



Department of  
Primary Industries

# Valuing seasonal climate forecasts in Australian agriculture

Cotton 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 dryland cotton farms. The key decision identified by industry was whether to leave the field for fallow or plant cotton, and if so, when and to what skip row. The timing of this decision was early October for a rainfall forecast from November to February. Rainfall over this period can have an important influence on crop production. A skilful seasonal climate forecast is potentially valuable if it helps farmers make a different cotton planting decision compared with the decision made based on historical average rainfall. Five potential options were considered: fallow, cotton planted 15 October or 15 November to single or double skip row planting densities.

### Methods

A probabilistic climate forecast system was adopted to assess the value of SCFs. Three discrete climate states (dry, average or wet) were identified based on the lower, middle and upper tercile of November to February rainfall received at Bungunya, Queensland over the period 1889 to 2015. Each year was classified as belonging to one of these climate states. Crop yields for each of these climate states were obtained from outputs from the biophysical production model *APSIM-OZCOT*. These outputs were combined with crop production costs and built into an economic model to capture the links between climatic conditions and crop production. The economic model was used to select the most profitable cotton planting decision under a variety of scenarios.

A specific interest of this project was to understand how forecast and other important non-forecast decision variables interplay to influence forecast value. The use of a biophysical model allowed different amounts of soil moisture at sowing to be captured and outcomes to be explored in dry, average and wet climate states. Inclusion of various cotton price scenarios further helped to represent the context within which cotton growers make planting decisions.

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

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

### **Influence of non-forecast and forecast drivers on the decision to plant cotton**

The level of initial soil moisture was found to have a strong influence on the cotton planting decision. Higher soil moisture levels at planting led to an optimal decision to plant cotton in November at single skip row configuration in the absence of forecast information. In contrast, fallow was predominately selected under low initial soil moisture.

Cotton price and whether sowing rains were received had a moderate impact on the planting decision in the absence of a forecast. At a high cotton price and if sowing rains were received, cotton was planted when initial soil moisture 50% of plant available water capacity (PAWC). Conversely, with low cotton prices and in the absence of sowing rains, fallow was selected when initial soil moisture was 75% of PAWC.

Different planting decisions were selected when forecasts of different climate states were included. In general, a dry forecast more often led to fallow being selected. This reflected greater certainty of dry conditions and changed the optimal decision from planting a crop to fallowing the field to store water for a subsequent crop. Conversely, a wet forecast modified decisions towards planting cotton. In this case, greater certainty of a wet forecast allowed for more certainty of sufficient in-crop rainfall to carry a profitable crop.

### **Value of forecasts**

Forecasts of dry, average and wet climate states had different economic value. A climate forecast of average conditions was found to have no economic value under all decision settings. This is unsurprising as the without-forecast decision is based on long-term average rainfall over all years, which is normally close to conditions represented by average rainfall tercile.

Dry and wet forecasts were both found to be potentially valuable to growers, with the extent strongly dependent on initial soil moisture and, to a lesser extent, on cotton prices. The maximum value of a dry forecast improved returns by \$352/ha and the maximum value of a wet forecast improved returns by \$517/ha. These large values were found when the decision to fallow or crop was reversed.

Improved forecast skill was naturally found to be positively related to forecast value, although the extent to which value related to incremental improvements was dependent on the settings of initial soil moisture, cotton price and whether sowing rains were received.

### **Key findings**

A general finding was that forecasts that led to decisions that run contrary to the direction of conditions provided the most value. For example, a wet forecast under low initial soil moisture was valuable as it triggered a change from fallow to planting cotton. This finding has some parallels with observations of Hirshleifer and Riley (1992) that the 'news-worthiness' of information is a critical determinant of its value.

It is important to recognise that the decision investigated here represents only part of the risk cotton growers manage. The case study necessarily only represented one site and one production system and other sites, systems and decisions may find different results. However, it is likely that the general findings around the circumstances for which forecast value was found will provide insights for the use and value of SCFs for cotton growers more widely.

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## Contents

Executive summary.....	i
Contents .....	iv
Glossary of terms.....	6
1 Introduction.....	7
1.1 Background.....	7
1.2 Project objectives.....	8
1.3 Case study approach.....	8
2 Cotton production system.....	9
2.1 Industry overview .....	9
2.2 Description of production system and key decision point .....	11
2.2.1 Decision point .....	13
2.3 Previous studies evaluating the value of SCFs to cotton production systems.....	14
3 Methods.....	14
3.1 Crop biophysical simulation model.....	15
3.1.1 Fallow .....	16
3.2 Crop production costs .....	16
3.3 Key output and input prices.....	16
3.4 Seasonal climate forecasts .....	17
3.5 Economic model .....	18
3.6 Analyses .....	19
4 Results.....	20
4.1 Biophysical modelling .....	20
4.1.1 Crop yield according to climate state.....	21
4.2 Economic analyses.....	23
4.2.1 Without-forecast decision.....	23
4.2.2 Perfect-forecast decision.....	24
4.2.3 Perfect-forecast value .....	25
4.2.4 Imperfect-forecast value.....	25
5 Discussion .....	27
5.1 Crop choice made without seasonal climate forecasts .....	27
5.2 Crop choice made with seasonal climate forecasts .....	27
5.3 Comparison to previous findings .....	28
5.4 Limitations and assumptions.....	29
6 References .....	30
Appendix 1: Industry engagement.....	33
1 Industry overview .....	33

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2	Targeted consultation.....	35
3	Key climate-sensitive decision point.....	35
	Appendix 2: Gross margin values.....	38
	Appendix 3: Economic model.....	39
1	Overview of the modelling approach .....	39
2	Economic model description .....	39
2.1	Valuing the forecast system .....	41
	Appendix 4: Sowing rains results .....	43

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## Glossary of terms

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

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

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

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

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

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

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

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# 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.

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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<sup>1</sup> 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 cotton 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:

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

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

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

- 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 Cotton production system

### 2.1 Industry overview

Cotton production in Australia, and hence profitability, varies with seasonal conditions. For instance, the value of Australian cotton lint production for 2011–12 was \$2346m (ABS, 2014) but under the more challenging conditions of 2014–15, this more than halved to \$958m (ABS, 2016).

Cotton is grown predominately in New South Wales and Queensland, with each state contributing about half of Australia's total production. Figure 1 illustrates Australia's main production regions. Within New South Wales, the major production regions include areas along the McIntyre, Gwydir and Namoi rivers. In recent years production has also increased further south along the Macquarie, Lachlan and Murrumbidgee rivers. The main production regions in Queensland are along the McIntyre River and in the Darling Downs, St George and Dirranbandi regions.



Figure 1 Major Australian cotton growing regions (Cotton Australia, 2018)

Cotton can be grown as a dryland or an irrigated crop, with irrigated cropping dominant in Australia. However, growth in dryland cropping has increased due strong cotton prices and improvements in varieties, including better pest and disease resistance and yield performance.

When planting cotton, different skip row configuration can be used to alter the planting density (Figure 2). Higher density plantings (e.g. solid and single skip) lead to greater yields if sufficient water is supplied to the plant. Nonetheless, lower density skip row configurations (e.g. double skip) are often used in dryland cotton cropping as plants can access more water which can reduce risk in lower rainfall seasons. Other benefits of lower density plantings include lower planting, harvesting and management costs.

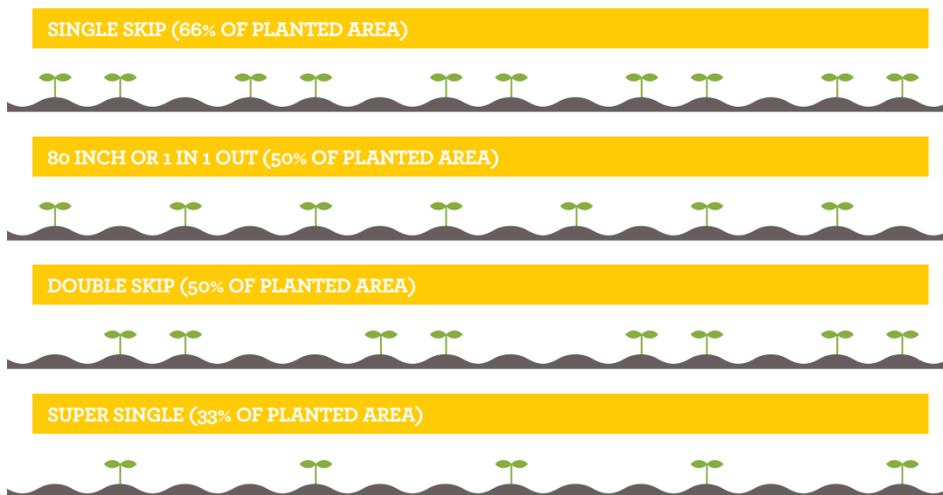


Figure 2 Skip row planting configuration options (Cotton Australia, 2013)

## 2.2 Description of production system and key decision point

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

The cotton case study was focused on a dryland cropping system based in Bungunya, Queensland (Figure 3). Dryland cotton production was selected due to the greater exposure dryland cropping has to in-season rainfall and hence greater potential for value of SCFs. The cropping rotation sequence was based on:

*dryland cotton – winter crop – long fallow – dryland cotton*

This case study was based on a farm size of 6000 ha with half the area (3000 ha) planted to cotton each year.

Key features of dryland cotton production in Bungunya are shown in Figure 4.

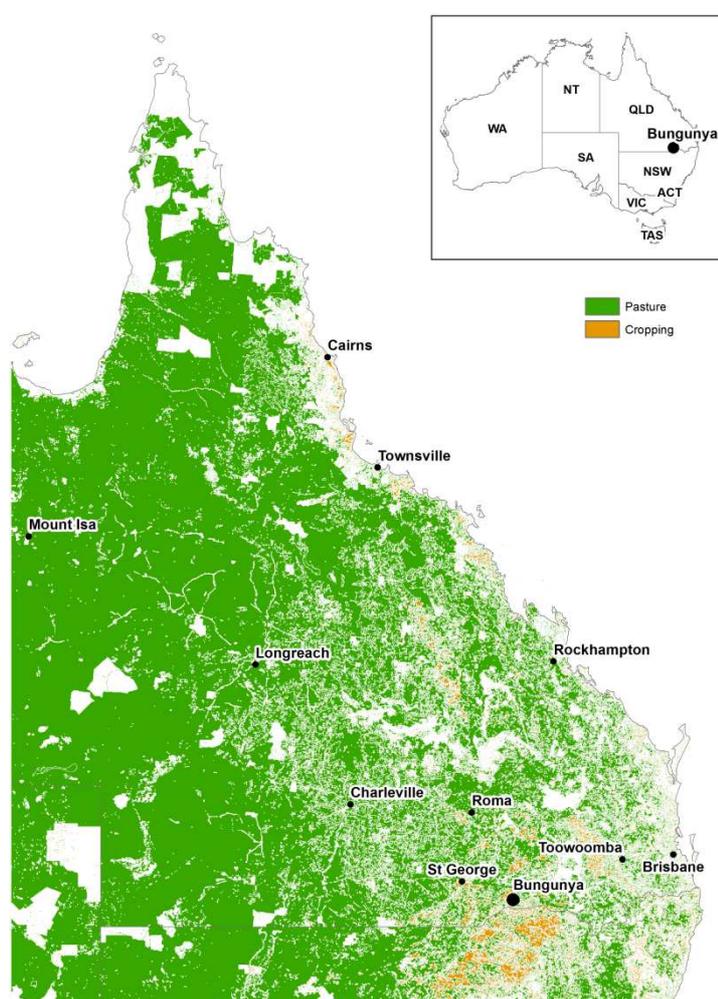
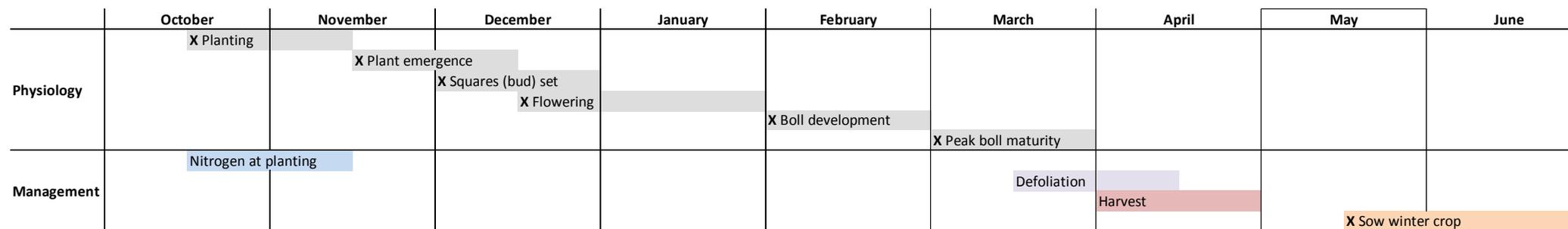


Figure 3 Map showing the location of Bungunya, the case study site

**Figure 4 Broad characteristics of dryland cropping for the cotton case study**



Note: These are estimated time of sowing and harvest, actual times will vary from season to season.

## 2.2.1 Decision point

The key decision point for this system was:

### *Will I plant dryland cotton?*

The time of the decision was October and the options were:

1. Plant cotton on 15 October to:
  - single skip row
  - double skip row.
2. Wait and plant cotton on 15 November to:
  - single skip row
  - double skip row.
3. Leave field to fallow.

In making this decision, four key decision drivers were identified:

1. Soil moisture at planting: higher soil moisture encourages planting, lower starting soil moisture encourages following.
2. Cotton price: higher prices encourage planting, lower prices discourage planting.
3. Sowing rains: sowing rains encourage planting, no sowing rains discourages planting.
4. Forecast of November to February rainfall: a wet outlook encourages planting, a dry outlook encourages following.

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

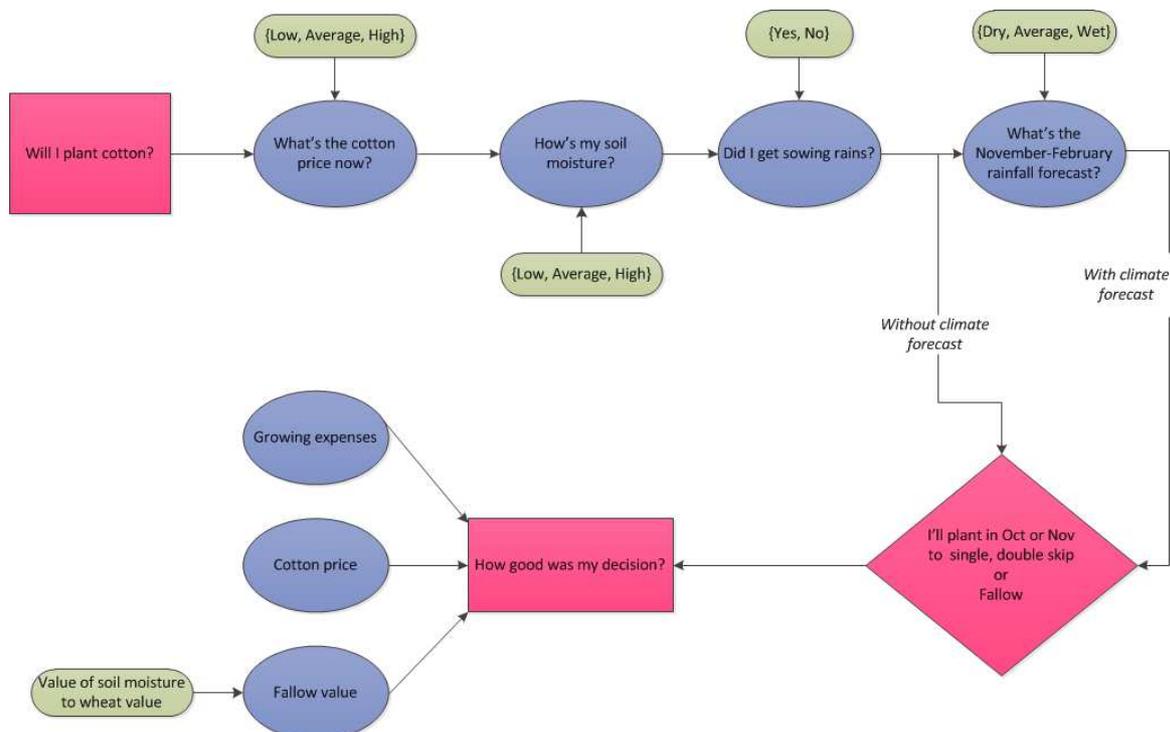


Figure 5 Decision pathway for planting dryland cotton including an evaluation of the decision made

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### 2.3 Previous studies evaluating the value of SCFs to cotton production systems

A number of studies have previously valued the use of seasonal climate forecasts for on-farm decisions for Australian cotton growers. McIntosh et al. (2005) conducted an analysis using sea surface temperature (SST) and the Southern Oscillation Index (SOI) phase forecast system to assess the value of seasonal climate forecasts in dryland cotton. They assessed the two forecasts systems for decisions to (a) plant cotton or wait to plant sorghum and (b) if cotton is planted, determine what row spacing should be adopted. They assessed these options for dryland cotton in Moree, New South Wales, assuming 50% initial soil moisture and a without-forecast scenario of planting cotton at double skip row spacing. They found that incorporating a SST or SOI phase forecast improved gross margins from the without-forecast management decision by \$40 to \$132/ha, respectively.

Carberry et al. (2000) investigated the use of SOI phase forecasts to assist with strategic management decisions regarding crop rotations of dryland cotton and sorghum. They tested a crop choice decision over two years within a three-year summer crop rotation for a hypothetical dryland farm in Dalby, Queensland. The system was set to crop sorghum in year 1 followed by a crop choice in year 2 (sorghum, cotton or fallow) followed by cotton in year 3. Crops were planted in October on 47% full soil moisture profile. The without-forecast decision was to use a fixed option of fallow in the year 2 crop choice. Their analysis considered changes to a variety of economic and biophysical indicators. Results that included the SOI phase forecast to determine the crop choice in year 2 increased gross margin returns by \$201/ha over two years but with increased financial risk. Overall, Carberry et al. (2000) noted that use of the SOI phase forecast provided some improvement in making a crop choice decision and that several financial and environmental elements should be considered when conducting these assessments.

Hammer et al. (2000) used the same data and assessment framework designed by Carberry et al. (2000) to expand their study to consider the value of four forecasting systems. These were a two-month and nine-month SOI phase system, a SST system and a projected SOI phase forecast using output from global circulation model runs. Inclusion of a SCF to make the cropping decision was found to improve gross margin returns compared with the without-forecast option for all forecast systems tested (\$185 to \$304/ha over two years). Financial risk also increased but only up to 5% more than the without-forecast strategy.

The potential value of SCFs to assist in setting cotton skip row spacing was investigated (Hammer, 2000). Using the simulation model *OZCOT*, cotton yields were estimated at Dalby, Queensland for solid, single and double skip row settings. Simulations were conducted assuming 100 mm of soil moisture at planting (PAWC 260 mm) with planting on 1 October. They used SOI phase forecasts to evaluate gross margin returns with and without a forecast. The without-forecast decision was to plant to solid skip row, the optimal setting across all simulation years. Use of a SOI phase forecast to alter the skip row decision yielded an average increase in gross margin of \$28/ha. Across all the years analysed, approximately 40% of years led to positive value, 40% no value and 20% negative value.

## 3 Methods

The potential value of SCFs was evaluated through maximising returns of the system by selecting the optimal planting decision under various system conditions. An overview of the methodology is outlined in Figure 6. Four key components are provided to the economic model which then evaluates the potential value of SCFs. Each of these components is described in the following sections.

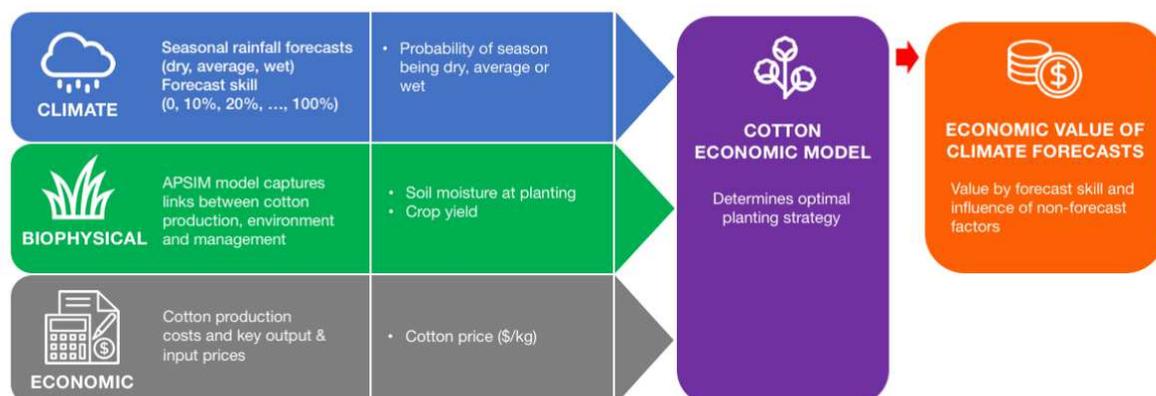


Figure 6 Methodological overview. Generation of biophysical data, crop production costs, crop prices and climate state classification of historical data and probabilistic forecasts are used in the economic model to select cotton crop choice based on maximising returns.

### 3.1 Crop biophysical simulation model

The links between planting choice, climate conditions and yield were captured through detailed biophysical modelling using the Agricultural Production Systems sIMulator (*APSIM*) version 7.9 (Holzworth et al., 2014). The *APSIM-OZCOT* model consists of a cotton module and other modules that incorporate processes of soil water, nitrogen, crop residues, crop growth and development and their interactions in farming systems, driven by daily climate data. The *APSIM-OZCOT* model contains processes that simulate cotton phenological development, floral initiation, and development of fruiting bodies. *APSIM-OZCOT* has been applied widely in Australian agricultural research. It has been validated against field measurements used for analyses of cotton crops investigated in this case study (Hearn, 1994; Milroy et al., 2004; Williams et al., 2015; Yang et al., 2014).

*APSIM-OZCOT* was executed using climate data sourced from the SILO patched point dataset (Jeffrey et al., 2001) for station 042030 (Bungunya School). The soil parameters used in the simulation were based on red sodosol soil characterisation (APSoil No: 850; Bungunya) derived from APSoil (<https://www.apsim.info/Products/APSoil.aspx>) for the Bungunya region. A total of 20 scenarios were tested, involving four levels of initial soil moisture at sowing (25, 50, 75 and 100% of PAWC) and five planting choices (fallow or plant cotton on 15 October or 15 November to single or double skip row configurations). The *APSIM-OZCOT* model configurations are detailed in

Table 1. Soil conditions were reset annually on 14 October with soil moisture set to one of the four options.

Table 1 *APSIM-OZCOT* configuration for cotton

Cotton simulations	
Date of sowing	15 October and 15 November

Sowing density (plants/m <sup>2</sup> )	7
Sowing depth (mm)	50
Cultivar	Ozcot_cotton
Row spacing (mm)	1000
Skip row	Single skip and double skip
Fertiliser at sowing (kg/ha)	100

### 3.1.1 Fallow

Summer fallow was included as a land use option. Summer fallowing allows the build-up of soil moisture and contributes to the yield and profitability of the subsequent wheat crop<sup>2</sup>. To assess the economic value of fallow, a winter wheat crop was simulated at varying levels of soil moisture using *APSIM-OZCOT*. The wheat simulation assumed a fixed application of 100 kg/ha of urea fertiliser at sowing, with an additional amount applied at floral initiation based on a soil nitrogen deficit rule, which typically amounted to 140 kg urea/ha. The cultivar Lancer was selected as a suitable variety for the production system (NSW DPI, 2015) confirmed by personal communication with Darren Aisthorpe (Queensland Department of Agriculture and Fisheries). Wheat was sown on 15 May in the simulation.

A key aspect of wheat simulations was that the starting soil moisture was set according to stored soil moisture, recorded either after a cotton crop was harvested or after a period of summer fallow. The stored soil moisture was calculated as the average over 12–18 May to minimise anomalous results due to individual rainfall events. The soil moisture values were then categorised into 5 mm increments and were used to reset the wheat *APSIM* model. The performance of the wheat crop sown at these various soil moisture levels was then evaluated for 1889 to 2015.

## 3.2 Crop production costs

Crop production costs for cotton and wheat were obtained from gross margin budgets produced by NSW DPI and AgEcon (Appendix 2: Gross margin values). Both sets of budgets provide detailed information on management practices and input costs associated with sowing, managing crop nutrition, pests, weeds and disease throughout the growing season, and harvesting.

## 3.3 Key output and input prices

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

Modelling was conducted for low, medium and high cotton prices. These were calculated according to the 10<sup>th</sup>, 50<sup>th</sup> and 90<sup>th</sup> percentile of the cotton prices (Table 2). The wheat price used was fixed at the 50<sup>th</sup> percentile (\$261/t) and the price of urea was set to \$560/t following nitrogen costs supplied in the gross margins used in the analysis (Appendix 2: Gross margin values).

**Table 2 Crop prices used in economic analyses representing low (10<sup>th</sup> percentile), medium (50<sup>th</sup> percentile) and high (90<sup>th</sup> percentile) prices**

<sup>2</sup> Fallowing can also provide good disease and weed control but focus here is only on the benefits of soil moisture.

	Low price	Medium price	High price
Cotton (\$/bale)	\$429	\$460	\$512
Cotton seed (\$/t)	\$258	\$339	\$526

### 3.4 Seasonal climate forecasts

A probabilistic climate forecast system, in line with currently used operational forecast systems, was adopted to assess the value of SCFs. Three discrete climate states (dry, average, wet) were identified based on the lower, middle and upper tercile of November–February rainfall received at Bungunya over the period 1889 to 2015. Each year was then classified as belonging to one of these climate states: dry was categorised by rainfall less than 186 mm, average as rainfall between 186 mm and 271 mm, and wet as rainfall in excess of 271 mm (Figure 7).

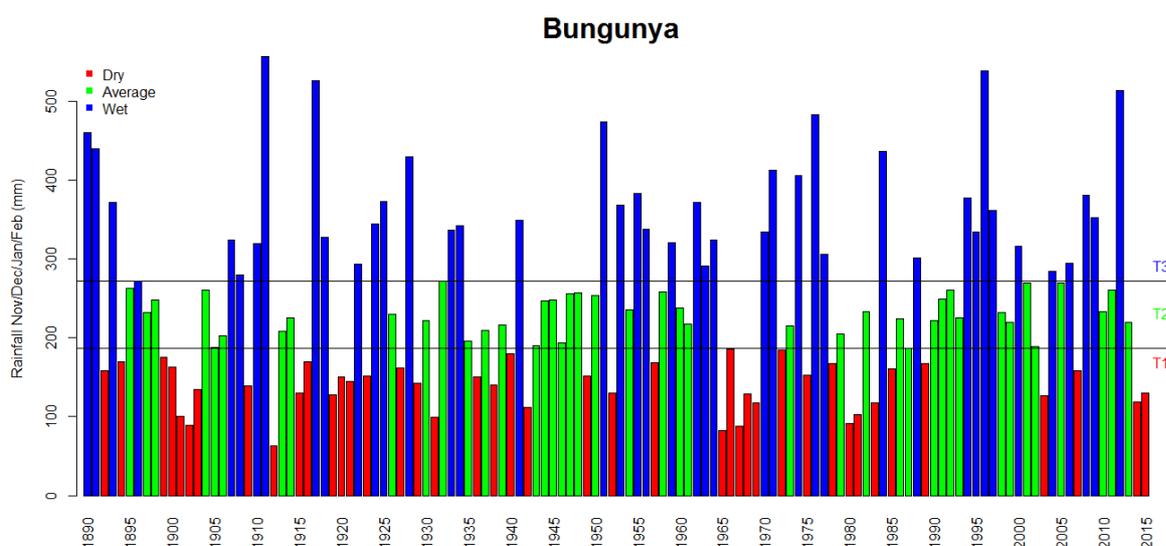


Figure 7 Total rainfall for November through February at Bungunya for 1889–2015 sourced from SILO (Jeffrey et al., 2001). Dry, Average and Wet represent terciles 1, 2 and 3.

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

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

In this study, 11 probabilistic forecasts were created for each of the three climate states (dry, average, wet), each representing a different level of forecast skill (0 to 100%). These probabilistic forecasts are incorporated into the economic model by assigning a probability to the occurrence of each climate state based on forecast skill. The definition for forecast skill with

reference to prior (without-forecast) and posterior (with-forecast) probabilities was as defined in Equ 1.

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

where  $\pi_{s|f}$  is the posterior probability of state  $s$  given forecast  $f$  and  $\pi_s$  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,  $\pi_s$  is set at its long-term climatological mean of 0.33 for each tercile.

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

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

Applying this equation to a forecast of a dry state with an assumed skill of 20% results in a weighting assigned to dry, average and wet states (Equ 3).

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

$$\text{Avg} = \text{Wet} = y \frac{(y.00 - \pi_{dry|f})y}{2y} = y \frac{(y.00 - 0.47)}{2} = 0.27y \quad [\text{Equ 3}]$$

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

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

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

### 3.5 Economic model

The economic model used key outputs from *APSIM-OZCOT* to capture the links between climatic conditions and crop production. Combining these outputs with information on crop production costs and crop prices allows net returns to be estimated for each cropping option (i.e. planting timing to which row configuration and fallow). The economic model evaluates the relative returns offered by each option under dry, average and wet climate states and under varying levels of plant available water (PAW) at the start of the season. To take into account soil moisture effects, the model considers net returns over an 18-month period (July year 1 to December year 2).

The profitability of each option was assessed under each forecast state (dry, average, wet). The economic model maximises returns by choosing the option that has the highest return weighted across the three climate states according the prescribed forecast skill. The economic model takes the form of a discrete stochastic programming (DSP) problem which can be solved through adapting a conventional linear programming model and is represented in Equ 4 and 5.

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

$$y_s = \sum_{j=1}^{Jy} c_{1j} x_{1j} + \sum_{n=1}^N c_{2ns} x_{2ns} \quad [\text{Equ 5}]$$

In Equ 4,  $\pi_s$  is the probability of state  $s$  and  $y_s$  is the net return in state  $s$ .

The left-hand term of Equ 5 represents the total costs of growing selected crops. This is reflected in  $c_{1j}$  which is the per hectare cost of growing crop  $j$  and  $x_{1j}$  which is the area of crop  $j$  sown.

The right-hand term of Equ 5 is the net revenue realised from planting cotton or fallowing in each state. This is reflected in  $c_{2ns}$ , the net revenue from activity  $n$  in state  $s$  (crop price less yield dependent costs related to harvest, levies, freight and processing) and  $x_{2ns}$  which is the level of activity  $n$  chosen in state  $s$  in stage 2 (bales of cotton sold, value of soil moisture). Structuring the model in this way reflects practical decisions to be made about harvesting and sale of crops, which is important in dry years when yields can be very low.

The value of soil moisture is also captured in the right-hand term of Equ 5, as the amount of soil moisture accrued depends on land use and the rainfall state. As described above, *APSIM* was used to estimate wheat yields under residual soil moisture levels after each cotton crop or fallow. These yields were used to estimate a return for the following wheat crop. The resulting return was expressed as a net present value because of the eight-month delay (December versus April) in receiving returns from the following wheat crop relative to the more immediate returns offered by a cotton crop. A 10% annual discount rate was applied to these returns in order to appropriately value soil moisture.

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

The introduction of a climate forecast with skill greater than 0% leads to a revision of the probabilities in line with the extent of forecast skill. A skilful forecast of a dry season results in the assignment of a higher probability to a dry state so the outcomes of a dry state are given more weight in the objective function of the model (see Table 3 for example). The change in weighting given to a dry state may lead to a change in the cropping decision (e.g. leave field to fallow) and this creates economic value from forecast use.

The modelling approach has a number of strengths in the context of valuing seasonal climate forecasts. First, because production in each state of nature is explicitly recognised, it is straightforward to assess the consequences of different crop decisions in each state. This is an important feature when considering the value of imperfect forecasts. Second, the modelling reflects the ability of farmers to consider state-contingent responses, something readily observed in practice. Third, with operational forecasts being probabilistic in nature, rational farmers will interpret probabilistic forecasts as a shift in the odds. This can be readily reflected in a DSP model through the assignment of posterior probabilities to each state based on forecast skill.

A more detailed description of the economic model is contained in Appendix 3: Economic model.

### 3.6 Analyses

The potential value of a probabilistic theoretical SCF was evaluated as the marginal benefit of the forecast; specifically, the change in returns using SCF information compared to the return obtained without a forecast. In this analysis, without-forecast is represented by 0% skill, which is

equivalent to equal weighting in results between dry, average and wet climate state outcomes (33% each). Economic value was calculated in terms of net returns per hectare (\$/ha).

The value was assessed for several different decision settings (starting soil moisture levels, delivery of sowing rains, cotton price) and for 11 levels of forecast skill for each of the three climate forecasts (dry, average, wet). This produced 792 results representing various decision environment setting, forecasts and forecast skill levels (Table 4).

**Table 4 Variables and value levels assessed to evaluate forecast value**

Variable	Values tested
PAW at planting	25, 50, 75, 100% PAWC
Sowing rains <sup>3</sup>	yes, no
Cotton price	low, medium, high
Forecast state	dry, average, wet
Forecast skill (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

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

## 4 Results

### 4.1 Biophysical modelling

Historical variability in initial soil moisture conditions at planting (15 October) was assessed to determine the frequency of soil moisture states. For this purpose, initial soil moisture was not reset annually within *APSIM-OZCOT* and a cotton crop was grown followed by long fallow each year. Annual soil moisture at sowing (15 October) was extracted by taking the mean of seven days centred on 15 October after long fallow. The percentage of years which fell into each PAW category (25, 50, 75 and 100% of PAWC) was then found across 1889–2015 with the initialisation years 1889–1899 removed to ensure stabilisation of the soil conditions (Table 5).

The largest number of years fell into the 75–100% and 100% categories, 64 and 28% of the years, respectively. Only a few years recorded soil moisture levels in the other categories with zero years falling into the less than 25% of PAWC category. This highlights the value of long fallow for soil moisture accumulation. Note, these results will vary depending on crop rotation, inclusion of fallow (or not) and other management strategies.

**Table 5 Percentage of years for which soil moisture on 15 October fell within each quartile category (1899–2015) at Bungunya.**

	<25%	25-49%	50-74%	75-99%	100%
Percentage of years (%)	0	4	5	64	28

A similar analysis of frequency of sowing rains was conducted with the percentage of years in the historical data for which 20 mm of rainfall or more fell in the week centred on 15 October was

<sup>3</sup> Sowing rains was calculated as 20mm on the day before sowing and 0mm for the remainder of the week. No sowing rains was 0mm for the week from sowing.

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calculated. Only 16% of years met the sowing rains criteria. This highlights that the sowing rains criteria, which was set after consultation with growers, does not occur frequently.

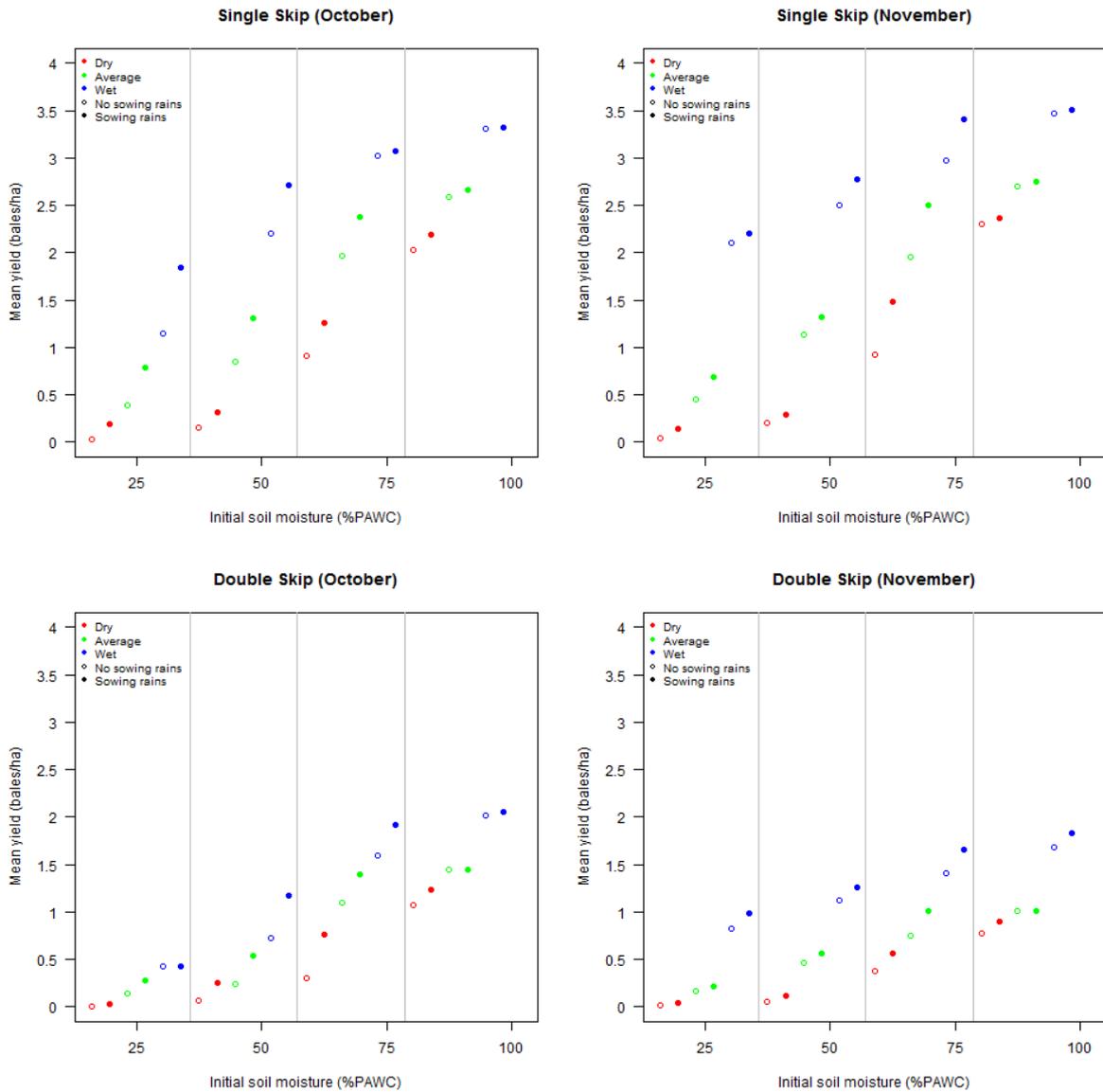
#### **4.1.1 Crop yield according to climate state**

Average crop yields were calculated for each cotton planting option all of the decision environment settings for each climate state (Figure 8). In general, greater yields were obtained for:

- wet climate states followed by average and dry
- soil moisture of 100% of PAWC at planting followed by 75%, 50% and 25%
- single skip row followed by double skip
- November planting followed by October
- sowing rains followed by no sowing rains.

An important finding from the biophysical modelling is the significant yield advantage that single skip has over a double skip row configuration. A sizeable saving in production costs needs to exist for double skip to become a viable alternative to single skip, both with and without a climate forecast.

The difference in yields based on different climate states (separation between red, green and blue colours) for many decision environment settings establish a basis for SCFs to assist with dryland planting decisions and hence be of benefit.



**Figure 8** Average yield (bales/ha) for each of the planting options (planting time and skip row) assessed when planted to 25%, 50%, 75% and 100% of PAWC. 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 rainfall November-February. Solid circles are if sowing rains in October were received and open are for if sowing rains were not received.

In order to assess the value of fallow, stored soil moisture was extracted for the week centred on 15 May for each cotton crop and after fallow. Using this result, a winter wheat crop was grown to value the stored soil moisture. Figure 9 provides an example of these analyses for no sowing rains. The figure shows that the stored soil moisture available for a winter wheat crop depended on the planting decision. Fallowing always increased stored soil moisture in May compared with planting cotton. The single skip planting configuration tended to deplete the soil moisture the most and therefore also led to the lowest wheat yields.

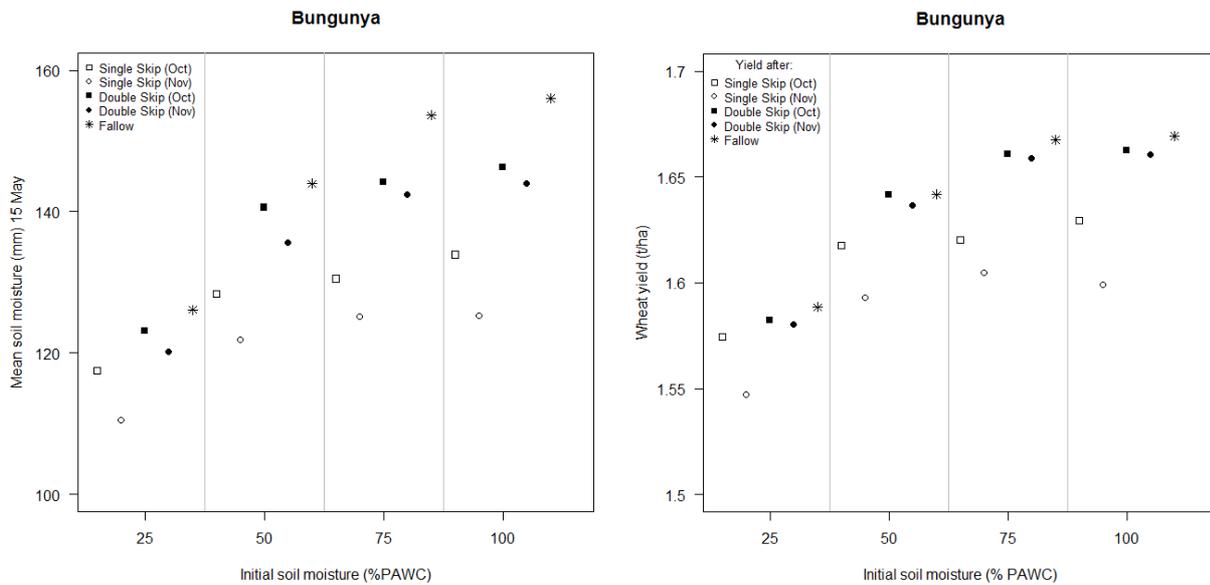


Figure 9 Mean soil moisture (mm) on 15 May (left) and mean wheat yield (right) for each soil moisture setting at planting (i.e. 15 October), planting date, skip row and fallow option. These results are without sowing rains.

## 4.2 Economic analyses

### 4.2.1 Without-forecast decision

The optimal planting decision without a forecast (0% skill) must be first evaluated prior to calculating the potential value of SCFs. Figure 10 shows the optimal without-forecast planting decision for each combination of the decision drivers (Table 4).

The yield advantage of cotton planted under a single skip versus double skip row configuration found in the biophysical modelling flowed through into the economic results. The outcome was that single skip was selected as a most profitable cotton option under all settings.

Soil moisture was found to have an important effect on decision making. With high initial soil moisture settings (100% of PAWC), the decision was to plant in November to single skip row configuration with and without sowing rains and across all price settings. This illustrates the value of planting with high soil moisture levels as production risk is lowered. At lower initial soil moisture (25% and 50% of PAWC), fallow was selected for all combinations, except at high cotton prices and with sowing rains. At 75% of PAWC the decision was to either fallow the field or plant to single skip, depending on cotton price and sowing rains settings.

When cotton was planted, November timing was selected in all circumstances except when initial soil moisture was at 75% of PAWC. In this case, the yield from cotton planted in November was slightly below that of cotton planted in October (0.05 bales/ha). This resulted in a small difference in returns between the two planting times (\$10/ha).

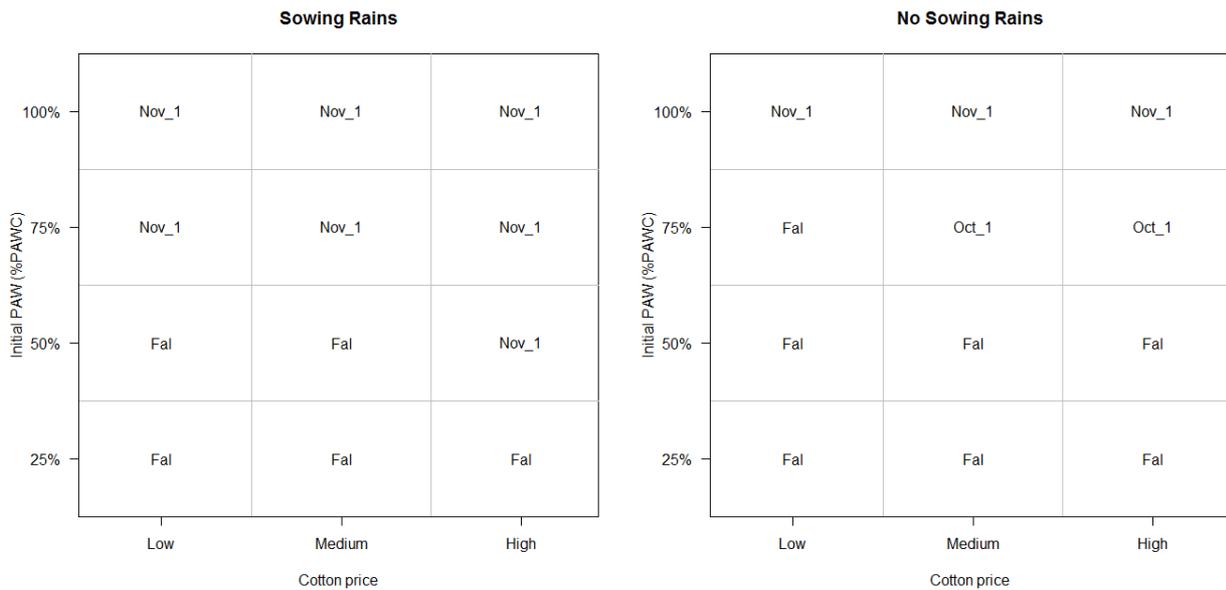


Figure 10 Optimal without-forecast planting decision with sowing rains (upper) and without sowing rains (lower). Four levels plant available water (25, 50, 75 and 100% of PAWC) are represented in the four internal rows and cotton price (low, medium, high) is represented in the internal columns. Oct\_1, Nov\_1 and Fal represent November planting to single skip, October planting to single skip and fallow, respectively.

Results without sowing rains will be presented in the next sections as sowing rains, as defined here, are generally not received (84% of years). Note that the equivalent results with sowing rains are contained in Appendix 4: Sowing rains results.

#### 4.2.2 Perfect-forecast decision

The optimal decision for perfect forecasts of dry, average and wet climate states (100% skill) were evaluated for each combination of the decision drivers (Figure 11). For a dry climate state, fallow was selected for almost all soil moisture settings unless there was a full soil moisture profile at planting. With a full profile, cotton was planted across all price levels. This shows that even under a dry climate state, a full water profile is sufficient to carry a profitable crop.

For a wet climate state, a cotton crop was planted for all soil moisture and cotton price settings (Figure 11). In these results, the most notable difference to the without-forecast decision was that cotton was planted for all soil moisture and price settings. For an average climate state, the optimal cotton crop decision was the same as the without-forecast choice for settings (compare Figure 10 and Figure 11).

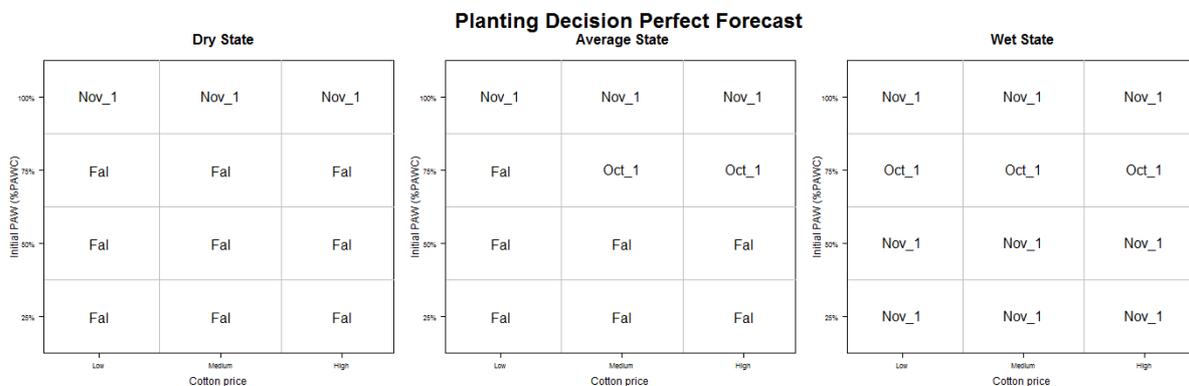


Figure 11 Optimal with-forecast planting decision without sowing rains. Dry, average and wet climate states are represented in each box. The four levels of plant available water (25, 50, 75 and 100% of PAWC) are represented in the four internal rows and cotton price (low, medium, high) is represented in the internal

columns. Oct\_1, Nov\_1 and Fal represent October planting to single skip, November planting to single skip and fallow, respectively.

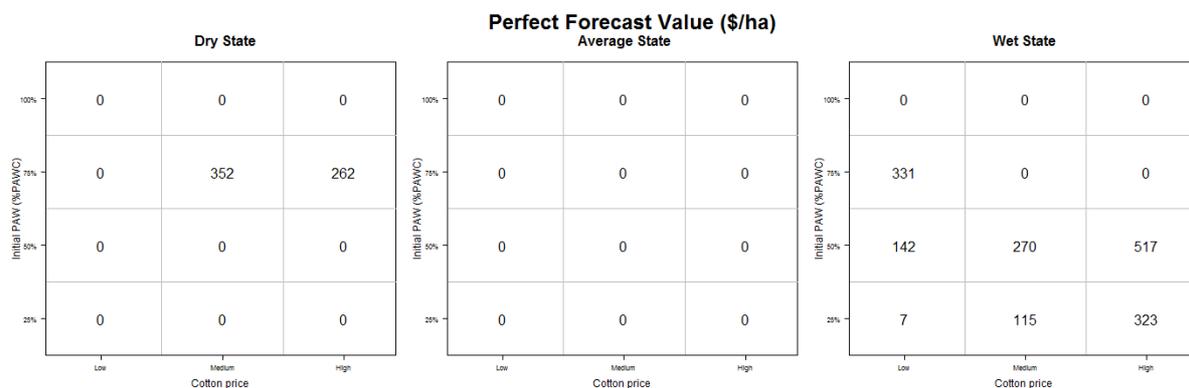
### 4.2.3 Perfect-forecast value

The range in the value of a perfect forecast (100% skilful) across decision settings and the three climate states was \$0 to \$517/ha. The results highlight the importance of the decision environment settings in economic returns (Figure 12).

Dry and wet climate forecasts triggered switches between planting cotton and fallowing and hence provided significant economic value. For example, a perfect forecast of a dry state provided a benefit of \$352/ha under an initial soil moisture 75% of PAWC and medium cotton prices. This resulted in a change in decision from planting cotton in October to single skip to fallowing the field (compare crop decisions in Figure 10 and Figure 11). The maximum value of a wet forecast of \$517/ha was found with initial soil moisture of 50% of PAWC and high cotton prices. Here, the planting decision changed from fallow to planting in November to single skip (compare crop decisions in Figure 10 and Figure 11).

Cotton prices were also found to have some an influence on forecast value but the effect was inconsistent across different climate states. The value of wet forecasts increased under higher cotton prices with the switch from fallow to planting being a more profitable change. Conversely, the value of dry forecasts fell under higher cotton prices with the switch from planting cotton back to fallowing becoming a less profitable change.

No value was only found for the average climate state, highlighting the limited value of an average SCF that does not greatly diverge from the historical average (which was used to calculate the without-forecast planting decision).



**Figure 12** Perfect forecast value without sowing rains (\$/ha). Dry, average and wet climate states are represented in each box. The four levels of plant available water (25, 50, 75 and 100% of PAWC) are represented in the four internal rows and cotton price (low, medium, high) is represented in the internal columns.

### 4.2.4 Imperfect-forecast value

The forecast value differed with forecast skill and for each climate forecast (dry, average, wet) and decision driver (Figure 13). These plots provide greater detail of the results in Figure 12, illustrating the value of forecasts with various skill levels. Most of the forecast value was for dry or wet forecasts and increased as forecast skill increased (Figure 13). The minimum skill required to yield value varied from 10% up to 70%.

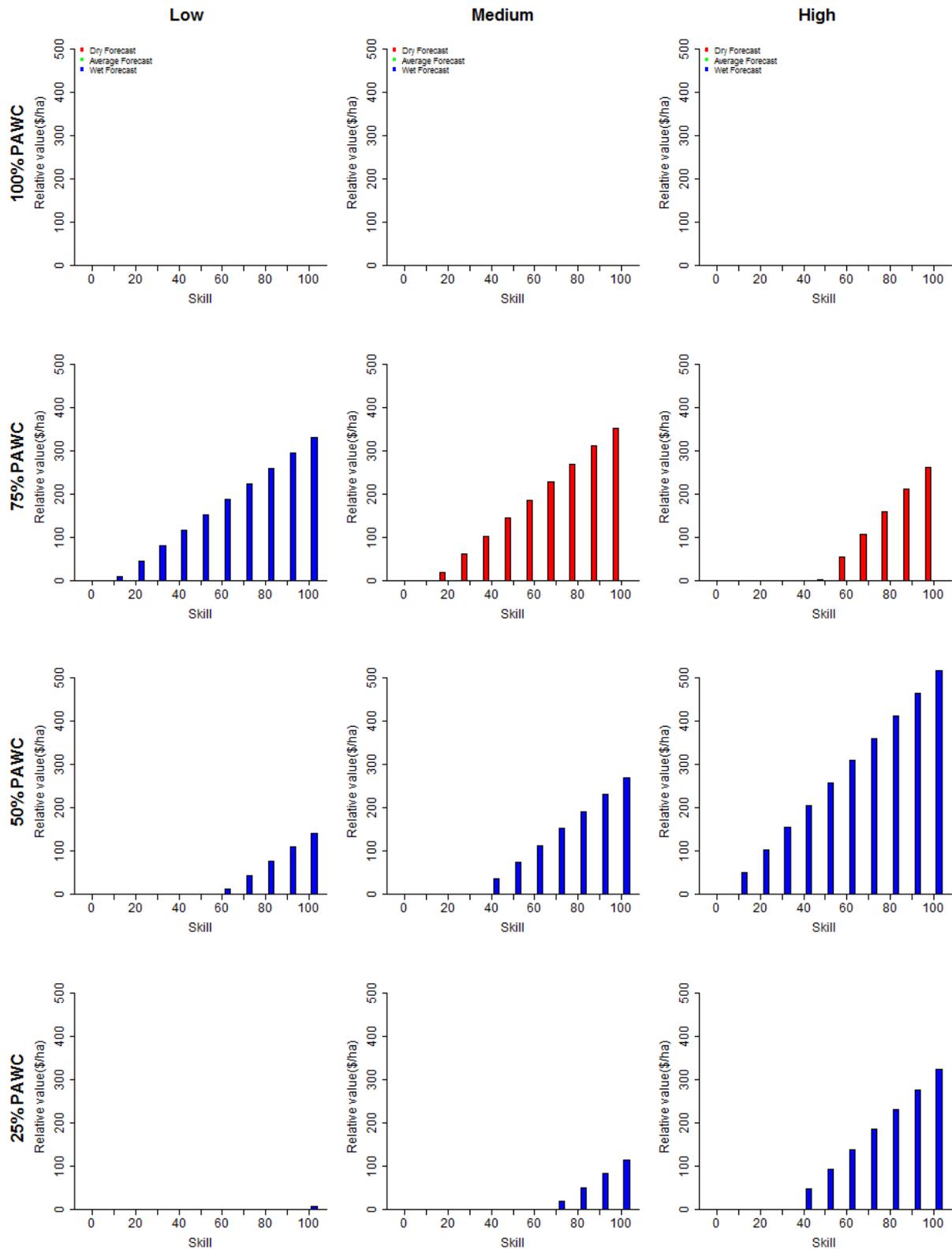


Figure 13 Imperfect forecast value (\$/ha) if sowing rains were not received. Four levels plant available water (25, 50, 75 and 100% of PAWC) are represented in the four rows and cotton price (low, medium, high) is represented in the columns. Skill (%) is represented on the x-axis as calculated in Table 3.

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## 5 Discussion

The key production decision sensitive to SCFs identified by the cotton industry was the planting decision. That is, plant cotton in October or November, to a particular skip row, or leave the field to fallow. This decision considers the performance of these different planting options and the associated productive value of the following winter crop.

Initial analysis indicated that sowing rains occur fairly infrequently and have a modest effect on planting decisions considered here, so our focus here is on the without sowing rains scenario. Full results for sowing rains are contained in Appendix 4: Sowing rains results.

### 5.1 Crop choice made without seasonal climate forecasts

Initial soil moisture strongly influenced the planting decision in the absence of a forecast. Broadly, at initial soil moisture levels of 25% or 50% of PAWC, fallow was selected. At high initial soil moisture levels (75% and 100% of PAWC), planting cotton to single skip row configuration was most frequently selected (Figure 10). These results reflect the good storage capacity of soils, with a cotton crop more profitable than fallow if soil moisture was 75% of PAWC or greater (noting that with initial soil moisture of 75% of PAWC, the decision was variable depending on cotton price).

### 5.2 Crop choice made with seasonal climate forecasts

Inclusion of perfect (100% skilful) forecasts of dry, average and wet conditions led to different decisions to the without-forecast choice for a number of the decision drivers tested. A climate forecast of an average climate state was found to be of no economic value under all decision settings. The lack of value of an average forecast state is a reflection of the limited change in climate conditions compared to the without-forecast decision, which was based on climatology. As climatology is the mean of the climate, the limited and small forecast value of a forecast of the average climate state (middle tercile of climate data) is unsurprising.

Both dry and wet forecasts were found to be valuable. Two examples will be used to explore the different circumstances for which dry and wet forecasts have value. With initial soil moisture of 75% of PAWC and a medium cotton price, the without-forecast decision was to plant cotton in October to single skip configuration. With a perfect **dry** forecast, the optimal decision changed to fallow, driven by poor yields produced by marginal soil moisture at planting and dry in-crop conditions. A perfect forecast (100% skilful) of a dry state resulted in an improvement in returns of \$352/ha under this scenario.

A scenario of initial soil moisture at 50% of PAWC and high cotton prices provides an example of the benefit of a **wet** forecast. The without-forecast decision in this scenario was to fallow the field. With a perfect wet forecast, the optimal decision changed to planting cotton. The wet forecast provided greater surety about the occurrence of additional in-crop moisture, increasing cotton yields and making cotton a more profitable choice. A perfect forecast of a wet state resulted in an improvement in returns of \$517/ha under this scenario.

In broad terms, most forecast value was obtained at low levels of initial soil moisture. Putting these results in context requires some assessment of the relative likelihood of these starting conditions occurring. Assuming a cotton–wheat–long fallow rotation, the distribution of soil moisture conditions in October was evaluated (Table 5). Almost all years simulated resulted in soil moisture at planting being 75% of PAWC or more (91% of years). So while forecasts can be valuable at low initial soil moisture levels, these conditions do not occur very often under this rotation (i.e. in less than 10% of years). Consequently, more emphasis needs to be placed on the more frequent initial soil conditions which realised a maximum value of \$352/ha. Note, that given the large range of management practices, assessment of the distribution of initial soil moisture for any particular farm is difficult to calculate.

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This discussion highlights the maximum possible value of SCF under different scenarios through assuming the forecast was perfect or 100% skilful. However, in reality, SCFs are imperfect and different levels of skill were analysed to assess the value of improvements. Positive value of SCFs was obtained for most initial soil moisture and cotton prices (Figure 19). To realise value in a SCF, forecast skill ranged between 10% and 70%, depending on the decision environment settings (Figure 19), and noting that at lower skill levels the value was also lower.

### 5.3 Comparison to previous findings

Previous studies into SCF value have found a range of forecast value. For example, McIntosh et al. (2005) found that the SOI phase forecast could improve returns by \$49/ha when considering whether to plant a cotton crop and if so, to which skip row. Also using the SOI phase forecast system, Carberry et al. (2000) found \$201/ha value across a two-year period when the forecast was used to assist in a cropping choice decision (cotton, sorghum or fallow). Considering the same crop choice decision for a greater number of forecast systems, Hammer (2000) found a range in value of \$184 to \$304/ha over a two-year period.

In contrasting these previous studies with the results in this case study, important differences are worth noting. Firstly, here a theoretical forecast was used while other studies have, more or less, assessed the value of operational forecasts. The benefit of the approach taken here is that the potential maximum value of a 100% skilful forecast (of rainfall terciles) was identified. This sets the upper limit for forecast value.

Secondly, in this analysis a range of decision environment settings were evaluated: initial soil moisture, the price of cotton and whether sowing rains were received (see Appendix 4: Sowing rains results). Previous studies have focused on a subset of these conditions. Here, soil moisture at planting was found to be an important determinant of forecast value (Figure 12). Previous studies have largely assessed value at a single initial soil moisture value, typically about 50% of PAWC (Carberry et al., 2000; Hammer et al., 2000; McIntosh et al., 2005). Notable forecast value was found at this initial soil moisture setting here, between \$0 and \$517/ha (Figure 12). However, analyses of likely starting conditions indicate these initial soil conditions are unlikely to occur in a traditional long fallow–cotton–wheat rotation. This highlights the importance of considering various decision environment settings and their likelihood of occurrence to appreciate the likely frequency of the potential forecast value reported.

Thirdly, the approach to define the without-forecast decision differs between studies. Here, to determine the without-forecast decision, the economic model was optimised across states with dry, average and wet states all having an equal probability of occurrence. Other studies have assumed farmer practices (which may strictly not be the most profitable) to compare with decisions made with a SCF (McIntosh et al., 2005). A common approach has been to define a fixed set of practices to reflect the without-forecast scenario and variable practices to represent the with-forecast scenario (Carberry et al., 2000; Rodriguez et al., 2018). With the extent of forecast value contingent upon the without-forecast scenario, some care needs to be taken in comparing outcomes. To ensure value is correctly attributed to the forecast, studies need to adopt approaches that focus on the marginal benefits of introducing forecast information into a situation where some prior knowledge exists.

As mentioned previously, initial soil moisture settings were found to be important in delivery of forecast value. This finding is supported by Carberry et al. (2009) who assessed dryland cotton yields in Dalby, Queensland at soil moisture levels of 25, 50, and 75% of PAWC in relation to SOI phases. Their results showed greater variability in yields based on initial soil conditions than between SOI phases. This finding was concisely interpreted by bankers participating in the research by concluding that the “poorest yields at 75% starting soil water are still better than average yields when starting with 25% soil water”. Further, a grower survey found this sentiment is present amongst growers with many respondents emphasising that stored soil moisture and/or

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stored irrigated water were more influential than a SCF in making on-farm decisions (Roth Rural, 2016).

#### 5.4 Limitations and assumptions

The case study used particular parameter settings both within the *APSIM* production model and the economic model. *APSIM* has been used widely to investigate climate variability and climate change assessments. Recent examples (Rodriguez et al., 2018; Williams et al., 2015) and limitations (Angus and Van Herwaarden, 2001; Chauhan et al., 2017; Hanan and Hearn, 2003; Robertson et al., 2000) have been previously outlined. The *APSIM* settings used in this assessment used details from industry consultation to provide a representative farm. These characteristics will likely be different for individual farms. For instance, crop rotation and proportion of the farm to different production activities will likely differ. Thus, this case study is simply an example of the potential value of SCFs, not a comprehensive assessment for all possible enterprise arrangements.

*APSIM* is a simulation model and does not include potential impacts of weeds, pests or diseases on yields. These and other production assumptions in the model means optimistic results are likely produced. This may have been reflected in this analysis. For example, planting to single skip configuration was the most often selected skip row arrangement. Through industry consultation, however, we know that both single and double skip configurations have been adopted in the industry. This divergence may be reflection on the biophysical and economic modelling not fully reflecting the benefits of the two systems across different environments.

A single decision was assessed here in response to industry engagement. There are other decisions throughout the season (e.g. harvest timing), and for other production systems (e.g. irrigated cotton). Some additional potential decision points that would be suitable for similar assessment have been identified elsewhere (McIntosh and Bange, 2017).

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

Like operational forecasts, the theoretical forecasts used in this analysis provided an indication of the likely climate state (dry, average or wet) not the precise evolution of weather conditions. The value of a higher resolution forecast, such as a decile forecast, may be greater. This sets a challenge to the forecasting community. For instance, the Bureau of Meteorology currently operates on a two-state climate forecast (above or below median). The current percent consistent score for the Bungunya region for November to January rainfall is approximately 65%, equating to a skill score used here of 30%.

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## Appendix 1: Industry engagement

Engagement for the development of the cotton case study was conducted following advice from the Cotton Research and Development Corporation (CRDC) with initial industry consultation followed by targeted individual engagement.

Primary industry consultation was conducted in Orange with Jon Welsh (CottonInfo) on 15 April 2016 with project members Rebecca Darbyshire, Michael Cashen and Jason Crean. Through this engagement, key aspects of cotton production in Australia were discussed and avenues for further targeted engagement established.

### 1 Industry overview

Initially, a description of the industry, growth areas and water sources was identified with the key points summarised in Figure 14 and Table 6.

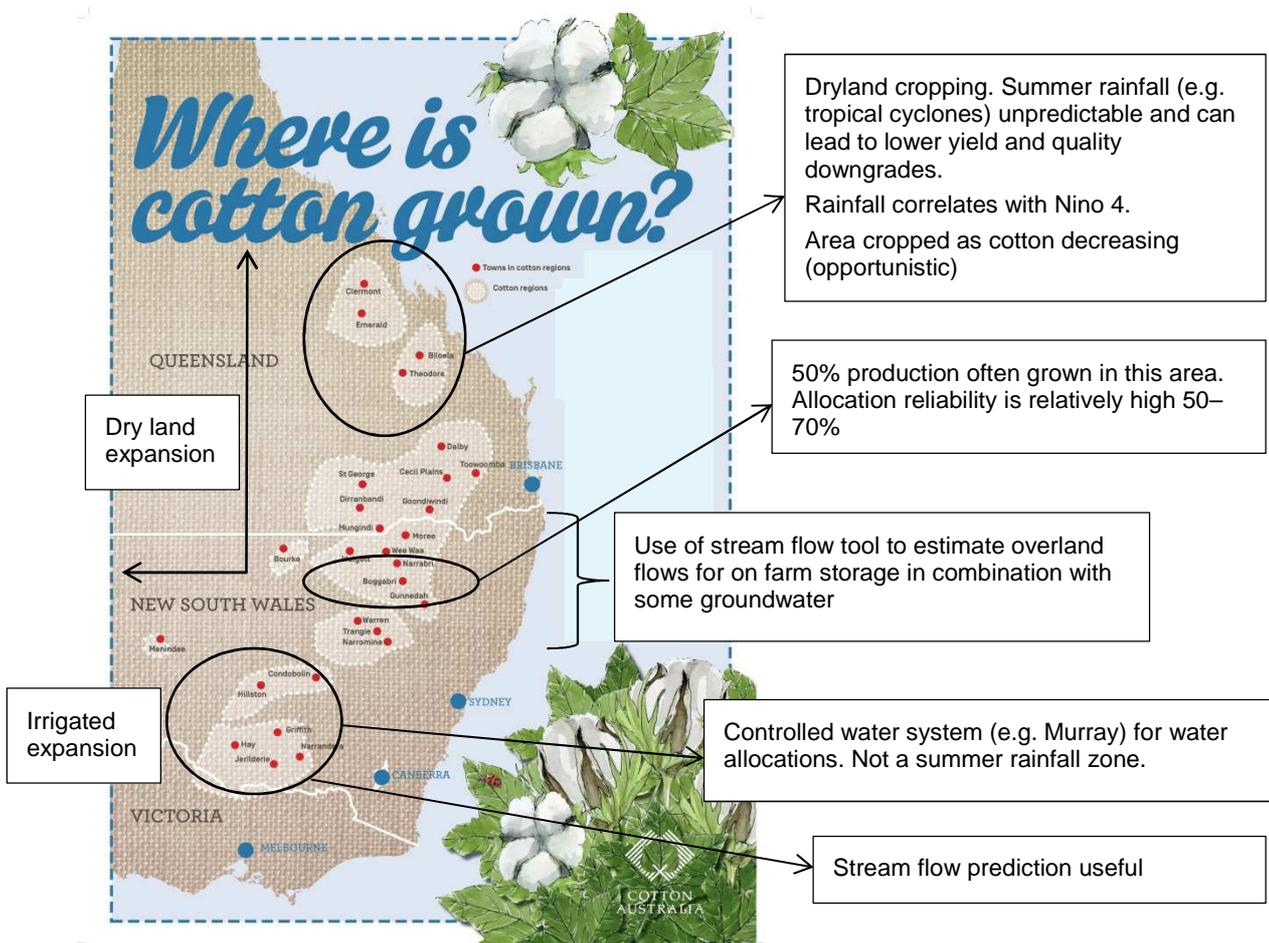


Figure 14 Overview of cotton industry (Cotton Australia, 2018)

Table 6 Cotton industry general discussion points

Aspect	Discussion
Currently available seasonal forecast information	BoM stream flow forecasts <sup>4</sup> used by some growers, particularly those with access to overflow water
	Changeable in-season allocations add uncertainty to decisions, some locations more reliable (Namoi, Gwydir) which assists decision-making
	Use of temperature conditions more likely to be associated with weather forecasts (1–10 days). For instance, BoM heatwave prediction <sup>5</sup> with 3–5 day warning is helpful to plan irrigation scheduling to align with increase in plant water demand, ensure pumps are working, order diesel.
Current industry activities	CRDC hold pre- and mid-season meetings to help growers prepare and manage crops. These existing activities provide points into which seasonal climate forecast information could be integrated.
Farm location implications	The importance of seasonal climate forecast information may differ depending on the farm location. For example, different soil types. Heavy soils have a higher holding capacity than sandy soils and can act as a buffer between rainfall events.
Farm operations	Aligning planting with picking is important logistically
	Southern (irrigated) farms have the ability to forward sell crops as more secure water allows greater certainty of a crop.
	Most costs associated at harvest not at planting
Water costs	Costs associated with pumping groundwater are greater than those for capturing overflow.

The two main forms of cropping in the northern regions, dryland and semi-irrigated, were discussed in more detail. Using the Namoi as an example region, farms are typically mixed cropping operations (6 000 ha) on grey vertisol soils with a cropping rotation of cotton–wheat–fallow.

<sup>4</sup> <http://www.bom.gov.au/water/ssf/?ref=fr>

<sup>5</sup> <http://www.bom.gov.au/australia/heatwave/>

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A semi-irrigated example in the Macquarie catchment would typically be a mixed cropping operation (4 000 ha) on grey vertisol soils with a typical rotation of cotton–wheat–fallow.

## 2 Targeted consultation

Based on advice from industry engagement, Rob Holmes (MCV Climate Champion based in Moree) and Tony Taylor (grower and consultant based in the Goondiwindi region) were each consulted on two occasions (8 June 2016 and 3 August 2016) regarding key decision points for integration of seasonal climate forecast information into farming decisions. Consultation with two leading researchers (Mike Bange, CSIRO and Janelle Montgomery, NSW DPI) was also carried out on 27 October 2016.

For both dryland and irrigated operations, it was highlighted that seasonal management decisions are made within the scope of established longer-term farm management strategies (e.g. rotational history of paddocks). Discussion of the use of seasonal forecast information focused on dryland cotton as participants identified that this type of cropping is more sensitive to seasonal conditions and industry expects expansion in dryland cropping area in the coming years.

## 3 Key climate-sensitive decision point

Decisions at sowing are two-step:

*(1) Will I plant cotton? and (2) If I plant cotton, what skip row spacing will I use?*

In discussing this decision point, four key drivers were identified which influence planting decisions:

1. Cotton price at planting: Higher prices encourage planting, while lower prices discourage planting under riskier conditions.
2. Soil moisture levels: high stored soil moisture encourages planting, low stored soil moisture discourages planting.
3. Sowing rains received: planting is encouraged if with sowing rains and discouraged without sowing rains.
4. Forecast seasonal rainfall: Forecast above average rainfall encourages planting, a dry forecast discourages planting.

Figure 15 illustrates this decision 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.

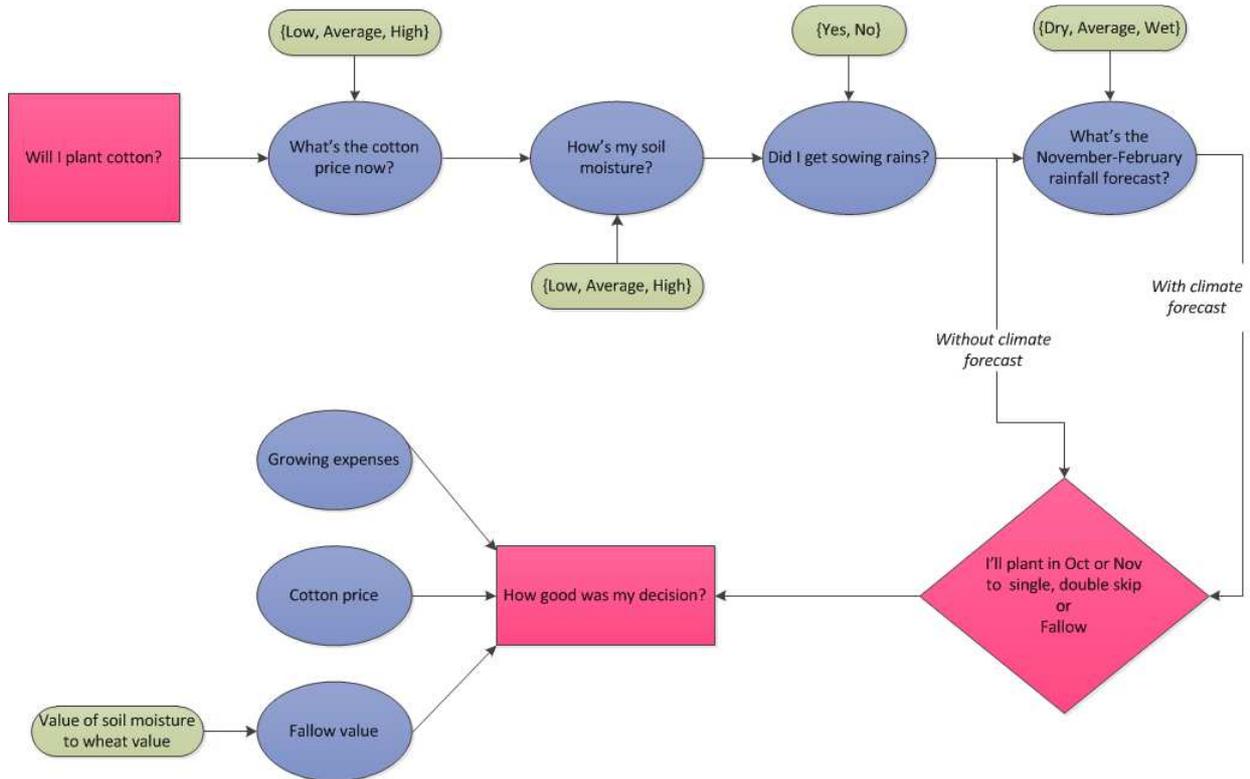


Figure 15 Decision pathway for deciding area of cotton planted and row spacing option

The critical timeframe for the forecast is August/September, being one month prior to planting in September/October. Just prior to planting (August/September), the sowing plan (area, row configuration) is determined through evaluation of water. The forecast period is for November–February, after flowering (a critical physiological phase).

Through discussion, the complexity in decisions around planting were evident. Key aspects of these discussions are listed below with some additional comments in Table 7.

- With soil moisture half full or less, do not sow regardless of other conditions.
- Full soil moisture profile, plant regardless of other conditions and assuming prices were not depressed.
- For 60% full profile or more combined with a wet forecast, plant at single skip.
- For 60% full profile or more combined with a dry forecast, plant at double or super single skip.
- For 60% full profile or more combined with an equal chance forecast, plant 80% to double skip, 10% each to super single and single skip.
- Do not plant on soils with less than 170–180 PAW, regardless of other conditions.
- Assuming adequate soil moisture and a dry forecast, plant to super single.
- Assuming adequate soil moisture and a wet forecast, plant to single skip.
- Price plays a role depending on the other conditions. \$600/ba with a less than full profile and a mostly wet outlook would prompt planting at double skip.
- Even higher prices would further encourage planting, likely at wider row configurations.

Table 7 Summary of some broad commentary on dryland cotton sowing decisions

Soil moisture	Sowing rains	Climate outlook (Nov, Dec, Jan, Feb)	% Area planted	Industry comment
75%	Yes	Equal chance	100%	Important to have sowing rains for successful germination
75%	No	Equal chance	0%	
75%	Yes	Dry	100%	Only if 'soaking' sowing rains
75%	No	Dry	0%	
75%	Yes	Wet	85%	Plant area up on soil moisture and positive forecast
75%	No	Wet	15%	
100%	Yes	Equal chance	100%	
100%	No	Equal chance	0%	Perhaps some sowing without rains, opportunistically
100%	Yes	Dry	60%	On 'normal' sowing rains Perhaps some sowing without rains, opportunistically
100%	No	Dry	0%	
100%	Yes	Wet	100%	
100%	No	Wet	30%	

It is acknowledged that other aspects of farming also contribute to this decision. For instance, crop rotation, farmer financial status, experience and risk appetite. Nuances in seed price fluctuations should also be appreciated. Penalties surrounding late seed purchase vary depending on early demand. High demand in seasons with good soil water and water availability will lead to higher seed prices, particularly for late orders. Alternatively, in lower water season, decisions to buy seed late will not incur the same price penalty. Equally important is the timing of costs incurred within the cropping cycle. A majority of costs are incurred at harvest (contract harvesting, ginning fees, licence fees), meaning a lower proportion of costs of production have to be carried by the grower through the season.

## Appendix 2: Gross margin values

Crop production costs for summer cropping options in this study were based on the Northern Zone East (Figure 16). The budgets were sourced from NSW DPI and AgEcon/CottonInfo (<https://www.dpi.nsw.gov.au/agriculture/budgets>) and provide detailed information on management practices and input costs associated with sowing, managing crop nutrition, pests, weeds and disease throughout the growing season, and harvesting. These budgets were used as a basis to determine area and yield based costs which are combined with *APSIM-OZCOT* crop simulation data to determine annual cropping returns. A summary of key variable costs used are provided in Table 8.

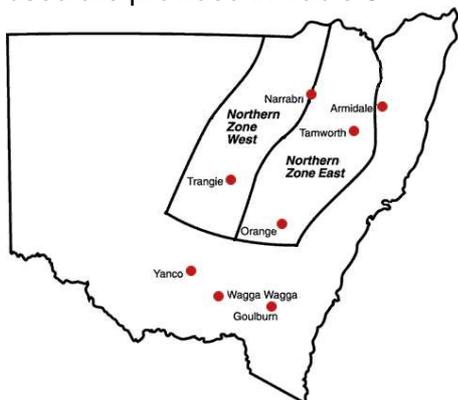


Figure 16 Crop production zones in NSW

Table 8 Summary of key variable costs – North East NSW

	COTTON – Single Skip	COTTON – Double Skip	WHEAT
<b>INCOME</b>			
<b>A. Total Income</b>	<b>\$1,858.00</b>	<b>\$1,651.00</b>	<b>\$687.50</b>
<b>VARIABLE COSTS<sup>6</sup></b>			
Fallow management	\$93.00	\$93.00	\$0.00
Sowing/Planting	\$90.00	\$73.00	\$55.00
Crop protection, app, licence	\$347.00	\$304.00	\$0.70
Fertiliser application	\$18.00	\$18.00	\$186.00 <sup>7</sup>
Herbicide & application	\$123.00	\$117.00	\$55.00
Fungicide & application	\$0.00	\$0.00	\$25.00
Defoliation	\$82.00	\$64.00	
Picking/Ginning/Harvesting <sup>8</sup>	\$602.00	\$511.00	\$65.00
Insurance <sup>9</sup>	\$40.00	\$30.00	\$14.00
Levies	\$0.00	\$0.00	\$7.00
Farming: Post-crop	\$45.00	\$45.00	\$0.00
<b>B. Total Variable Costs</b>	<b>\$1,440.00</b>	<b>\$1,255.00</b>	<b>\$407.70</b>
<b>C. Gross Margin (A-B)</b>	<b>\$418.00</b>	<b>\$396.00</b>	<b>\$280.10</b>
<b>Source</b>	<i>AgEcon/CottonInfo</i>	<i>AgEcon/CottonInfo</i>	<i>NSW DPI</i>

<sup>6</sup> Note that the description of specific categories of variable costs varies between sources and crops. Additional variable cost categories have been included to reflect the way costs are described in each budget. Detailed information on practices and costs can be obtained from <https://www.dpi.nsw.gov.au/agriculture/budgets>.

<sup>7</sup> Fertiliser and application

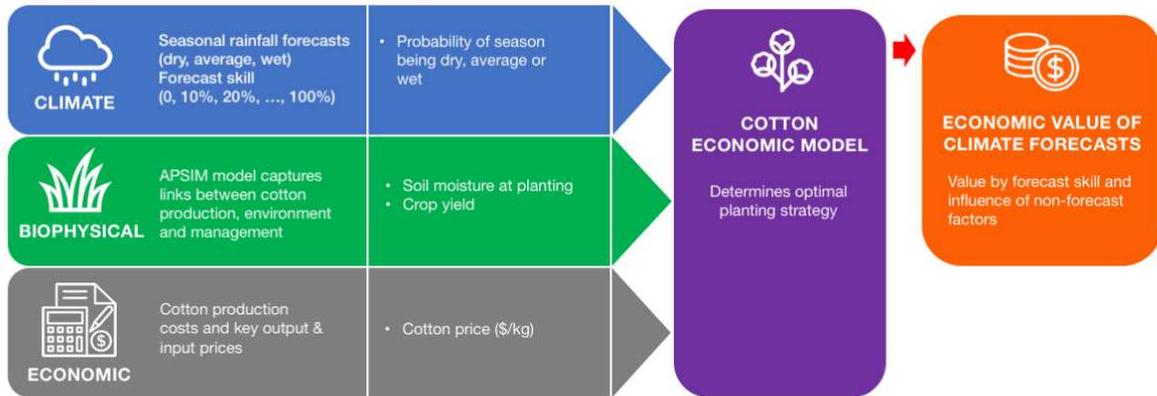
<sup>8</sup> Includes CRC levy

<sup>9</sup> Not included in model assessment

## Appendix 3: Economic model

### 1 Overview of the modelling approach

COTTON



### 2 Economic model description

The economic model used key outputs from *APSIM* to capture the links between climatic conditions and crop production. Combining these outputs with information on crop production costs and key output prices (crop prices) allows net returns to be estimated for each cropping option (i.e. cotton planting options and fallow). The economic model evaluates the relative returns offered by each cropping option under dry, average and wet climate states and under varying levels of PAW at the start of the season.

A two-stage discrete stochastic programming (DSP) model was developed for the dryland cotton case study where time was divided into the 'present' and the 'future'. A standard linear programming model was developed into a DSP model by introducing a second period decision. The  $x \rightarrow s$  format of static linear programming changes to  $x_1 \rightarrow s \rightarrow x_2 (s, x_1)$  in the DSP case. Here  $x_1$  represents Stage 1 decisions (crop options – cotton and fallow in October),  $s$  is the state of nature (tercile rainfall – dry, avg and wet) and  $x_2 (s, x_1)$  represents Stage 2 decisions (bales of cotton harvested). These Stage 2 decisions are contingent upon earlier Stage 1 decisions and the state of nature that occurs. The farm-planning problem is to choose the optimal crop mix in October to maximise the expected level of return across climatic states. In algebraic terms, the main elements of the model are as follows.

$$\text{Max } E[Y] = \sum_{s=1}^3 \pi_s y_{sy} \quad [\text{Equ 1}]$$

$$y_s = \sum_{j=1}^{Jy} c_j y_j x_j + \sum_{n=1}^N c_{2nsy} x_{2nsy} \quad [\text{Equ 2}]$$

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subject to:

Land, labour and capital constraints

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

Use of crop outputs

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

Where model parameters are:

$\pi_s$  probability of state  $s$

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

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

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

$c_{2js}$  the net return from activity  $n$  chosen in state  $s$  in Stage 2 (crop price less yield dependent costs related to harvest, levies, freight and processing)

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

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

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

$b_i$  the availability of resource  $i$

and the model variables are:

$y_s$  the net return in state  $s$

$x_{1j}$  the area of crop  $j$  planted in Stage 1

$x_{2ns}$  the level of activity  $n$  chosen in state  $s$  in Stage 2 (tonnes of grain sold, bales of cotton sold, value of plant available water)

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

The two-stage decision process is reflected in returns for each state (Equ 2). The left-hand term of Equ 2 indicates a commitment of input costs (variable costs of growing cotton) based on the selection of Stage 1 activities ( $x_{1j}$ ), while the right-hand term reflects state-contingent revenue derived from Stage 2 activities ( $x_{2ns}$ ) (harvest and sale of crop). The inputs committed through Stage 1 decisions are the same in every state of nature, while outputs in Stage 2 are specific to each state. While production is state-contingent, as per the outputs from the biophysical model, the prices of inputs and outputs (e.g. cotton prices) were assumed to be independent of climatic conditions. With a high proportion of Australian crop production sold into international markets, this was considered a reasonable assumption.

Constraints in the economic model are reflected in Equ 3 and 4. Equ 3 constrains the choice of crops to available land, labour and capital as per conventional farm level linear programming models. In this application, the only constraint introduced in the model is the area of land available for dryland cotton cropping. This is set at a level of 3000 ha based on the available summer crop area for a typical farm in North East NSW based on industry engagement (see Appendix 1: Industry engagement).

Linkages between decisions taken in Stage 1, and state-contingent outputs in Stage 2, are captured in Equ 4. For example, the commitment of inputs to grow cotton in Stage 1, combined with the intervening rainfall state, leads to cotton output in state  $s$ , represented by  $a_{1mjs}$ . This output forms a resource that can be utilised by Stage 2 activities ( $x_{2ns}$ ) which is simply an opportunity to harvest and sell cotton up to the amount physically produced. Importantly, in some sowing combinations (e.g. low PAW at sowing) that result in low yields, it may be uneconomic to proceed with harvest in a dry state because the cost of harvest, levies and cartage (i.e. yield dependent costs) may actually exceed the crop price on a per tonne basis. The model will not harvest in this instance and therefore avoids compounding losses.

The modelling approach has a number of strengths in the context of valuing seasonal climate forecasts. First, because production in each state of nature is explicitly recognised, it is straightforward to assess the consequences of different planting decisions in each state. This is an important feature when considering the value of imperfect forecasts. Second, the modelling reflects the ability of farmers to consider state-contingent responses, something readily observed in practice. Third, with operational forecasts being probabilistic in nature, rational farmers will interpret probabilistic forecasts as a shift in the odds. This can be readily reflected in a DSP model through the assignment of posterior probabilities to each state based on forecast skill.

## 2.1 Valuing the forecast system

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

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

The value of the forecast system is derived from optimal decisions taken with and without the forecast. Expected returns in the DSP model ( $Y$ ) is a consequence of non-stochastic returns in Stage 1 (prior to uncertainty being resolved) and stochastic returns in Stage 2 (after the state of nature is revealed). With a risk-neutral objective function of the DSP model [Equ 1] and the hypothetical forecast system described elsewhere, the value of a specific forecast  $f$  within this system was defined as:

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

where:

$y_{sf}^*$  denotes the net return in state  $s$  resulting from implementing the optimal crop choice  $x_{sf}^*$  based on forecast  $f$ , and

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$y_{so}^*$  denotes net return in state  $s$  resulting from implementing the optimal crop choice  $x_{so}^*$  based on the prior probabilities (assumed to be historical climatology).

This is simply a statement that the value of forecast  $f$  is equal to the difference in expected net return with and without the forecast. The forecast will have no value in the event that  $x_{sf}^* = x_{so}^*$  (i.e. where the with forecast and the without forecast decision is the same). The estimated value of a particular forecast accounts for both the decisions made in Stage 1 (October) and the state-contingent tactical adjustments made in Stage 2 (April).

The value of a forecast system is obtained by weighting the value of each forecast within the system by the frequency with which each forecast occurs. If  $\mathbf{F}$  denotes a forecast system and  $q_f$  is the frequency with which each forecast occurs, then the value of a forecast system with three possible forecasts can be defined as:

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

The value of the forecast system is influenced by attributes of the forecast system and attributes of the decision setting. The main attribute of the hypothetical forecast system assessed is forecast skill. An increasingly skilful forecast allows the DSP model to divert more resources towards production in the forecasted state. With a forecast of three rainfall states ( $f = f_{dry}, f_{avg}, f_{wet}$ ) and eleven skill levels ( $\sigma = 0, 10\%, 20\%, \dots, 100\%$ ), the DSP model is solved 33 times in order to value the hypothetical forecast system for a given set of conditions (PAWC, sowing rains and crop price scenarios).

## Appendix 4: Sowing rains results

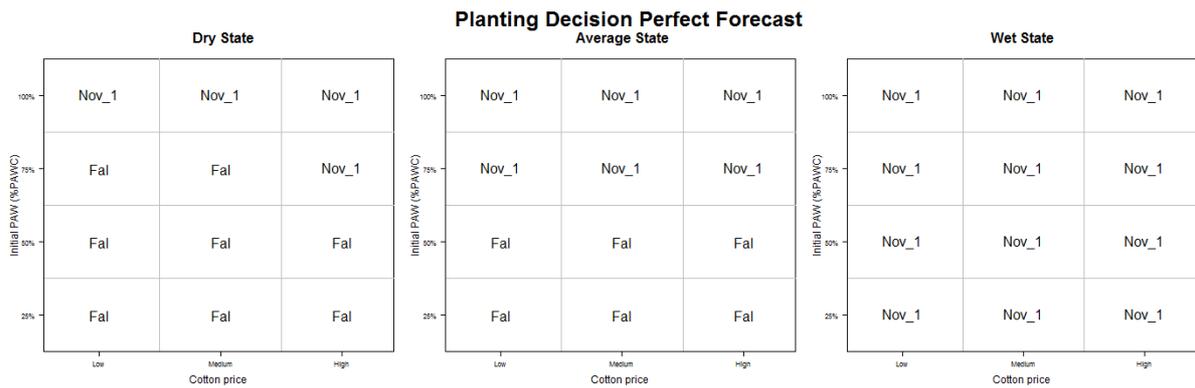


Figure 17 Optimal with forecast planting decision with sowing rains. Dry, average and wet climate states are represented in each box. The top row is with sowing rains, the bottom row is without sowing rains. The four levels plant available water (25, 50, 75 and 100% of PAWC) are represented in the four internal rows and cotton price (low, medium, high) is represented in the internal columns. Nov\_1 and Fal represent November planting to single skip and fallow, respectively.

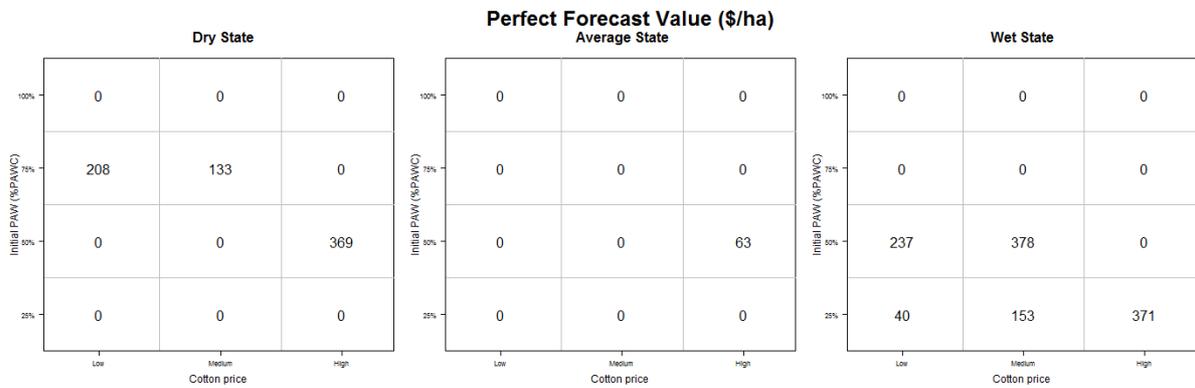


Figure 18 Perfect forecast value with sowing rains (\$/ha). Dry, average and wet climate states are represented in each box. The top row is with sowing rains, the bottom row is without sowing rains. The four levels plant available water (25, 50, 75 and 100% of PAWC) are represented in the four internal rows and cotton price (low, medium, high) is represented in the internal columns.

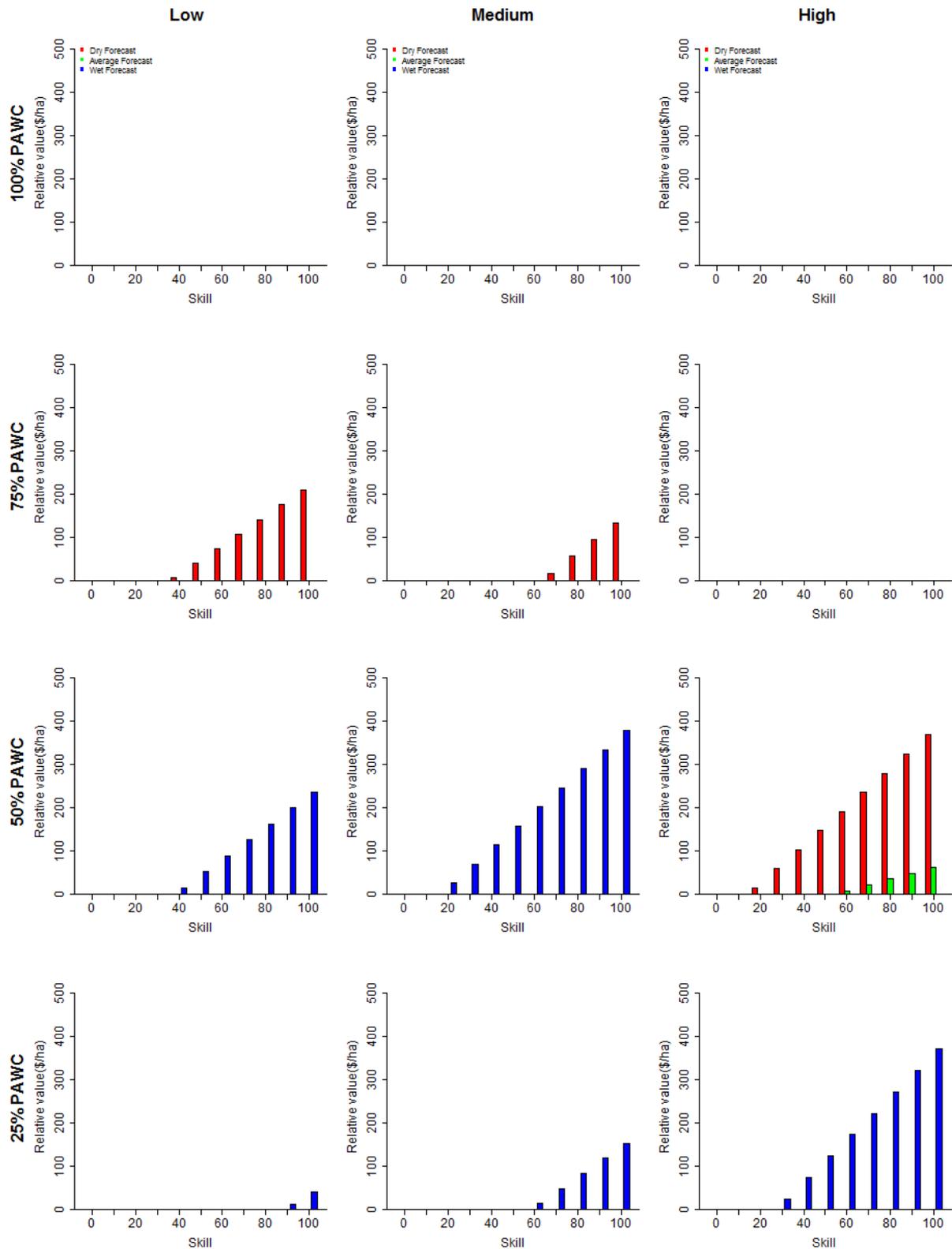


Figure 19 Imperfect forecast value (\$/ha) with sowing rains. Four levels plant available water (25, 50, 75 and 100% of PAWC) are represented in the four rows and cotton price (low, medium, high) is represented in the columns. Skill (%) is represented on the x-axis as calculated in Table 3.