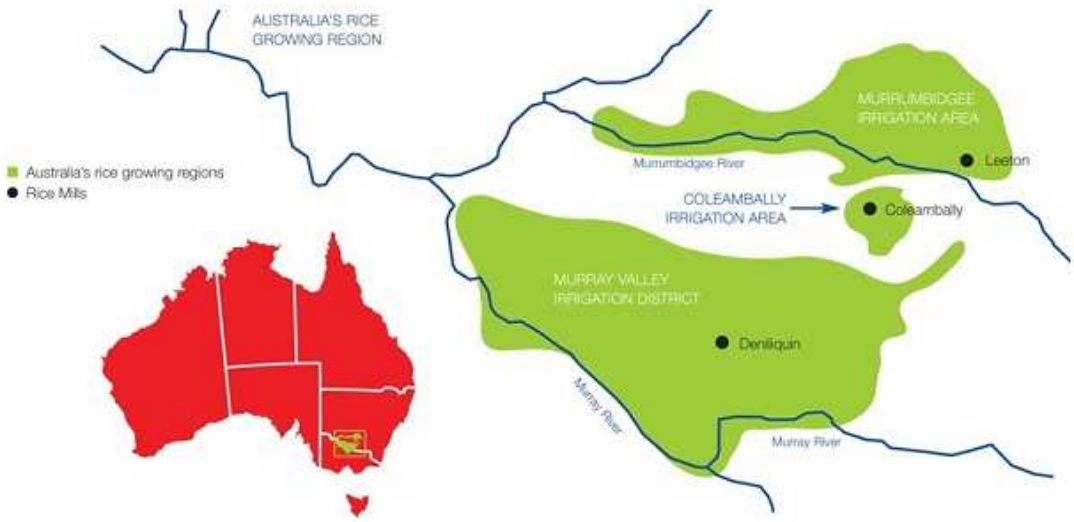


Figure 1 Australia's rice production regions (RGA, 2016)

2.2 Producing rice in Australia

Rice is grown in ponded conditions, with the height of water varying during the season from 5–30 cm (NSW DPI, 2016). With irrigation water becoming more valuable with supply constraints and the expansion of water trading, water use efficiency is an important factor affecting the profitability of rice production. In general, a rice crop requires 14–16 ML/ha (NSW DPI, 2016) with some variability based on soils, paddock layout and seasonal conditions (i.e. evaporation rates).

In Australia, rice is grown within a cropping rotation system with winter cereals and periods of fallow. Some farmers also include livestock within their operations. Typically, within these farming systems, rice is the cornerstone crop and the critical profit component for the grower.

2.2.1 Irrigation water

Rice is grown as an annual summer crop in Australia with the bulk of rice grown in winter-dominant rainfall areas where production is dependent on stored irrigation supplies. Water management is a key factor to growing successful and profitable rice crops. Irrigation water is applied to meet the plants' water demand, manage weeds and provide thermal buffering through January to protect sensitive growing parts (panicles) from temperatures less than 15 °C (Ye et al., 2009).

Seasonal irrigation water availability for rice growers is dependent on various factors. Of prime importance are major irrigation dam levels. These dam levels are the result of previous rainfall throughout the catchment and water policy decisions and regulations. Major dams that supply the major rice production areas are located in the upper part of the Murray and Murrumbidgee catchments, a substantial distance away from where production actually occurs. As such, upcoming local seasonal rainfall does not influence a grower's decision to plant a crop.

The temporary water market, like all markets, sets the price of water based on supply and demand. Interested parties other than rice growers, such as other irrigated industries and state and federal governments, participate in water trading. When purchasing or selling water, rice growers must consider the price of water and the net returns that growing a rice crop will generate. In low water availability years, water prices tend to increase, reducing returns from growing rice and potentially making it more attractive for farmers to sell their available water at a high price, or not buying temporary water.

2.2.2 Rice quality

Subsequent to growing and harvesting a rice crop it is milled. SunRice operates the milling and marketing of Australian rice. Under current marketing arrangements, growers are also SunRice shareholders and directly benefit from SunRice profits.

Like many agricultural sectors, the value of a rice crop relates to both yield and quality. Under good management and sufficient irrigation supply, yield should not vary noticeably from season to season due to the moderating influence of irrigation water. The main exception is when cold temperatures are experienced during the flowering period, reducing yields (Ghadirnezhad and Fallah, 2014).

Wholegrain percentage is a key grain quality marker. Higher wholegrain percentages lead to higher market premiums. Grains with low wholegrain percentages tend to crack in the milling process, with broken grains only suitable for secondary rice products (e.g. rice crackers). Low wholegrain percentage rice also require mills to run at slower, sub-optimal rates, increasing the cost of milling.

To incentivise grower management to increase wholegrain percentage, SunRice applies a quality premium/discount based on wholegrain percentage. Standardised to the seasonal average wholegrain percentage for a particular variety, a $2.00 per tonne premium/discount is applied for each 1% wholegrain above/below the seasonal average (SunRice, 2015).

Wholegrain percentage of rice is largely driven by environmental conditions during drainage of rice fields, which occurs prior to harvest. In deciding when to drain, the field growers must balance two objectives (Troldahl and Dunn, 2014):

1. Ensure soil moisture is sufficient for the crop to reach physiological maturity (26–28% grain moisture) to avoid moisture stress and associated yield and quality loss (i.e. reduced wholegrain percentage).
2. Ensure the field dries out sufficiently to permit access of harvest machinery to avoid damaging the soil surface when the grains still have high moisture levels (20–22%).

To assist growers with drainage decisions, a guide was produced by NSW DPI (2016) (Table 5).

Table 1 Drainage time suggestions, based on physiological stage, for crops with various maturity times and for quick (land-formed, drill sown, loam soil) and slow (contour layout, aerial sown, clay sown) drying fields

Time of crop maturity	Drainage time – quick-drying field	Drainage time – slow-drying field
Late February to early March	Late dough stage	No milky grains
Early March to mid-March	No milky grains	5% milky grains
Late March to early April	5% milky grains	10–15% milky grains

2.3 Description of climate-sensitive point

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

Appendix 1: Industry engagement.

The case study selected in this analysis was a rice specialist farm based in Deniliquin, New South Wales (Figure 2). The production system is based on paddock rotation of rice – short fallow – rice – long fallow – wheat – short fallow – barley – long fallow (Figure 3).

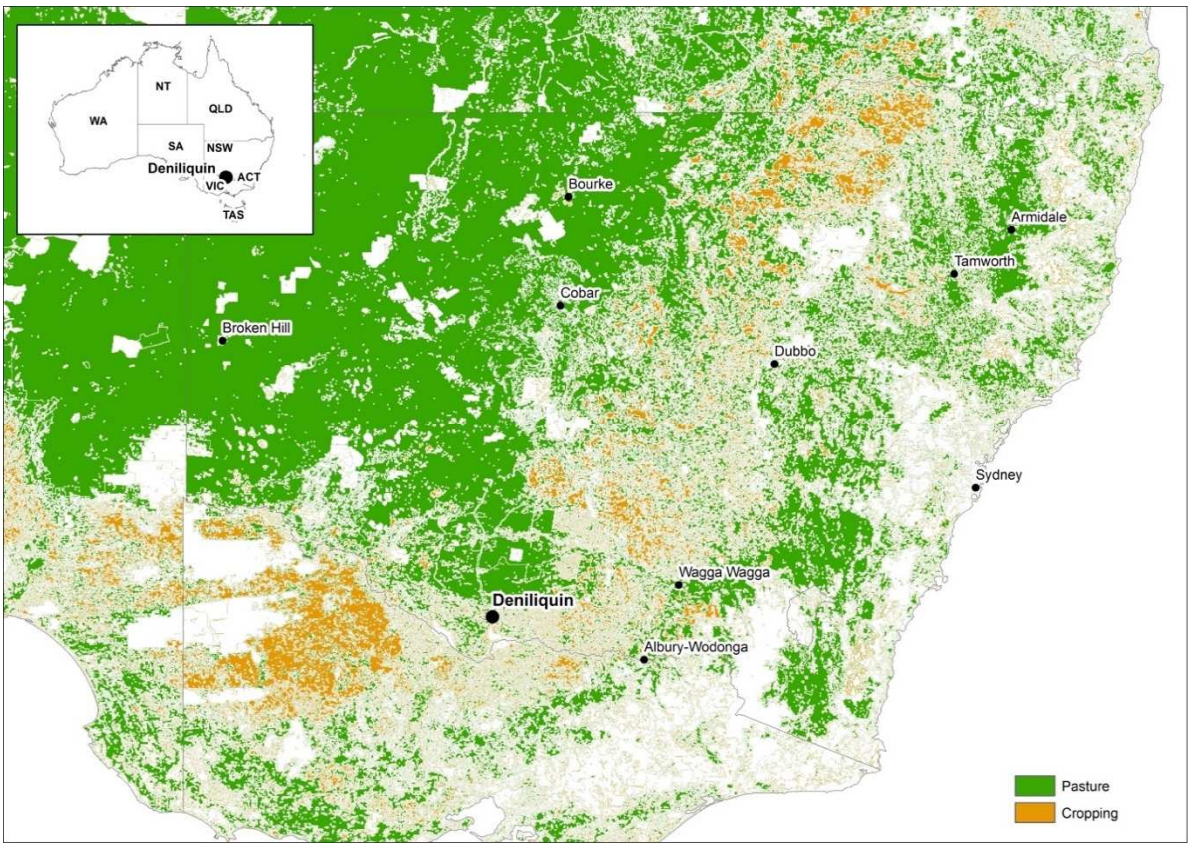
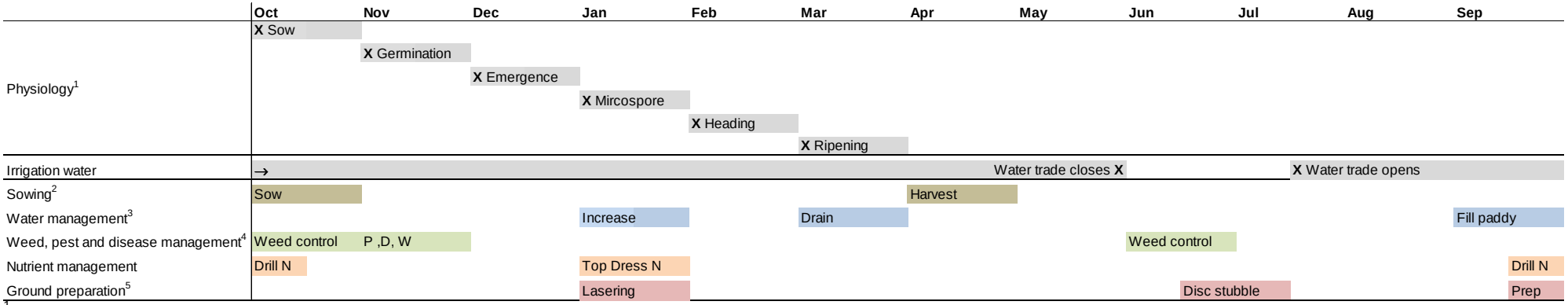


Figure 2 Map showing the location of Deniliquin, the case study location

Figure 3 Broad system characteristics of rice case study



[1]For the variety Reiziq.
[2] Sowing may not occur in all years depending on irrigation water availability. Different varieties (long, medium, short) will be sown at different times.
[3] Water levels must be kept at a certain height for plant growth throughout the season (5–15 cm). At microspore, water height must be increased (~25–30 cm) to protect panicles from cold shock (temperatures <15–18 °C).
[4] Pest disease and weed (P, D, W) control dependent on seasonal conditions and P, D, W mix as to products used and number of activities.
[5] Lasering is done periodically (~4–5 years). Ground preparation includes offset plough, levelling, reform banks, ridge roll and potentially burning in September.

2.3.1 Decision point

The key decision point for this system was:

When will I drain my rice field?

The window for this decision extends from mid-February through to early April, with drainage typically occurring from March to early April, dependent on variety and crop phenology. It is the seasonal variation that makes the draining decision most challenging to farmers (Troldahl and Dunn 2014). The forecast is for evapotranspiration and the forecast period is for the time between the potential drainage day and harvest.

As drainage occurs every year prior to harvest, the predominant influences on the decision around drainage timing are:

1. Water price: higher prices will encourage early drainage, lower prices will encourage later drainage.
2. Forecast of evapotranspiration: low evapotranspiration rates will encourage early drainage, high evapotranspiration rates will encourage later drainage.

Figure 4 illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including SCFs against decisions made without SCFs. Further details on the process of defining this decision point and the decision drivers are contained in

Appendix 1: Industry engagement.

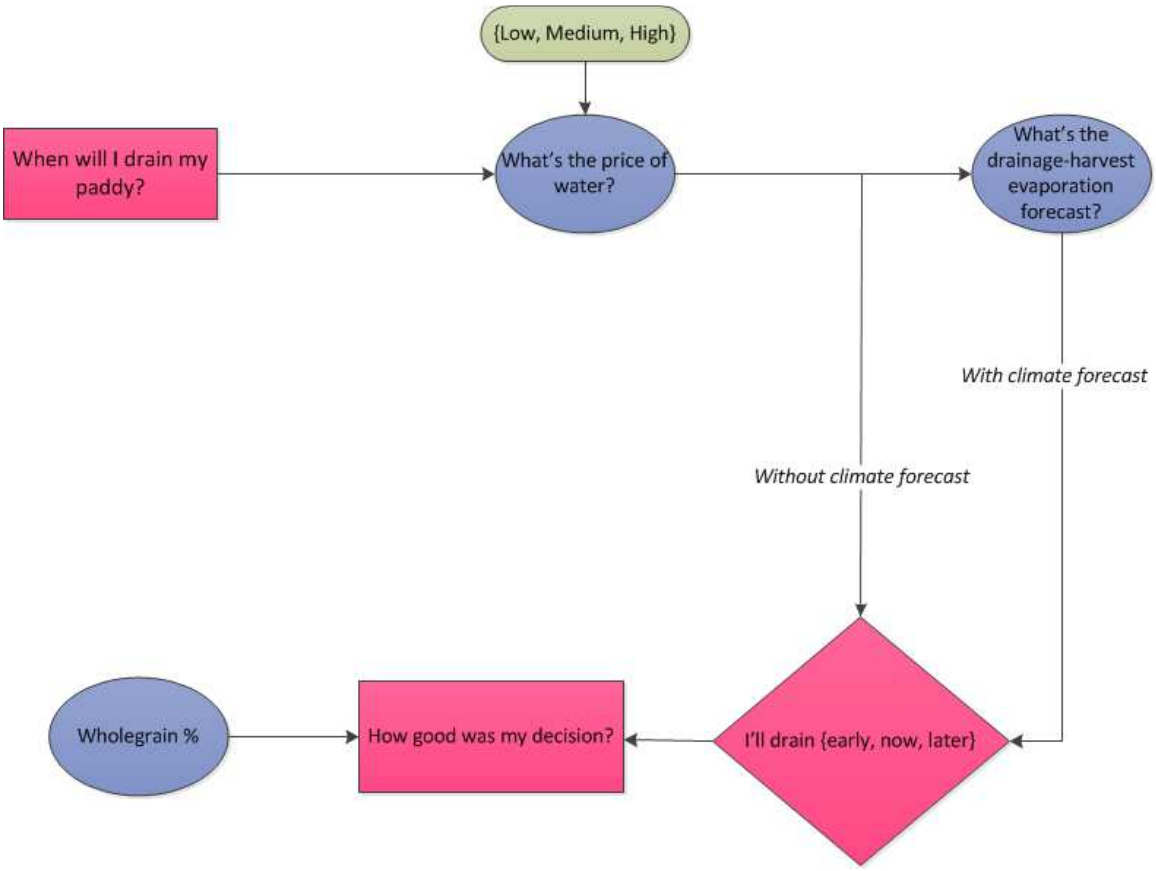


Figure 4 Decision pathway for when to drain a rice field including an evaluation of the decision made.

2.4 Previous studies of SCFs in rice production systems

No studies were located on the application of climate forecasts to Australian rice production (Parton and Crean (2016).

3 Methods

The potential value of forecasts of evapotranspiration (ETo) was evaluated through maximising returns of the system by selecting the optimal drainage day under various system conditions. An overview of the methodology is outlined in Figure 5. The main components include a rice drainage model to simulate wholegrain percentage, a set of output and input prices that values rice production and water use, respectively, and an ETo forecast. Each of these components is described in the following sections.

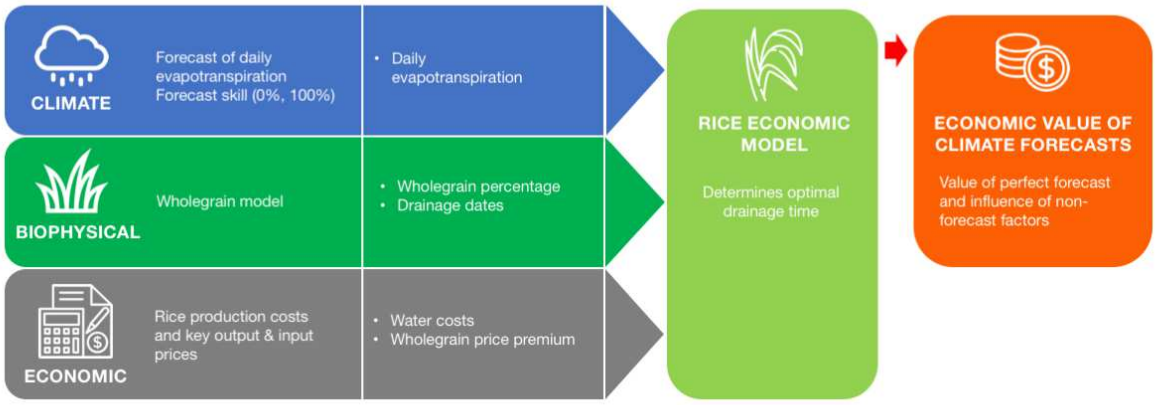


Figure 5 Methodological overview. Generation of biophysical data, water prices, price premium/discounts for wholegrain percentage and evapotranspiration (ETo) were analysed to quantify the potential value of forecasts in setting drainage date decisions based on maximising returns.

3.1 Rice wholegrain simulation model

A holistic rice simulation model that includes a feature to estimate wholegrain percentage based on various drainage date timing is not available. However, the rice industry has previously invested in research to develop key relationships between environmental conditions and resultant rice wholegrain percentages (Clampett et al., 2004). In this research, algorithms were developed to estimate rice wholegrain percentage based on soil characteristics, grain moisture and weather conditions (evaporation). The algorithms estimated wholegrain percentage with an average error of 6.3% for the target variety, Amaroo (Clampett et al., 2004).

Using the findings from Clampett et al. (2004), a wholegrain percentage predictive model was developed for this case study. To calculate wholegrain percentage, the model uses daily ETo values which determine the soil drying rates and grain moisture content. Grain moisture and wholegrain percentage are related mathematically (Clampett et al., 2004) with wholegrain predicted from grain moisture values.

A full mathematical description of the model is provided in Appendix 2: Wholegrain model description.

Key assumptions of the model were:

- The crop was at an appropriate maturity phase on the drainage date.
- The field is uniform and drainage is consistent.
- Harvest occurred on the first day that soils were dry enough to be trafficable. The wholegrain on this first trafficable day was taken as the wholegrain percentage obtained for the drainage day-of-year.

Key parameters of the model were:

- Maximum possible wholegrain percentage is 70%.
- Maximum grain moisture percentage on the drainage date is 26%.

- The soil factor must be 2.6 or higher for soils to be trafficable. This represents the first possible harvest date. See Appendix 2: Wholegrain model description for a description of the soil factor.

The wholegrain model was run for each year in the period 1889–2016. For each year, wholegrain percentage on the first harvestable day for each tested drainage day (46–90 day-of-year) was recorded. Associated cumulative ETo was recorded for each year and drainage day tested. This was the sum of daily ETo from day-of-year 47 (i.e. the second allowable drainage day) to the allocated drainage day. For example, if the tested drainage day was 56, ETo for day-of-year 47–56 was summed and recorded. This provided an estimate of additional water required to drain at a day later than the first allowable drainage date.

The wholegrain model was compared with industry-collected commercial wholegrain percentages. This was to assess the model in relation to field wholegrain percentages. SunRice provided historical appraisals of the variety Amaroo (matching the variety of the model algorithms) for 1997–2010 across 23 of their growing regions. The model was run using coincident historical climate data at Deniliquin and Griffith (Jeffrey et al., 2001) to estimate wholegrain percentage for each allowable drainage day-of-year. This annual distribution of potential wholegrain percentages according to the model, based on different drainage dates, was then compared with distribution of grower wholegrain percentage values. Note the commercial data was restricted to values over 40% on recommendation from SunRice (pers. comm. Chris Quirk).

3.2 Key input and output costs

Sensitivity analysis to temporary water prices was conducted to consider if the value of ETo forecasts vary under different price settings. Three water prices were assessed. These were the 10th, 50th and 90th percentiles of historical (2006–2015) temporary water prices in the Murray Valley (Murray Irrigation, 2017) adjusted to real prices (ABARES, 2015) (Table 2). Note, these prices are a large range with the low and high prices representing the bounds of likely prices which do not occur often (10% of the dataset).

Table 2 Temporary water prices ($/ML) assessed based on historical (2006–2015) prices (Murray Irrigation, 2017)

	Low	Medium	High
Temporary water price ($/ML)	27	93	491

Premium/discounts of the wholegrain percentage obtained were calculated using the current SunRice system where each 1% wholegrain higher/lower than the seasonal average receives a price benefit/penalty of $2/t (SunRice, 2015). To apply this, it was assumed that the seasonal average wholegrain percentage was 63%. This is a relative assessment and as such, the relative difference of returns is the key finding. Fixing this seasonal average value to a different wholegrain percentage will not change the findings.

3.3 Climate forecasts

Evapotranspiration (ETo) forecasts were used as an input variable to the wholegrain model to assess likely wholegrain percentage for various potential drainage dates. Historical data were sourced from the SILO database (Jeffrey et al., 2001) for Deniliquin (station 74128). In this dataset, ETo is estimated using the FAO Penman-Monteith formula, commonly referred to as FAO56.

The forecast period of interest is from 15 February, the first allowable drainage date, until the last allowable harvest date, 31 May. Drainage dates which resulted in harvest after 31 May were excluded from analysis. This whole period is required to assess all possible drainage options.

The decision in this case study centres on evaluating different dates to drain with the action, draining the field, fixed. This is a point of difference from many other applications of seasonal climate forecasts which tend to have a fixed time for which a variety of actions can be selected (e.g. various nitrogen top dressing rates at a fixed time (Asseng et al., 2012)).

In this analysis, annual daily sequences of ETo were used. The data were not aggregated into broader climatic groups, such as dry, average or wet, as some others have done (Crean et al., 2015). This categorisation was not conducted as this decision is changing the time of the decision and hence the classification of years into any aggregated category will change based on the forecast time period, which is non-constant.

To provide an example of the variation in the potential classification of ETo, historical data at Deniliquin was summarised from 15 February to 31 May (Figure 6). The lowest (2011) and highest (1892) cumulative ETo years across the whole drainage period are used as examples. Considering these two extreme years, it can be seen that the highest/lowest ETo years do not consistently track at the extremes of the dataset (Figure 6) and hence sectioning the data into broader categories would lead to different years being classified differently depending on the forecast period investigated.

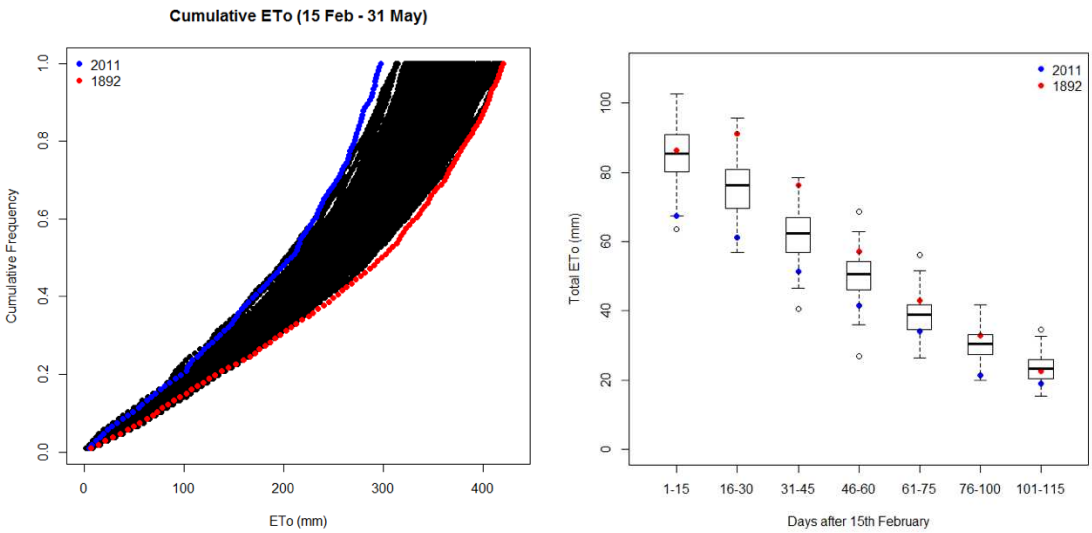


Figure 6 Cumulative ETo at Deniliquin for 15 February to 31 May (left) and for 15-day windows from 15 February (1889–2016).

Investigation into a perfect forecast of daily evolution of ETo was evaluated using historical data (1889–2016). These results were compared to a without-forecast option. The without-forecast option was evaluated as the most common (mode) drainage day across the perfect-forecast values (1889–2016) which led to the highest return. This is the most frequent best drainage date option according to the historical data and does not use any forecast information.

3.4 Economic analyses

Output from the wholegrain model in combination with water prices and wholegrain quality premium/discounts were used to assess the optimal drainage day. The optimal drainage day was calculated as the day which maximises returns (Equ 1).

$$R_d = (WG_d - M_d)$$

$$Opt_d = Max(R_d) \qquad \text{[Equ 1]}$$

Where d is drainage day-of-year, R is return, WG is premium/discount based on wholegrain percentage from draining on day d, M is the water cost of draining at a date later than the first allowed day.

3.5 Analyses

Wholegrain percentage for each year (1889–2016) was calculated for the 46 drainage days assessed (46–90 day-of-year). Deviation of the wholegrain percentage from the assumed average of 63% was calculated. Assuming a 9t/ha crop, the premium/discount of ±$2/t for each 1% wholegrain higher/lower was calculated.

A 9t/ha yield was assumed across all years. This was applied using data (1990–2010) supplied by NSW DPI rice agronomist (pers. comm. Brian Dunn). Variability in rice yield is primarily driven by sub-optimal temperatures or management during the reproductive phase. As this phase is prior to the forecast period of interest, it was assumed yield was constant. The evaluation therefore focused only on seasonal variability during the drainage time period.

For each water price assessed (Table 2), the cost of keeping water levels constant for later drainage dates was calculated. Water use was calculated as total evaporation from day-of-year 47 (the second allowable drainage date) to the target drainage date. This was standardised to a per hectare value which was then multiplied by the water price to provide the cost of draining later in terms of additional water requirement.

Returns were then calculated (Equ 1) for each drainage date, year and water price. A total of 138 different decision environment settings were evaluated for two forecast levels with 276 results produced. The scenarios are outlined in Table 3.

Table 3 Variables and value levels assessed to evaluate forecast value

Variable	Values tested
Water price ($/ML)	Low (27), medium (93), high (491)
Drainage date (day-of-year)	46–90
Forecast skill (%)	0, 100

The relative difference in returns with and without a perfect forecast were evaluated for each year in the data set and for each water price. This represents the maximum potential value of a forecast related to making drainage decisions.

4 Results

4.1 Wholegrain percentage modelling

Initially, output from the wholegrain model for Deniliquin and Griffith was compared with historical grower wholegrain percentage values for the variety Amaroo (Figure 7). The annual distribution in the modelled results is from wholegrain percentage for drainage for day-of-year 46 to 90 (i.e. 44 data points). The distribution in the commercial data is from across 23 regions and different consignments. The results indicate that the modelled wholegrain percentage distribution generally sits within the commercial variability. In several years the model overestimates wholegrain percentage compared with the median grower values (e.g. 1997, 2005). The model under-estimated median grower values in some circumstances (1999, 2000). Hence, there does not appear to be a consistent bias, although there is a tendency for the modelled results to fall within the upper section of the grower distribution.

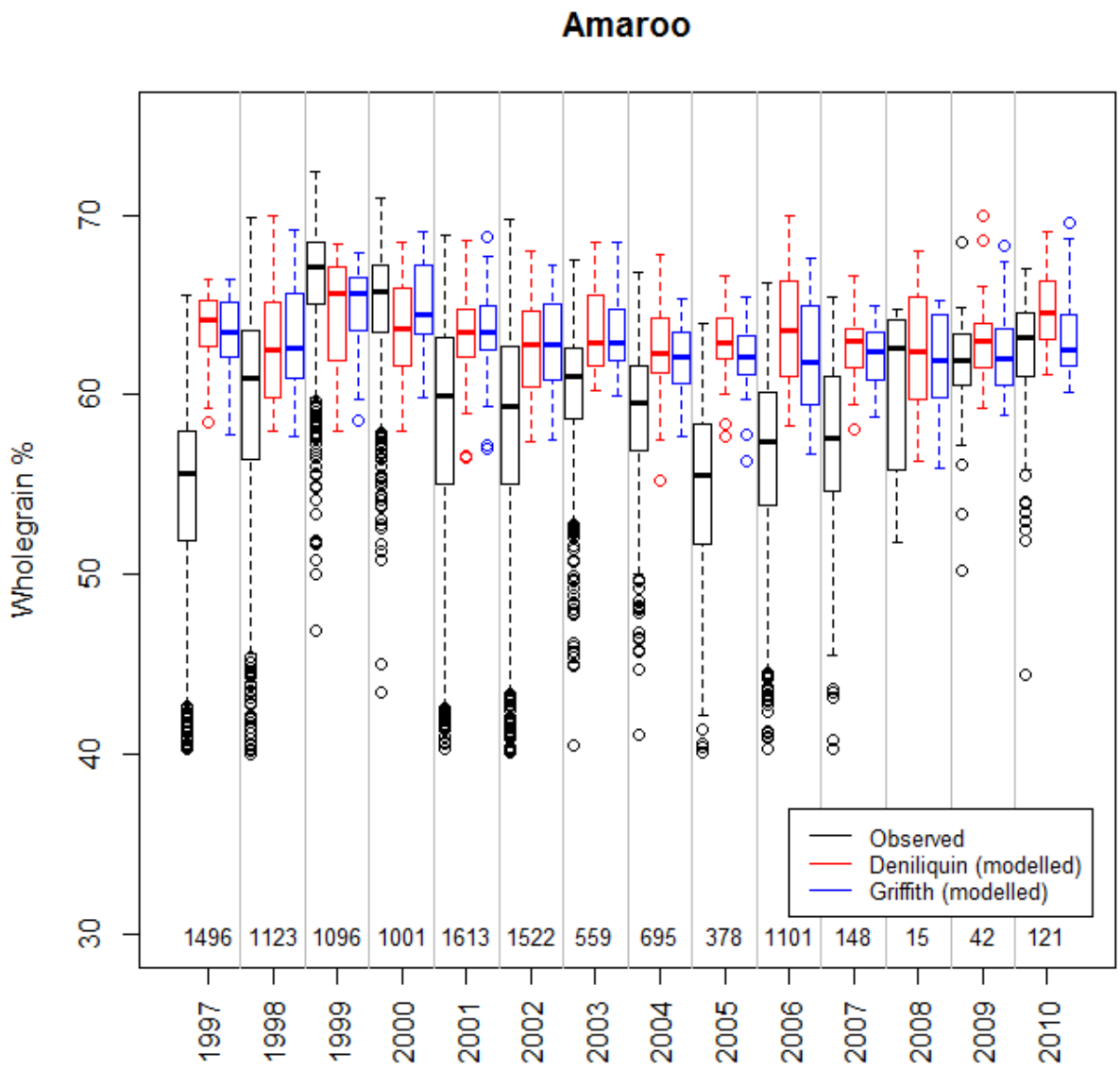


Figure 7 Distribution of average observed wholegrain percentage and modelled values for wholegrain percentage calculated at Deniliquin and Griffith, NSW. Numbers on the bottom indicate the number of SunRice data points included in the boxplots. The modelled data each had 44 data points, reflective of the different drainage dates.

There are a few key reasons why the wholegrain model produces higher wholegrain percentages than those observed. First, the wholegrain model, like most farm biophysical models, does not account for sub-optimal management (e.g. poor nutrient management). Second, non-modelled environmental aspects (e.g. rain during harvest, uneven drainage or different soil type) could influence wholegrain percentage other than ETo. Thus, it is expected that the model would be optimistic.

In spite of these unaccounted aspects of potential variability, encouragingly the model does fall within observed wholegrain percentage values. These results, in combination with the analysis in this case study focusing on relative benefit of a forecast, give confidence that the wholegrain model developed here is suitable for further analyses.

4.2 Economic modelling

4.2.1 Without-forecast decision

To evaluate the potential value of forecasts of ETo, the optimal sell decision made without a forecast must be first evaluated. The without-forecast drainage date decision was calculated from the historical data. That is, the optimal drainage date based on returns was found for all years and for the three water price values. The mode, or most frequent, drainage day across the years (1889–2016) was classified as the without-forecast drainage date decision (Table 4).

Table 4 Without forecast drainage date for each of the three water prices

	Low water price	Medium water price	High water price
Drainage day-of-year	90	90	46

4.2.2 Perfect-forecast decision

The perfect-forecast drainage date decision was evaluated by taking the drainage day-of-year that led to the highest return for each year by each water price (Figure 8). The influence of price is clear on both the drainage day-of-year value and the variability of day-of-year. The high water price favours an early drainage day-of-year in almost all years. The optimal drainage day-of-year for the low price is much later and some increase in year-to-year variability is seen. The medium water price tends to select a later drainage day-of-year with notable year-to-year variability.

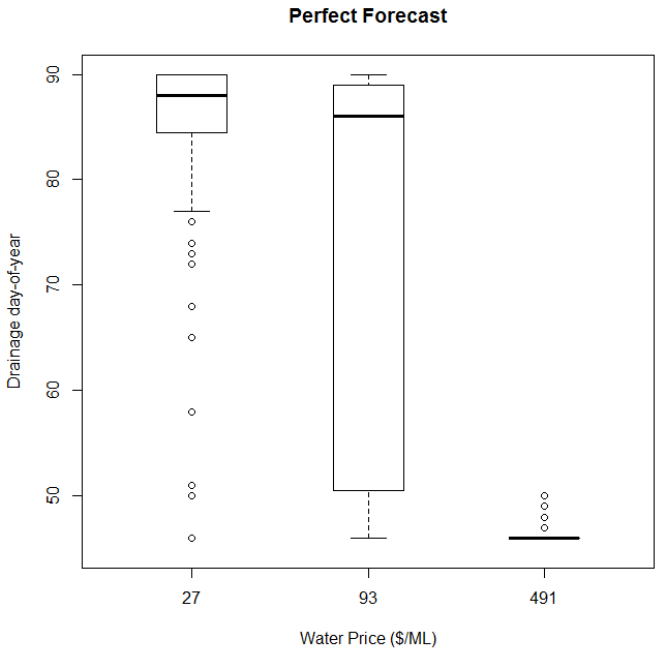


Figure 8 Drainage day-of-year for each year (1889–2016) using a perfect forecast for each water price level

4.2.3 Perfect-forecast value

Water price was found to have a strong influence on the value of a perfect forecast (Figure 9). The greatest value was found for medium water prices ($93/ML). The medium value of a perfect forecast was $15.80/ha, while extremely high values are possible with a single year, recording a value of $130/ha. The value and variability in the results using the medium water price highlights that at this price point trade-offs between the wholegrain price premium and cost of water are more seasonally sensitive.

At high water prices ($491/ML), the median value was $0/ha with a single year recording a maximum value of $63.80/ha. This result highlights that when water prices are high, the best strategy is to mostly drain the rice field early (Table 4 and Figure 8) to minimise water costs, as

the premium for higher wholegrain percentage does not offset the cost of water. Hence, under these circumstances, the value of a perfect forecast is low.

Similarly, the value of a perfect forecast when water prices are low ($27/ML) was small, with the median value $0.90/ha with a single year recording a maximum value of $60.30/ha. This highlights that when water prices are low. the best strategy is mostly to drain the rice field late (Table 4 and Figure 8) to maximise wholegrain percentage, as the cost of additional water is small compared with the wholegrain price premium. Greater variability was found for low water prices compared with high.

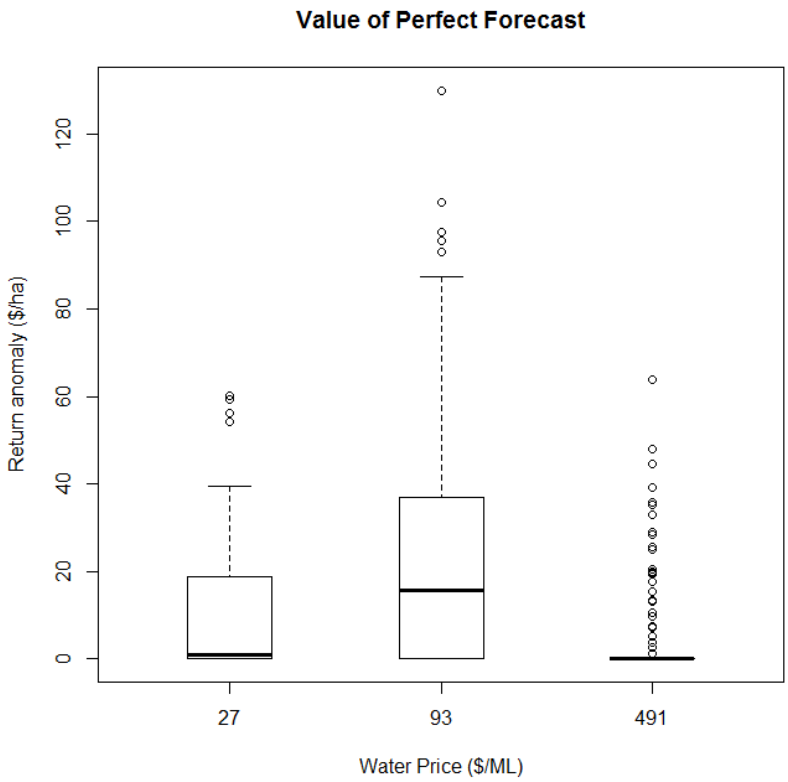


Figure 9 Value of perfect forecast to determine drainage day-of-year (1889–2016) compared to the without-forecast drainage day decision.

The valuation in this case study used a maximisation of returns to determine drainage decisions. By using this approach, different wholegrain percentages are likely based on water price and, to a lesser extent, in response to a forecast (Figure 10). This highlights that grain quality is linked to water price with lower grain quality likely in years with high water prices. Use of a perfect forecast did increase the wholegrain percentage marginally with median increase in wholegrain percentage of 0.4%, 0.3% and 0.6% for low, medium and high water prices, respectively. Advice from SunRice regarding the industry benefit of increasing crop wholegrain percentage suggested that 0.5% increase would translate to increased income of approximately $550 000 (assuming a 600 kT crop). In this case study, benefit to growers can be obtained both directly, as assessed, and indirectly as a result of an industry-wide increase in wholegrain percentage.

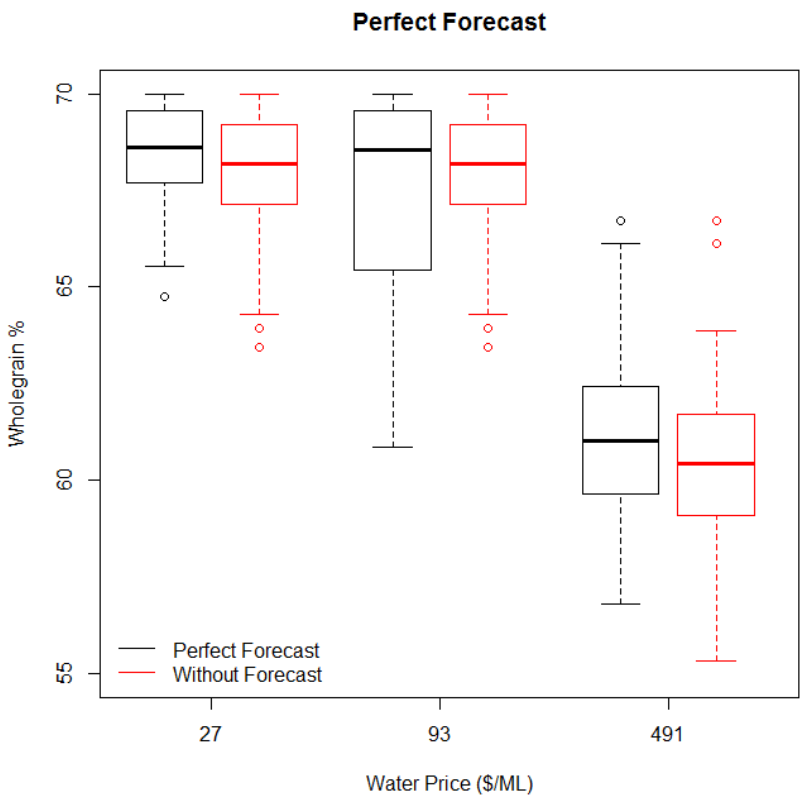


Figure 10 Wholegrain percentages (1889–2016) from utilising a perfect and without forecast strategy for each water price.

5 Discussion

The key decision with potential application of forecasts identified by industry was when to drain the rice field. This decision is a trade-off between draining later and gaining wholegrain percentage premium at higher water costs, and draining earlier with wholegrain percentage discounts and lower water costs. Water price had a strong influence on drainage date decision with and without the forecast (Table 4 and Figure 8). Using a perfect forecast with medium water prices tended to encourage later drainage dates, with this price leading to the greatest variability in drainage date across the historical dataset. High water prices encouraged early drainage to minimise water costs, while low water prices encouraged late drainage to maximise wholegrain percentage premiums.

Operationally, seasonal climate forecasts are typically delivered as probabilistic. For example, the Bureau of Meteorology issues probability forecasts of above or below median conditions (e.g. 70% chance of above median rainfall for the next month). Only perfect forecasts of ETo were investigated here. This was implemented as the decision in this case study differed from many other studies as the decision was fixed, drainage must occur, only the timing is to be decided. As such, the forecast period of interest changed with each drainage date assessment.

This case study has highlighted the potential application of forecast information that is currently not available. That is, daily evolution of ETo forecasts over several months. The maximum potential value of such a forecast was found to be over $120/ha. It is unlikely that such a precise forecast will be delivered in the near term. However, this case study highlights that for forecasts to have application and value to agricultural sectors, they need greater tailoring to key climate-sensitive decisions. The format and validity of a probabilistic daily ETo forecast for application to the rice industry, and likely to other irrigated industries, is a challenge for the forecast community to meet.

In interpreting these results, it is necessary to contextualise the wholegrain model used in the assessment. The model was evaluated against commercially collected wholegrain percentages (Figure 7) and was found to fall within the range of observed wholegrain percentage. The model did tend to lie at the upper range of observed data. Given the many possible sources of variability (field layout, soil type, field uniformity) the wholegrain model performed adequately for the purpose of this study, providing a standardised production output for use in an economic evaluation. The without-forecast drainage date decision (Table 4) fell at either end of the allowable drainage day-of-year. This highlights two potential deficiencies in the model. Firstly, a key assumption is that the crop is at the appropriate maturity level for all drainage dates. In reality, maturity will vary seasonally, and the extremes of the drainage window will not always be viable options. Secondly, the influence of rainfall was not included in the model. Rain could have two influences on potential wholegrain percentage. Rain will wet up soils, delaying when harvest equipment can operate in the field. This delay could lead to a decline in wholegrain percentage as metabolic processes continue. Rain may also have a direct influence on the algorithms that relate grain moisture to wholegrain percentage (Clampett et al., 2004).

This case study has applied the model of Clampett et al. (2004) and identified that using the relationships in a forecasting context could be of value as a farm risk management tool. If a wholegrain percentage model is identified by industry as a potentially useful tool, further research and calibration will be required, specifically: reassessment of key relationships for currently commercially important varieties (e.g. Reiziq), validation of soil factor drying rates, development of soil factor relationships for the major soil types, determination of a soil factor which allows for soils to be trafficable, impact of other weather during drainage period (e.g. rainfall, extreme heat) and testing of key assumptions and parameter settings.

SunRice has designed a premium/discount system to encourage management behaviour to increase industry-wide wholegrain percentage. This provides good motivation to drain at a time to increase wholegrain percentage when water prices are low. However, at high water prices the premium is insufficient to offset the cost of water. Depending on the limit of gains to SunRice for high wholegrain percentages, a premium/discount system that tracks with water price may result in greater consistency in higher wholegrain percentage across different season.

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Appendix 1: Industry engagement

Engagement for the development of a case study for rice was conducted in consultation with key people in the rice industry, following advice from Dr John de Majnick, Senior Program Manager, RIRDC (on 23 May 2016), who referred the team to Andrew Bomm, Executive Director, Rice Growers Association.

A workshop was subsequently held in Deniliquin (25 July 2016) to explore the rice system in order to identify seasonal climate-sensitive decision points. Those present were: Ian Mason, Bruce Simpson, Troy Mauger (RGA), John Fowler (MLLS), Anthony Vagg (RRAPL) and two project members, Rebecca Darbyshire and Michael Cashen.

Secondary engagement was held on 19 October in Deniliquin with Troy Mauger (RGA) and John Fowler (MLLS) with project members, Rebecca Darbyshire and Michael Cashen.

1 Identifying climate-sensitive decision points

Discussions focused on a theoretical representative farm system. The group selected East Deniliquin. A typical cropping system was described which includes a mix of rice, winter cereals and fallow area. It was noted that double cropping of individual paddocks is not a feature of these systems, as winter crop harvesting overlaps with summer crop sowing times. A typical rotation for a paddock was outlined as:

rice – short fallow – rice – long fallow – wheat – short fallow – barley – long fallow

The group noted that for rice, the cornerstone crop, there were no clear management decisions using a seasonal climate forecast (months scale). Some value in seasonal climate forecasts was identified in relation to management of the winter cereal component of the system. Longer term (years) estimates of likely inflows into key catchment regions were identified as being of use to rice growers.

Greater value for improved management decisions on a shorter forecast timeframe (weeks) were much clearer. Opportunities to include shorter forecasts (weeks) were further explored as well as the use of seasonal climate forecasts to assist with winter cropping decisions.

1.1 Multi-week forecasts

Three rice crop management decisions were identified to be sensitive to multi-week forecasts.

1. **Stubble management**

Rice stubble is commonly burnt in September. Information regarding prevailing winds during this period would allow growers to manage burning in a fashion that aligns with community expectations in relation to public health.

2. **Protection against cold damage**

In January and February, rice field water levels are increased to protect sensitive tissues (panicles) against cold damage. Temperatures less than 15–17 °C are sufficient to cause damage. Knowledge of the first occurrence of damaging temperatures while plants are in this sensitive growth phase would assist in ensuring water levels are increased in time to provide this protection.

3. **Drainage**

Prior to harvest, paddies must be drained. Typically harvest will occur 2–3 weeks after drainage. The timing of this decision depends on likely weather conditions (rainfall, temperature, radiation) which influence evaporation and hence soil drainage, grain moisture and wholegrain percentage at harvest. Drainage timing can impact grain quality and hence profits.

1.2 Seasonal climate forecasts for winter cereals

Two decision points regarding seasonal climate forecasts were identified in relation to management of winter cereals. These both concern the use of irrigation water for winter cereals, which may influence rice production through the amount of irrigation water available for rice.

1. **Pre-irrigation**

In April, close to the end of the current water year, water decisions are made. At this point growers can choose to sell any remaining water, carry-over or use/buy water to pre-irrigate winter crops. A seasonal rainfall forecast at this time would assist in deciding whether pre-irrigation will be implemented. Other pre-conditions are also important in this decision, including starting soil moisture, amount of irrigation water left, water price, grain price and expected future allocations (e.g. dam levels).

2. **In-season irrigation**

In August, growers review winter crop performance and apply an optional in-season irrigation to finish the crop. A seasonal rainfall forecast would inform crop water requirements and assist in the decision to apply in-season irrigation or not. This decision coincides with the opening of the water season, with other considerations influencing this decision including water allocation, water price and soil moisture.

2 Decision point

It was decided that the two decisions surrounding winter cereal irrigation decisions did not apply directly to rice production and modelling the water allocation and trading system would be required, which is outside the scope of this project.

Of the three rice-focused decision points, drainage was highlighted as a particularly difficult decision for which greater understanding would be beneficial to the industry. Better managing stubble burning, although beneficial for the community and industry standing within the community, does not lend itself to farm economic assessment. Finally, increasing water levels through January is a standard practice to combat cold shock risk, which is present every season in Deniliquin.

Thus, for the rice case study, use of multi-week forecasts for drainage decisions to improve grain quality in terms of wholegrain percentage at harvest will be investigated.

The key decision point for this system was:

When will I drain my rice field?

The timing for this decision occurs mid-February through March with drainage typically occurring from March to early April, dependent on variety and crop phenology. The forecast is for evapotranspiration and the forecast period is for the time between potential drainage and harvest.

As drainage must occur every year, the predominant influences on drainage timing are:

1. Water price: higher prices will encourage early drainage, lower prices will encourage later drainage.
2. Forecast of evapotranspiration: low evapotranspiration rates will encourage early drainage, high evapotranspiration rates will encourage later drainage.

Figure 4 illustrates this decision-making process, with an option to not include forecast information. This is necessary to evaluate the value of including SCFs against decisions made without SCFs.

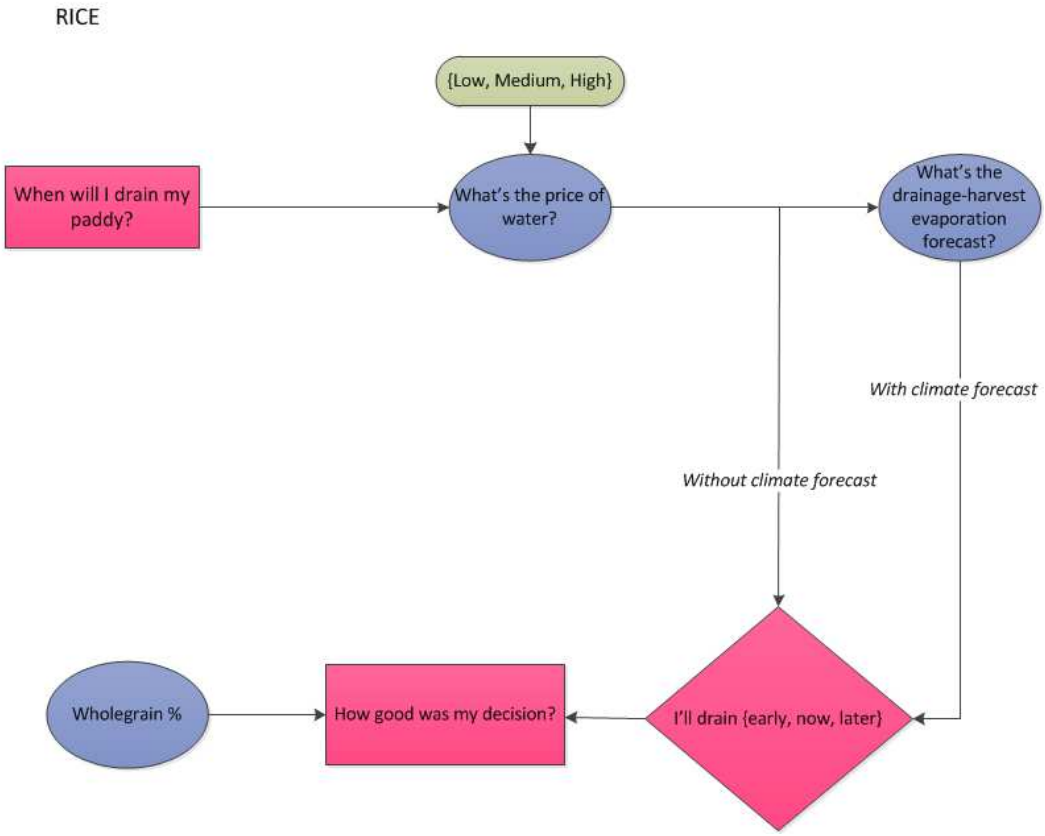

Figure 11 Decision pathway for when to drain a rice field including an evaluation of the decision made.

In evaluating the potential value of including a forecast in this decision, drainage management practices *in lieu* of forecast information must be described. To assist growers with drainage decisions, a guide was produced by NSW DPI (2016) (Table 5). This information can be used as drainage practice *in lieu* of forecast information.

Table 5 Guide to drainage time, based on physiological stage, for crops with various maturity times and for quick (land-formed, drill sown, loam soil) and slow (contour layout, aerial sown, clay sown) drying fields.

Time of crop maturity	Drainage time – quick-drying field	Drainage time – slow-drying field
Late February to early March	Late dough stage	No milky grains
Early March to mid-March	No milky grains	5% milky grains
Late March to early April	5% milky grains	10–15% milky grains

Appendix 2: Wholegrain model description

The wholegrain model used in this case study is based on algorithms from Clampett et al. (2004) and from an Excel tool provided by NSW DPI plant systems group (Dr Peter Snell).

The only variable input into the model is daily evapotranspiration (ETo_t). The model calculates wholegrain percentage based on drying rates of the soil and grain moisture percentage. Based on experimental data, maximum wholegrain percentage is 70%. Grain moisture above 23% does not contribute to any decline in wholegrain percentage, while lower values will progressively decrease wholegrain percentage. A soil factor, which represents the moisture status of the soils, is dependent on ETo_t with high ETo_t value drying soils faster and increasing the decline of grain moisture and wholegrain percentage. Harvest is only possible with soil factors 2.6 or greater, when soils have dried sufficiently to be trafficable.

2.1 Model algorithms

2.1.1 Over-arching model

$$if\ (GMdef_t \geq 0.23);\ \ \%WGdef_t = 0$$

$$if\ (ETo_t < 2.1);\ \ \%WGdef_t = 0$$

$$if\ (GMdef_t < 0.23\ \&\ ETo_t \geq 2.1\ \&\ SF_t \geq 2.6);\ \ \%WGdef_t = 0.032 \times (0.233 - GMdef_t) \times (ETo_t - 2.1)$$

$$\%WG_t = 0.7 - GMdef_t$$

Where t is the daily time step, $GMdef_t$ is the daily percentage grain moisture deficit, $\%WGdef_t$ is the daily wholegrain percentage deficit, ETo_t is daily evapotranspiration and $\%WG_t$is daily wholegrain percentage.

2.1.2 Soil factor sub-model

$$SF_t = SF_{t-1} + \left(\frac{ETo_t}{60}\right)$$

Where t is the daily time step, SF_t is the soil factor and ETo_t is daily evapotranspiration. The model is initialised with $SF_1 = 1.0$.

Soil factor represents different soil conditions with different values described in Table 6.

Table 6 Qualitative description of various soil factor values

Ground moisture key	Soil Factor
Complete water coverage	1.0
Puddled water coverage	1.0
Ground very moist	1.0
Moist and firm	2.0
Slightly moist and very firm	2.6
Dry and very firm	6.2

2.1.3 Grain moisture sub-model

Constrained to soil factor values 2.0 or larger as lower values will still provide moisture to the grain head.

$$if\ (SF_t < 2.0);\qquad GMdef_t = 0$$

$$if\ (SF_t \geq 2.0);\qquad GMdef_t = 0.00565 \times (GMdef_{t-1} - 0.14) \times SF_t \times ETo_t$$

Where t is the daily time step, $GMdef_t$ is the daily percentage grain moisture deficit, SF_t is the soil factor and ETo_t is daily evapotranspiration. The model is initialised with $GMdef_1 = 0.26$.