Department of Primary Industries

Valuing seasonal climate forecasts in Australian agriculture

Northern grains case study

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Executive summary

Importance of climate variability and forecasts

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

Objective of the project

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

Objective of this report

This report focuses on the value of SCFs to the management of grains farms in the Grains Research and Development Corporation (GRDC) northern panel region. The key decision identified by industry was which summer crop to sow. Four potential options were considered, sorghum, cotton, mungbean and summer fallow. The timing of this decision was early October for a rainfall forecast from October to December. 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 summer cropping decision compared with the decision made based on historical average rainfall.

Methods

To assess the value of SCFs, a probabilistic climate forecast system was adopted to assess the value of SCFs. Three discrete climate states (dry, average or wet) were identified based on the lower, middle and upper tercile of rainfall received at Gunnedah (October to December) 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*. 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 summer cropping decision under a variety of scenarios.

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

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

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

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

The level of initial soil moisture was found to have a strong influence on cropping decisions. Low soil moisture at sowing led to an optimal decision to either fallow or sow mungbean in the absence of forecast information. In contrast, cotton and sorghum were selected under high initial soil moisture.

Relative crop price was also found to be an important driver of decisions with a sensitivity analysis conducted for sorghum. High prices tended to encourage sowing of sorghum into marginally less favourable initial soil moisture and climate state conditions.

Alternate crop decisions were based on forecasts of different climate states. In general, a dry forecast more often led to cropping decisions with lower water requirements (fallow and mungbean) compared to the without-forecast decisions. Conversely, a wet forecast modified decisions towards sowing of higher value crops with higher water requirements (sorghum and cotton).

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 the least economic value under all decision settings. This is unsurprising as the without-forecast decision is based on long-term average rainfall over all years, which is normally close to conditions represented by average tercile rainfall. Dry and wet forecasts were both found to be potentially valuable to growers, with the extent dependent on initial soil moisture and relative crop prices. The maximum value of a dry forecast improved returns by $204/ha and the maximum value of a wet forecast improved returns by $188/ha. 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 and relative crop prices.

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 and high relative sorghum price was valuable as it triggered a change from mungbean to sorghum. This finding has some parallels with observations of Hirshleifer and Riley (1992) that the ‘news-worthiness’ of information is a critical determinant of its value.

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

Contents

Glossary of terms

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

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

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

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

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

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

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

1 Introduction

1.1 Background

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

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

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

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

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

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

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

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

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

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

1.2 Project objectives

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

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

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

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

1.3 Case study approach

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

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

This report contains findings of the northern grains case study.

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

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

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

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

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

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

2 Northern grains production system

2.1 Industry overview

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

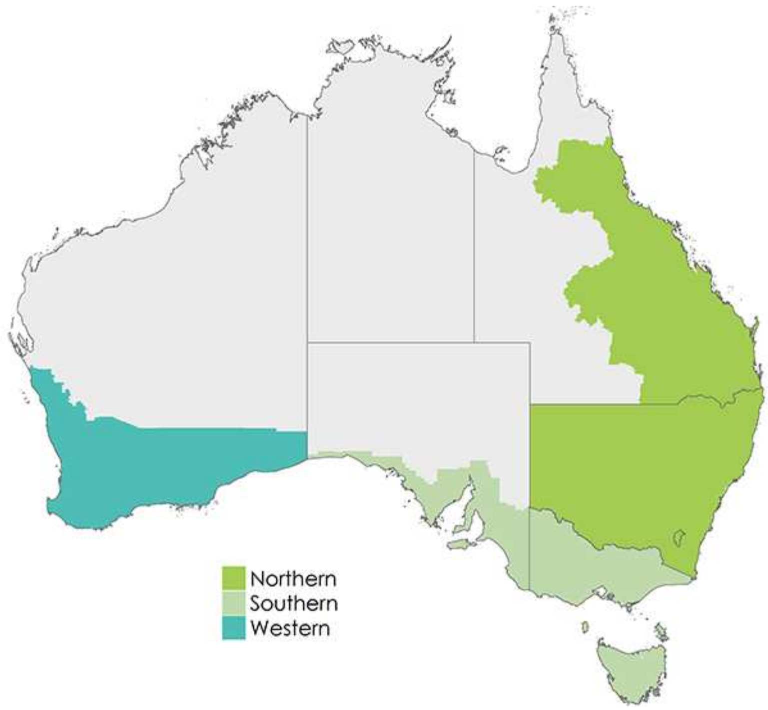


Figure 1 Regionalisation of GRDC research panels (ABARES, 2018)

The northern cropping region is characterised by typically high soil fertility with both summer and winter crops grown across much of the region (GRDC, 2018). This is particularly the case from northern New South Wales and into Queensland, in response to rainfall sources from both southern and northern weather systems.

2.2 Description of production system and key decision point

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

The northern grains case study was focused on a mixed dryland cropping grazing enterprise based in the Gunnedah (Liverpool Plains) region of New South Wales (Figure 2). Using farm descriptions in Scott et al. (2004) as a baseline, the group described a typical farm in the region as 1700 ha property on predominately fertile black and grey cracking clays. The proportion of farm under crop was 50% (850 ha) comprising 60% summer and 40% winter cropping.

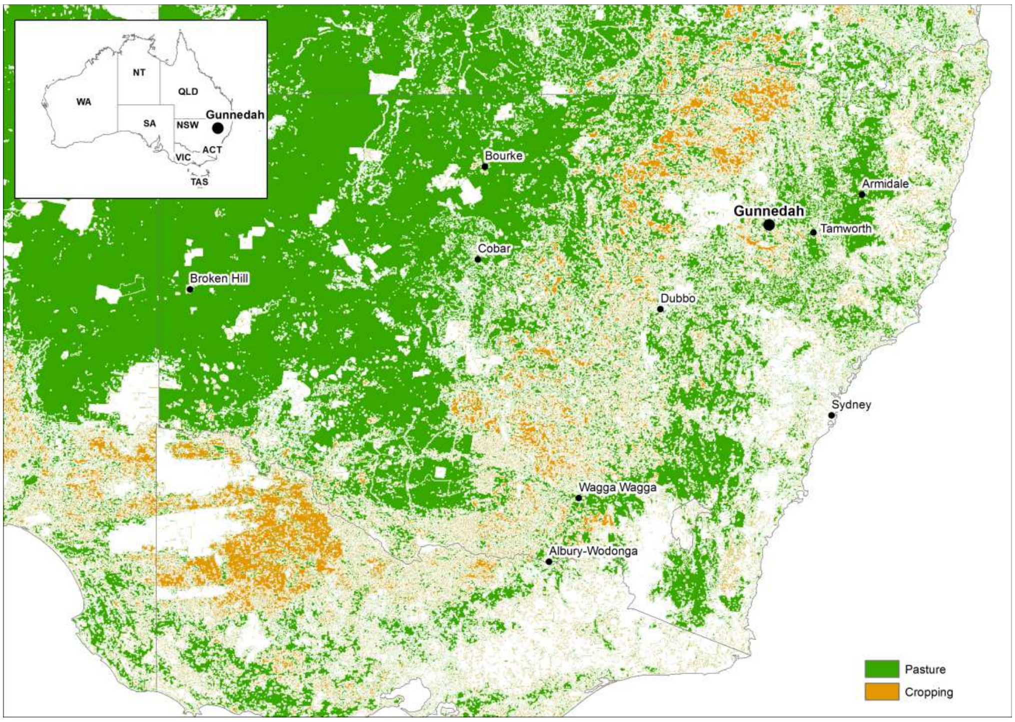


Figure 2 Map showing the location of Gunnedah, the case study site

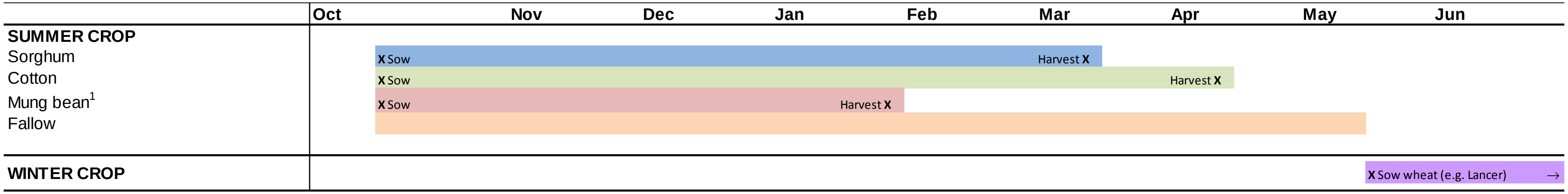
The cropping rotation sequence was based on:

summer crop – winter fallow – summer crop – winter crop – long fallow (summer/winter fallow)

Summer cropping options include mungbean, cotton, sunflower and sorghum. Winter cropping options include winter cereals such as wheat, barley and dual-purpose cereals for grazing, faba beans, chickpeas and canola. More emphasis was placed on the summer cropping decision with winter cropping considered a secondary decision.

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

Figure 3 Broad characteristics of the summer sowing decision for the northern grains case study



[1]Can be sown as spring crop or summer crop. Spring crop is represented here.

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:

What summer crop will I sow?

The time of the decision was October and the options considered were sorghum, cotton, mungbean or summer fallow. In deciding between these options, three key decision drivers were identified:

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

Figure 4 illustrates this decision-making process, with an option to not include SCFs. This is necessary to evaluate the value of including SCFs against decisions made without SCF information. Further details on the process of defining this decision point and the decision drivers are contained in Appendix 1: Industry engagement.

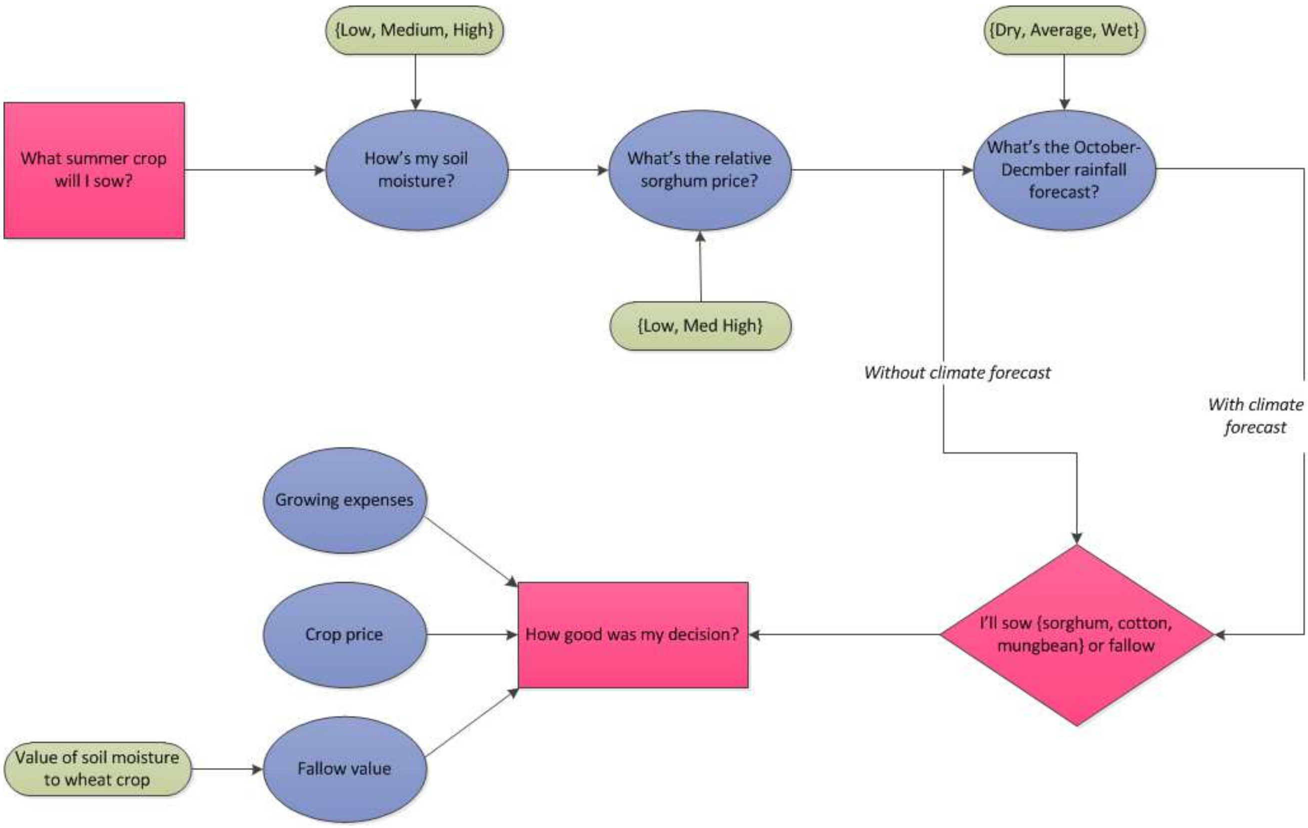


Figure 4 Decision pathway for northern grains case study including an evaluation of the decision made.

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

Several studies in Australia have evaluated the use of SCFs to improve profitability of summer cropping enterprises. Carberry et al. (2000) investigated the use of the Southern Oscillation Index (SOI) phase forecast to assist with strategic management decisions regarding crop rotations in grains enterprises. They tested a cropping 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. They tested a fixed option for each of the crop choices in year 2 as well as an option that varied crop choice based on SOI phase forecast.

Their analysis considered changes to a variety of economic and biophysical indicators. Their results, which included the SOI phase to determine the crop choice in year 2, increased gross margin returns by $201/ha over two years over the without-forecast strategy but with increased financial risk. Overall, Carberry et al. (2000) noted that use of the SOI phase forecast provided some improvement in making a cropping 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 sea surface temperature (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.

Crean et al. (2005) assessed the value of operational climate forecasts for an opportunity cropping decision in northern New South Wales. In contrast to traditional long fallow systems, opportunity cropping involves sowing a crop whenever soil moisture is considered to be adequate. They assessed how SOI and SOI phase systems could help growers make better choices between wheat-fallow and fallow-sorghum in an opportunity cropping system. The value of SCFs ranged from $0 to $8.15 ha/year depending on the level of soil moisture. They found that the overall economic value of a forecast system was often dominated by the value associated with following just one or two forecast types (e.g. a phase with the SOI phase system) within each system. While some forecast types were valuable, others had limited skill, were not influential in crop selections, and hence were of not of value. They concluded that defining the acceptable level of forecast skill in operational forecast systems has direct implications for forecast valuation.

McIntosh et al. (2005) evaluated two forecast systems, SOI phase and SST based, to consider cotton and sorghum sowing options in Moree, New South Wales. The decision analysed was to sow dryland cotton in October to a particular skip row configuration or sorghum. In their case study, assessments were conducted based on sowing on 50% stored soil moisture. They found that use of an SST forecast doubled the gross margin return.

A recent study evaluated the value of SCFs in informing sorghum cropping designs, which included over 176 million simulations across various options of sowing timing, soil type, soil moisture at sowing, skip row spacing, plant density, nitrogen application and cultivar (Rodriguez et al., 2018). Using SCFs generated by the Bureau of Meteorology's POAMA seasonal climate forecasting model interfaced with a biophysical model, the study estimated the value of a forecast by multiplying yields by price and subtracting growing costs. Their results found that the value of a SCF relative to an optimised, static, without-forecast strategy was $3 to $63/ha.

3 Methods

The potential value of SCFs was evaluated through maximising returns of the system by selecting the optimal cropping decision under various system conditions. An overview of the methodology is outlined in Figure 5. Four key components are provided to the economic model which then evaluates the potential value of SCFs. Each of these components are described in the following sections.

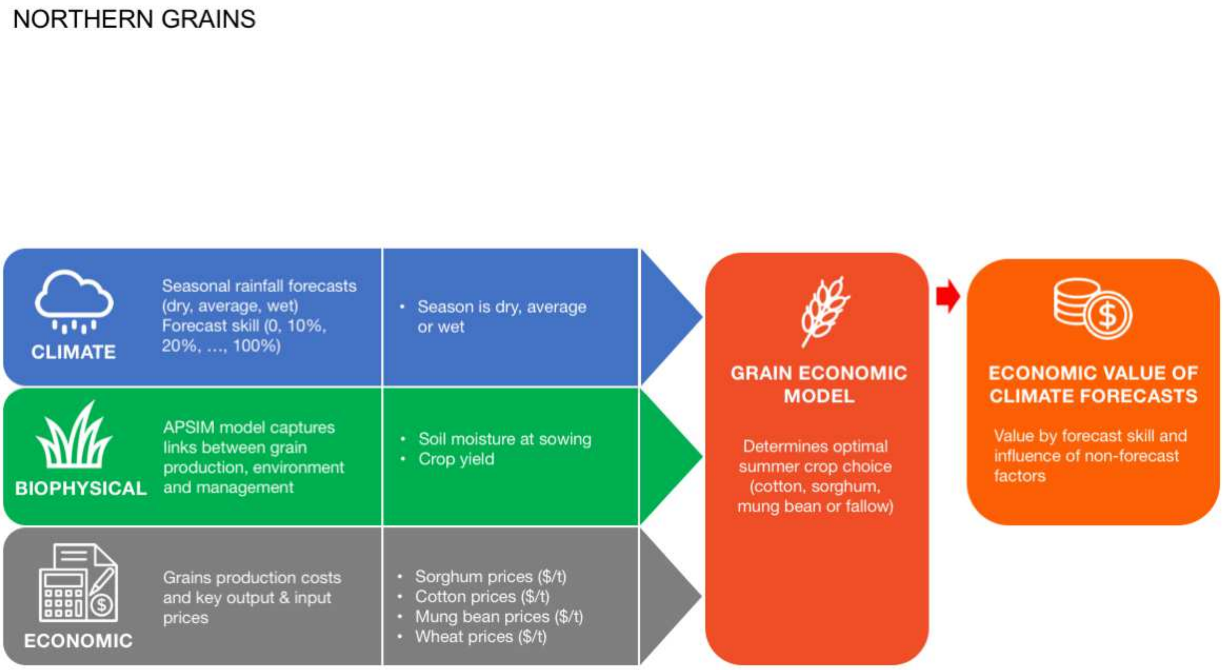


Figure 5 Methodological overview. Generation of biophysical data, crop production costs, crop prices and climate state classification of historical data and probabilistic forecasts are used in the economic model to select optimal cropping decision based on maximising returns.

3.1 Crop biophysical simulation model

The links between crop choice, climate conditions and yield were captured through detailed biophysical modelling using the Agricultural Production Systems sIMulator (*APSIM*) (Holzworth et al., 2014) version 7.9. The *APSIM* model simulates crop yields through the linkages of several 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. *APSIM* has been applied widely in Australian agricultural research including for analyses of crops investigated in this case study (Asseng et al., 2012; Rachaputi et al., 2015; Rodriguez et al., 2018; Williams et al., 2015).

APSIM was executed using climate data sourced from the SILO patched point dataset (Jeffrey et al., 2001) for station 055024 (Gunnedah Resource Centre). The soil parameters used in the simulation were based on grey vertosol soil characterisation (APSoil No: 1170; Mullaley) derived from APSoil (https://www.apsim.info/Products/APSoil.aspx) for the Gunnedah region.

Three summer crops (cotton, sorghum and mungbean), summer fallow and a winter wheat crop were simulated. The wheat simulations were used to place an economic value on residual soil moisture to the subsequent winter crop after a summer crop or fallow. All summer cropping options were assessed under four levels of initial soil moisture at sowing (25, 50, 75 and 100% of plant available water capacity (PAWC)). Soil conditions were reset annually on 14 October under each initial soil moisture level. *APSIM* model configurations for the three summer crops are detailed in Table 1. For sorghum, variable additional nitrogen was applied at floral initiation based on a soil nitrogen deficit rule[2] which

[2] Nitrogen was applied to meet a 140N target with the deficit calculated as140 minus total N in the top three soil layers.

typically amounted to 70–140 kg N/ha. For cotton, if harvest had not been triggered earlier, the simulation was set to conduct the harvest on 30 April.

Table 1 ***APSIM*** **configuration for cotton, sorghum and mungbean simulations**

	Cotton	Sorghum	Mungbean
Date of sowing	15 October	15 October	15 October
Sowing density (plants/m^2)	7	4	25
Sowing depth (mm)	50	35	40
Cultivar	Ozcot_cotton	Medium	Berken
Row spacing (mm)	1000	1000	500
Skip row	Single skip	Solid	-
Fertiliser at sowing (kg/ha)	100	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[3]. To assess the economic value of fallow, a winter wheat crop was simulated at varying levels of soil moisture. *APSIM* was similarly used to conduct this assessment. Like sorghum, variable additional nitrogen was applied at floral initiation based on a soil nitrogen deficit rule, which typically amounted to 140 kg N/ha. The cultivar Lancer was selected as it has a similar growth pattern to 'EGA_Gregory' used as a reference in a wheat trial in the region near Gunnedah (NSW DPI, 2015). It was sown with 100 kg/ha fertiliser on 11 May, which is within the recommend sowing window for Gunnedah.

A key aspect of these wheat simulations was that the starting soil moisture was set according to stored soil moisture, recorded either after a summer crop was harvested (cotton, sorghum, mungbean) or after summer fallow. The stored soil moisture was calculated as the average over 8–14 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, based on availability after summer fallow or a summer crop, was then evaluated for 1889 to 2015.

3.1.2 Mungbean yield adjustment

Mungbean has an indeterminate flowering habit, with late season flowering possible if conditions are favourable. This can lead to a range of physiological stages (flowers, green and black pods) being present simultaneously and can make harvesting difficult.

If crops are not effectively desiccated, the plants and stems contain a lot of sap. This makes harvesting challenging as the plants are more difficult to cut, header blockages can occur and the seeds are more likely to be stained, reducing quality (NSW DPI, 2014). Conversely, harvesting when mungbean is dry can lead to yield losses due to bean shattering and weight loss (NSW DPI, 2014).

Industry has noted that due to these harvest challenges, yield losses at harvest can often exceed 30% (Australian Mungbean Association, 2015; GRDC, 2014) and up to 50% loss has been recorded (GRDC, 2014). This yield loss at harvest is one of the key management issues affecting the overall profitability of a mungbean crop. These harvest aspects associated with notable yield losses in mungbean are not captured by *APSIM*. To allow for this, simulated mungbean yields from *APSIM* were reduced by a constant factor of 30% to determine realistic paddock yields and economic returns.

3.2 Crop production costs

[3] Fallowing can also provide good disease and weed control but focus here is only on the benefits of soil moisture.

Crop production costs for sorghum, mungbean and wheat were obtained from gross margin budgets produced by NSW DPI. Crop production costs for cotton were obtained from 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

Sorghum, 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. A shorter time series of prices was available for mungbean. Historical monthly mungbean prices were obtained from Pulse Australia (2018) for 2010–11 to 2014–15. Historical prices for all crops were converted from nominal to real values and expressed in 2014–15 dollars using the Consumer Price Index reported in ABARES (2017).

Prices for all crops were set to their median value (50th percentile) and were assumed to be known at the time of sowing (Table 2). The analysis assumes that median prices are a reasonable basis for planning, keeping the emphasis on the use of forecasts to manage production variability. With crop prices identified as one of three key decision drivers in the Northern Grains Workshop (Appendix 1: Industry engagement), a sensitivity analysis was undertaken on shifts in relative prices. Sorghum is an important element of summer cropping programs in Gunnedah, so low (10th percentile) and high (90th percentile) sorghum price scenarios were also assessed. For these analyses, sorghum prices were set to $166/t and $279/t for the low and high relative price scenarios, respectively, while the other crop prices were fixed at their median values in Table 2. The price of urea was set to $560/t following nitrogen costs supplied in the gross margins used in the analysis (Appendix 2: Gross margin values).

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

	Price
Sorghum (/t)	$230
Mungbean (/t)	$882
Mungbean grading (/t)	$166
Cotton (/bale)	$460
Cotton seed (/t)	$339
Wheat (/t)	$261

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 October–December rainfall received at Gunnedah 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 134 mm, average as rainfall between 134 mm and 213 mm, and wet as rainfall in excess of 213 mm (Figure 6).

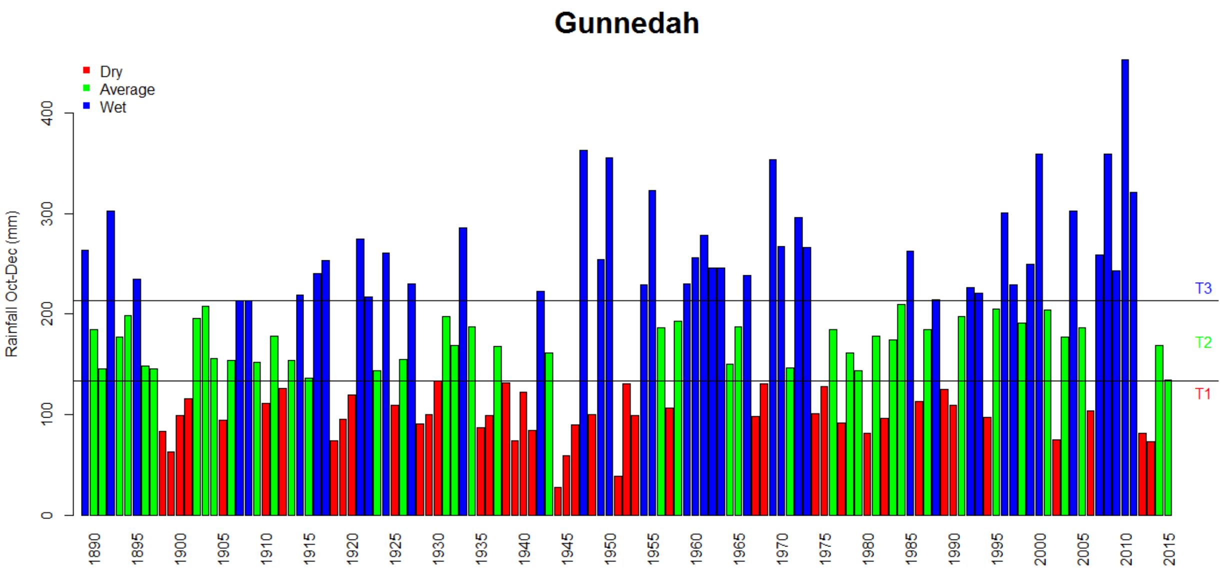


Figure 6 Total rainfall for October through December at Gunnedah for 1889–2015 sourced from SILO (Jeffrey et al., 2001). Dry, Average and Wet represent terciles 1, 2 and 3.

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

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

In this study, 11 probabilistic forecasts were created for each of the three climate states (dry, average, wet), each representing a different level of forecast skill (0 to 100%). These probabilistic forecasts are incorporated into the economic model by assigning a probability to the occurrence of each climate state based on forecast skill. The definition for forecast skill with reference to prior (without forecast) and posterior (with forecast) probabilities was as defined in Equ 1.

$$\sigma = \frac{\pi_{s|f} - \pi_s}{1.0 - \pi_s} \quad \text{[Equ 1]}$$

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

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

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

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).

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

Avg = Wet = $y\frac{(y.00-\pi_{dry|f})y}{2y} = y\frac{(y.00-0.47)}{2} = 0.27y$ [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%**
Weighting (%)	Dry	33	40	47	53	60	67	73	80	87	93	100
	Avg	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* 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. sorghum, mungbean, cotton 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 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 cropping option was assessed under each forecast state (dry, average, wet). The economic model maximises returns by choosing the option that has the highest return weighted across the three climate states according 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.

$Max\ E[Y] = \sum_{s=}^{S} \pi_s y_{sy}$ [Equ 4]

$y_s = \sum_{j=}^{Jy} y\ c y_j\ x y_j + \sum_{n=}^{N} c_{2nsy} x_{2nsy}$ [Equ 5]

In Equ 4, π_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 growing selected crops in each state. This is reflected in c_{2ns}, the net revenue from activity *n* in state *s* (crop price less yield dependent costs related to harvest, levies, freight and processing) and x_{2ns} which is the level of activity *n* chosen in state *s* in stage 2 (tonnes of grain sold, 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 summer 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 relative to the more immediate returns offered by a summer 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_{dry}, Y_{avg}, Y_{wet}) multiplied by the probability of each state occurring (π_{dry}, π_{avg}, π_{wet}). The optimal crop choice without a climate forecast is the one 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 a SCF compared with the return obtained without a forecast. In this analysis, the without-forecast scenario was represented by 0% skill, which is equivalent to equal weighting in results between dry, average and wet climate state outcomes (33% each). Value was calculated in terms of $/ha.

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

Table 4 Variables and value levels assessed to evaluate forecast value. PAW is plant avaliable water and PAWC is plant avalaible water capacity, set by the sorghum crop.

Variable	Values tested
PAW at sowing	25, 50, 75, 100% of PAWC
Relative sorghum crop price	low, medium, high
Forecast state	dry, average, wet
Forecast skill (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

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

4 Results

4.1 Biophysical modelling

Historical variability in initial soil moisture conditions at sowing (15 October) was assessed to determine the frequency of soil moisture states. For this purpose, initial soil moisture was not reset annually within *APSIM* and a sorghum crop was grown and harvested each year followed by winter fallow. Annual soil moisture at sowing (15 October) was extracted by taking the mean of seven days centred on 15 October. 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).

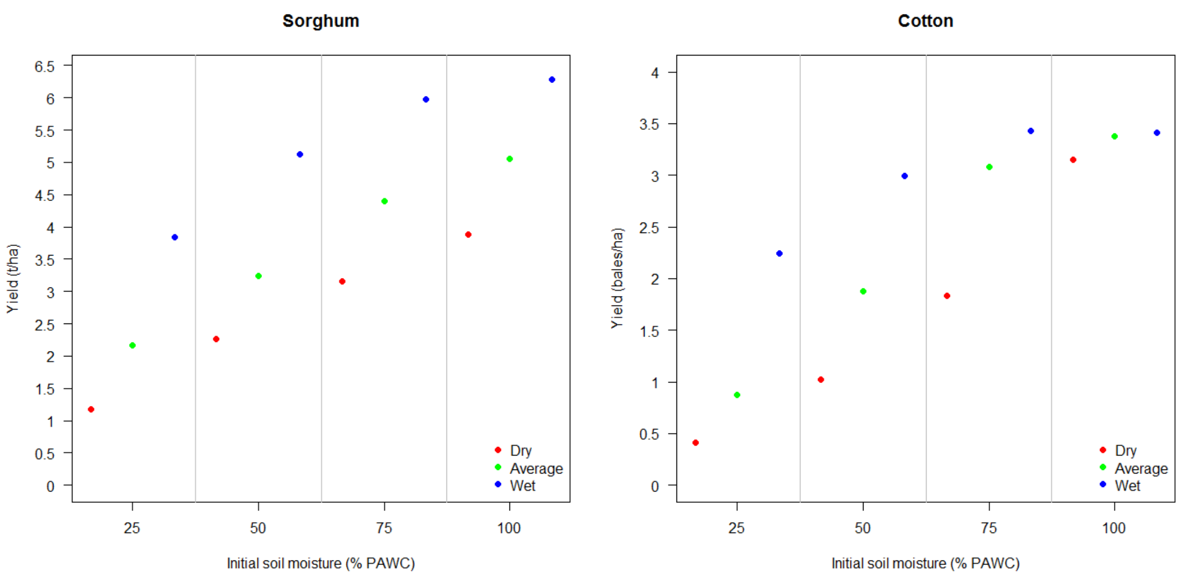
The largest number of years fell into the 50–75% and 75–100% of PAWC categories, with 23% and 36% of the years, respectively. Only a few years recorded soil moisture at sowing less than 25% of PAWC (5% of years). Note, these results will vary depending on crop rotation, inclusion of fallow (or not) and other management strategies.

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

	<25%	25–49%	50–74%	75–99%	
Percentage of years (%)	5	18	23	36	18

For each initial soil moisture level at sowing, average crop yields across 1889–2015 of sorghum, cotton and mungbean were found for the three climate states (dry, average and wet; Figure 7). For all crops, lower soil moisture levels at sowing (25% of PAWC) led to lower yields. Relative difference in the sensitivity of the crops to soil moisture levels at sowing was observed. Mungbean was the most stable across the different soil moisture levels tested, with similar results for 50, 75 and 100% of PAWC. This is a reflection of the lower water requirement of mungbean compared with sorghum and cotton.

Difference in yields based on climate state (dry, average, wet) was observed for each crop and under most initial soil moisture conditions. For instance, the dry climate state led to lower yields under all circumstances. Equally, the wet climate state tended to lead to higher yields. These differences in yields based on climate state indicate that there may be some benefit in including a SCF to assist with the summer cropping decision in Gunnedah.



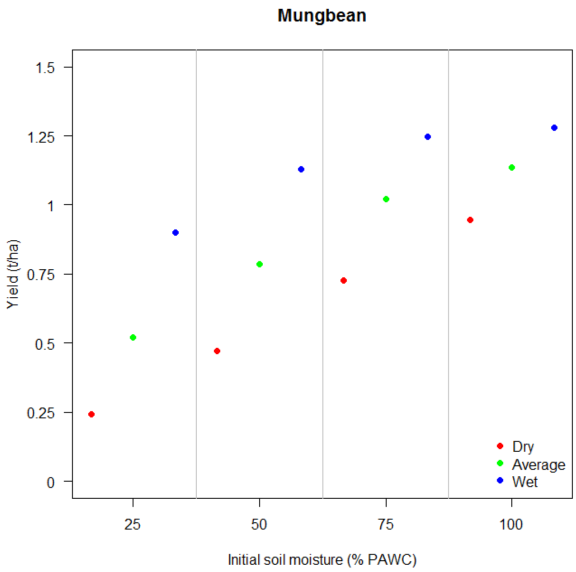


Figure 7 Average yields for each of the crops when sown at 25%, 50%, 75% and 100% of PAWC. The colours indicate the different tercile allocations of the historical data (1889-2015) with red for dry (lower tercile), green for average (middle tercile) and blue for wet (upper tercile). Climate states are for total rainfall October–December.

Summer fallow was also considered a potential option. In order to assess the value of fallowing, stored soil moisture was extracted for the week centred on 11 May and averaged after each crop and after summer fallow. Using this result, a winter wheat crop was grown. Figure 8 illustrates the range in soil moisture available for a winter wheat crop and the yield of a wheat crop depending on the preceding summer crop grown or if the field was fallowed. As expected, summer fallow led to the greatest amount of stored soil moisture for each soil moisture amount tested and hence the greatest yield in the subsequent wheat crop.

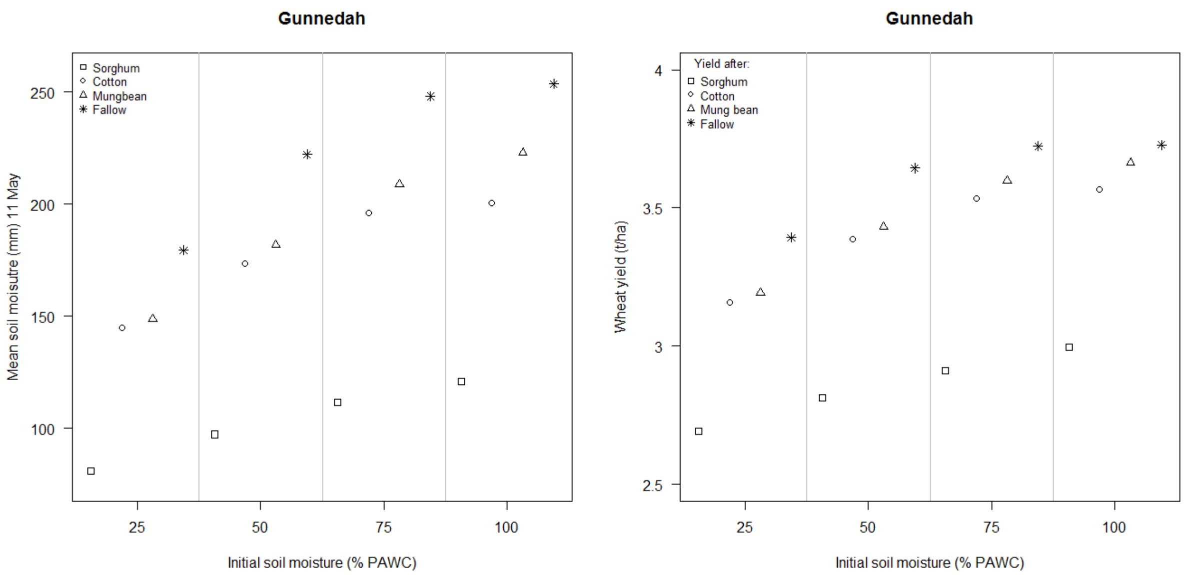


Figure 8 Mean soil moisture centred on 11 May (left) and mean wheat yield (right) for each preceding crop or fallow and initial soil moisture setting at sowing of the summer crops

4.2 Economic analyses

4.2.1 Without-forecast decision

The optimal summer cropping decision without a forecast (0% skill) must be determined prior to calculating the potential value of SCFs. Figure 9 shows the optimal without-forecast cropping decision for each combination of the decision settings (Table 4). The without-forecast decision illustrates the influence of the decision settings. With low initial soil moisture (25% of PAWC), mungbean is selected, regardless of relative sorghum price. With 50% and 75% of PAWC, mungbean is again selected, except when sorghum prices are high. With initial soil moisture 100% of PAWC, cotton is the optimal choice with sorghum selected under high relative prices. These results reflect the different water requirements of the crops and highlight the role of relative prices in changing the optimal decision.

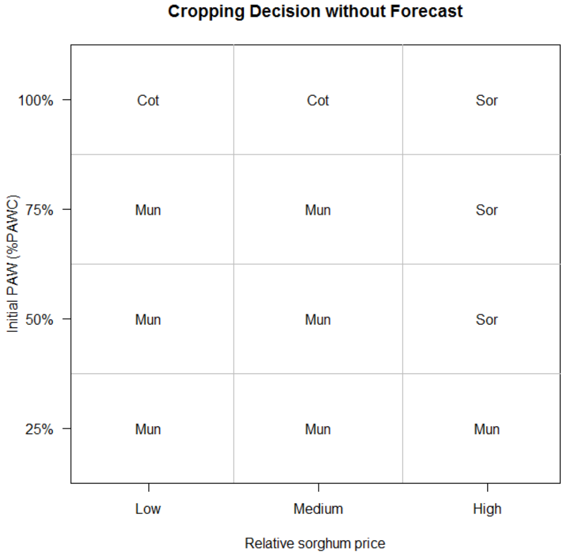


Figure 9 Optimal without forecast summer cropping decision. Four levels plant available water (25, 50, 75, 100% of PAWC) are represented in the four rows and relative sorghum price (low, medium, high) is represented in the columns. Sor, Cot and Mun represent sorghum, cotton and mungbean.

4.2.2 Perfect-forecast decision

The optimal cropping decision for perfect forecasts of dry, average and wet climate states (100% skill) were evaluated for each combination of the decision settings (Figure 10). For a dry climate state, fallow was selected at 25% PAWC, mungbean was selected for 50% and 75% of PAWC and cotton for 100% of PAWC. This was consistent across all sorghum prices. For the wet climate state, sorghum dominated the crop choice, except at low sorghum prices. Mungbean was only selected at low initial soil moisture and only for low and medium sorghum prices. Again, this highlights the importance of the different crop water requirements and relative prices.

For an average climate state, the optimal cropping decision was the same as the without-forecast choice for all decision environment settings except for a few circumstances (compare Figure 9 and Figure 10).

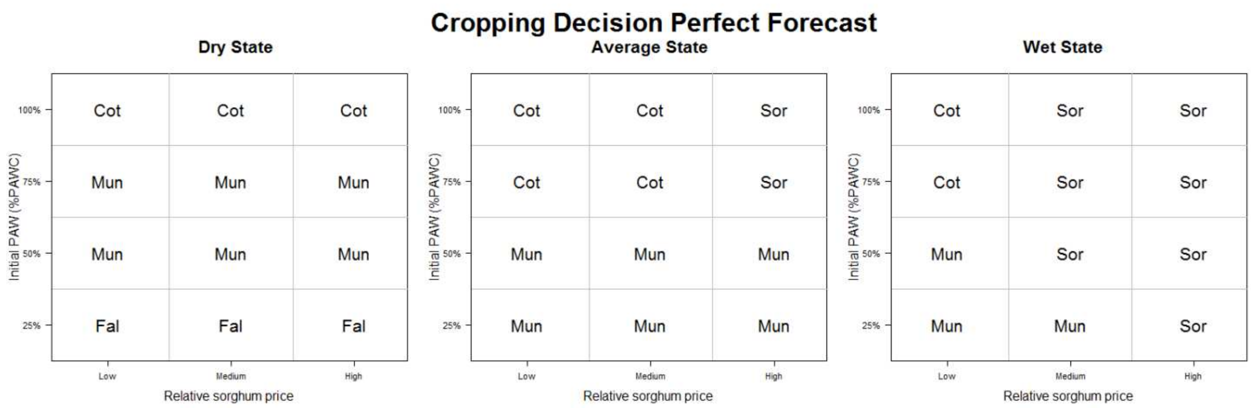


Figure 10 Optimal with forecast summer cropping decision. Dry, average and wet climate states are represented in each box, the four levels plant available water (25, 50,75,100% of PAWC) are represented in the four internal rows and relative sorghum price (low, medium, high) is represented in the internal columns. Sor, Cot, Mun and Fal represent sorghum, cotton, mungbean and fallow.

4.2.3 Perfect-forecast value

The range in the value of a perfect forecast (100% skilful) across the three climate states was $0 to $290/ha. The result highlighted the importance of the decision environment settings, and the combination of these settings, to deliver financial returns (Figure 11). For instance, a perfect dry forecast, with high sorghum prices, delivered $75–103/ha value through shifting away from sorghum to crops with lower water requirements. Alternatively, a wet forecast with medium sorghum prices shifted the crop choice towards sorghum, the higher water requirement crop.

Value was found for the average climate state for fewer decision environment settings. The value that was found stems from the difference in yields from an average climate state as opposed to the average climate (i.e. climatology) between the crops (Figure 7). In particular, cotton yields for initial soil moisture 75% of PAWC for an average climate state is close to that obtained for a wet state while sorghum yields for an average state are notably lower than for a wet state (Figure 7).

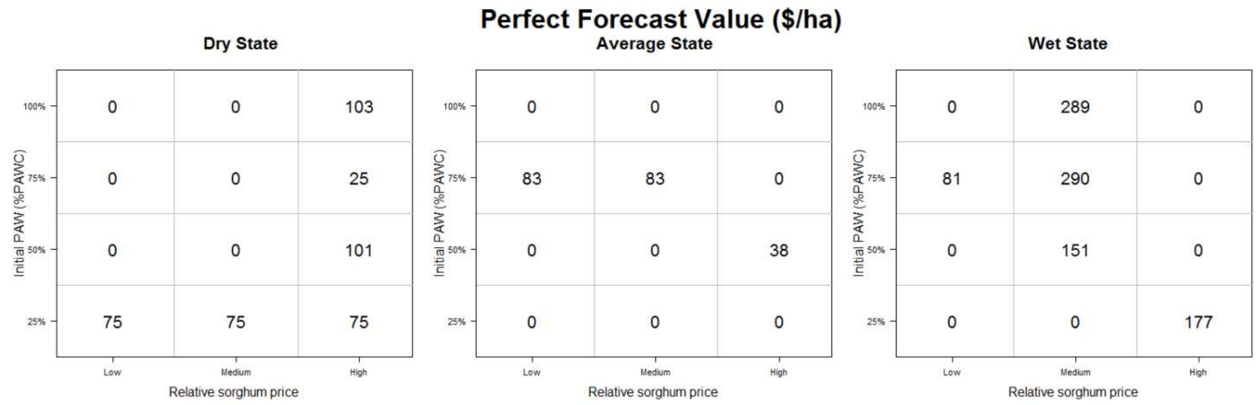


Figure 11 Perfect forecast value ($/ha). Dry, average and wet states in the three boxes, the four levels plant available water (25, 50, 75, 100% of PAWC) are represented in the four internal rows and relative sorghum price (low, medium, high) is represented in the internal columns.

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 12). These plots provide greater detail of the results in Figure 11, 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 12). The minimum skill required to yield value ranged from 10% to 100% and was often about 40%.

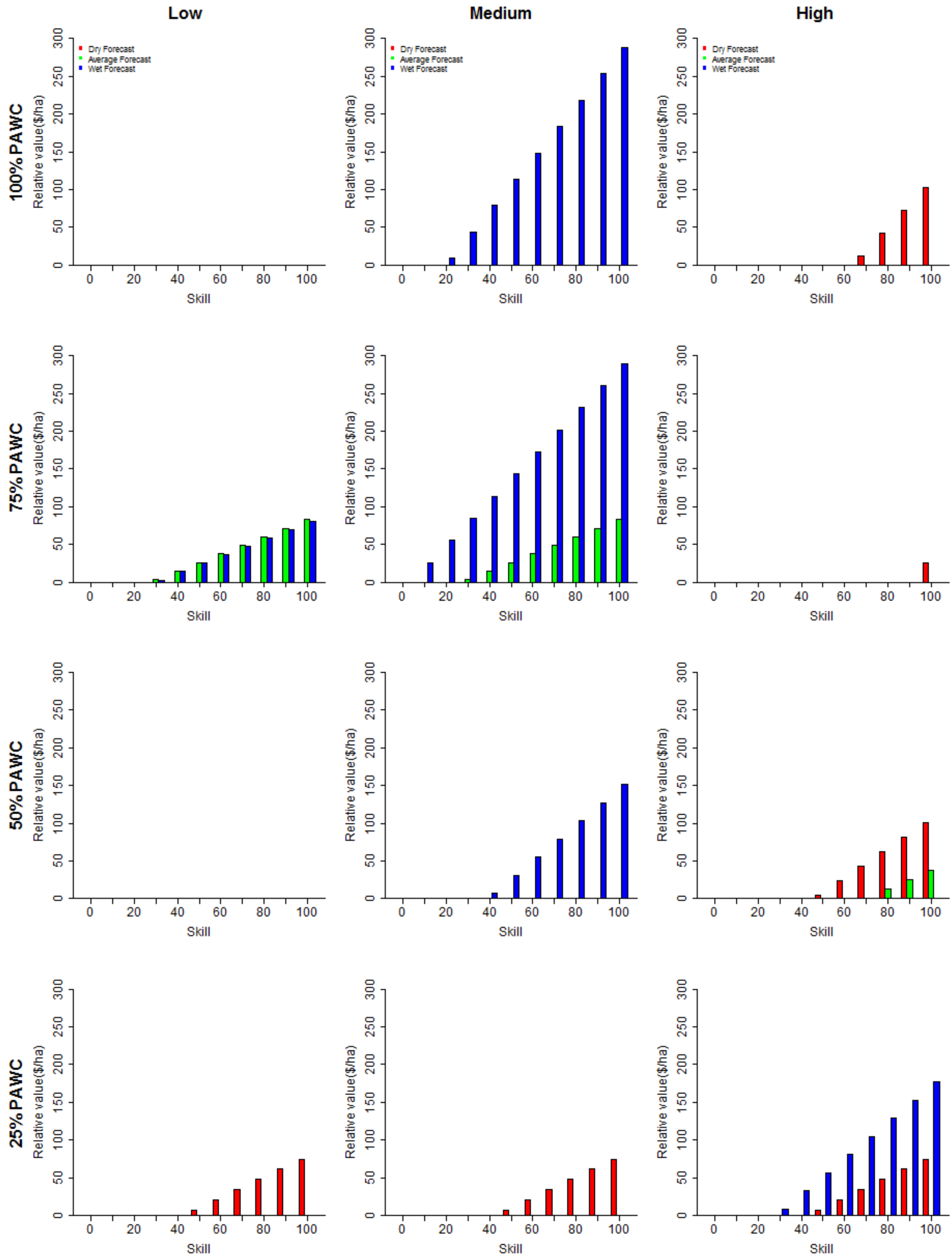


Figure 12 Imperfect forecast value ($/ha). Four levels plant available water (25, 50, 75, 100% of PAWC) are represented in the four rows and relative sorghum price (low, medium, high) is represented in the columns. Skill (%) is represented on the x-axis as calculated in Table 3.

5 Discussion

The key production decision sensitive to SCFs identified by industry was which summer crop to select. This decision considers the performance of several summer crops or fallowing and the soil moisture implications to the following winter crop.

5.1 Cropping decision made without seasonal climate forecasts

Without a SCF, mungbean was the most frequently selected crop. The exception was at high sorghum prices and for high soil moisture levels (100% of PAWC) (Figure 9). These results reflect the different water requirements of the crops, with mungbean requiring less water than cotton or sorghum. At initial soil moisture 100% of PAWC, cotton and sorghum become more profitable and were the optimal choice.

The modifying influence of relative price was evident. At higher relative sorghum prices, sorghum was selected for all initial soil moisture conditions, except at low levels (25% of PAWC) where mungbean was selected (Figure 9). This demonstrates the impact relative crop prices are likely to have on cropping decisions.

5.2 Cropping decision made with seasonal climate forecasts

Inclusion of perfect (100% skilful) forecasts of dry, average and wet conditions led to different crop choices to the without-forecast choice for a number of the decision settings tested. For a perfect dry forecast, fallow was selected as the optimal decision when initial soil conditions were low, translating to a value of $75/ha. Selection of mungbean was expanded for all initial soil conditions at 75% of PAWC with an associated value of $0–101/ha. These findings show that there is value of a perfect dry forecast through the selection of crops with lower water requirements (fallow and mungbean). Similarly, a perfect wet forecast encouraged selection of a higher water requirement crop more often (sorghum and cotton).

Relative prices had an impact on cropping decisions. With low sorghum prices, sorghum was not selected with or without a forecast, effectively reducing the number of crop options to three. With high prices and without a forecast, sorghum was selected for all initial soil moisture conditions except for 25% of PAWC (Figure 9). Sorghum was selected for all soil settings with a wet forecast but not selected with a dry forecast. This is a reflection that even with high prices, yields of sorghum and the subsequent wheat crop were insufficient to select sorghum under a dry climate state.

As the forecast value was found to be related to initial soil moisture levels, the relative likelihood of these starting conditions occurring needs to be considered. Assuming a period of winter fallow after a sorghum crop, the distribution of soil moisture conditions at sowing in October was evaluated (Table 5). Around half of initial soil moisture conditions under these assumptions led to soil moisture levels of 75% to 100% of PAWC (54% of years). For these initial soil conditions, the greatest value under each climate state was found: $103, $83 and $290/ha for dry, average and wet climate states, respectively (Figure 11). Equally, low soil moisture conditions (25% and 50% of PAWC) occurred less frequently (23% of years), with value found at these soil moisture levels therefore less likely to eventuate. This analysis provides an example of the likely frequency of initial soil conditions that lead to various forecast values, noting that this will vary significantly from farm to farm given varying management practices.

A climate forecast of an average climate state was found to be of limited economic value under most decision settings. Value was only found under high sorghum prices and led to a maximum value of $83/ha. The mostly low value of an average forecast state is a reflection of the limited change in climate conditions compared to the without-forecast decision, which is based on climatology. As climatology is the mean of the climate, the limited and small forecast value of a forecast of the average forecast state (middle tercile of climate data) is unsurprising.

Greater value of dry and wet forecast states was found (Figure 11). Two examples will be used to explore the different circumstances for which dry and wet forecasts have value. With a high relative sorghum price and initial soil conditions at 100% of PAWC, the without forecast decision was to sow sorghum. With a perfect **dry** forecast the optimal decision changed to sow cotton, driven by more profitable cotton and wheat yields (of the subsequent crop). A perfect forecast of a dry state resulted in an improvement in returns of $103/ha under this scenario.

A scenario of low initial soil moisture (25% of PAWC) and high relative sorghum prices provides an example of the benefit of a **wet** forecast. The without-forecast decision in this scenario was to sow mungbean, a reflection of the low initial soil water conditions. With a perfect wet forecast the optimal decision changed to sowing sorghum. In this example, a wet forecast provided greater surety about the occurrence of additional in-crop moisture that occurs in a wet state, increasing sorghum yields and, in combination with higher relative prices, making sorghum a more profitable choice. A perfect forecast of a wet state resulted in an improvement in returns of $177/ha under this scenario.

The above examples highlight the maximum possible value of SCFs under different scenarios through a perfect or 100% skilful forecast. However, in reality SCFs are imperfect and different levels of skill were analysed to assess the value of improvements. Positive value of SCFs was obtained for most initial soil moisture and relative sorghum prices (Figure 12). To realise value in a SCF, forecast skill often needed to be at least 40% (Figure 12).

5.3 Comparison to previous findings

In this case study the value of including a theoretical tercile forecast was found to range from $0 to $290/ha. The upper end of this range (highly skilful forecasts) shows substantial value but is consistent with previous studies that considered the value of SCF in summer cropping systems in Australia. McIntosh et al. (2005) investigated the potential value of a SST forecast to make a cropping decision between cotton and sorghum assuming soil moisture was 50% of PAWC. They found that a forecast could improve returns over the presumed farmer practice by $112/ha. The maximum forecast value evaluated for initial soil moisture at 50% of PAWC here was $151/ha (Figure 11).

Carberry et al. (2000) considered the potential value of an SOI phase forecast in deciding to sow sorghum or cotton with soil moisture at sowing 47% of PAWC. They found value of the forecast of $201/ha over two years. Using the same production system data Hammer (2000) evaluated more operational forecast systems and found forecast value of $184 to $304/ha over a two-year period.

In contrasting these previous studies with the results of this case study, two important differences need to be appreciated. Firstly, here a theoretical forecast was used while other studies have, more or less, assessed the value of operational forecasts. Secondly, the approach to define the without-forecast decision differs. Here, to determine the without-forecast decision, the economic model was optimised assuming average climate conditions. Other studies have defined farmer practices to compare with decisions made with a SCF (McIntosh et al., 2005), although some assessments of value against alternate fixed strategies have also been investigated (Carberry et al., 2000; Rodriguez et al., 2018). With the extent of forecast value contingent upon the assumed base case (without-forecast situation), 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. Nevertheless, under the most ideal conditions represented here, some similarity in SCF value between studies was found.

5.4 Limitations and assumptions

The case was study designed using 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., 2018) 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. As such, it likely produces optimistic results. Other parameterisations of the model may also influence results. For example, after the summer crops were harvested, the model was left to run for several more months so the soil moisture in May could be extracted to evaluate the performance of a wheat crop. During the period between harvest and May soils were left bare which likely encouraged soil moisture loss. This may have reduced the wheat crop performance after the summer crops, however as fallow was not frequently selected, this effect is unlikely to have notably impacted results.

Other management options are also possible, for example, different crop choices, skip row orientation, plant densities, nitrogen application and so on. Changing these settings may alter optimal crop choice. However, the assessment conducted here focused on the relative benefit of a SCF and for this purpose provides an example of potential benefit but does not include all possible farm or management options.

A large proportion of the Australian cotton, sorghum, mungbean and wheat crops are exported (ABS, 2018). As such, no correlation between prices was found or included in the analysis. This lack of correlation is due to prices being dictated by global production and markets for each crop and not related to local conditions.

Given this lack of price correlation, a sensitivity analysis of the value of SCFs for different sorghum prices was included (Table 2). The analyses showed that relative prices did change the without-forecast decision and also influenced the forecast value between the different price settings. For example, the maximum value for low sorghum prices was $156/ha and $204/ha for high sorghum prices. Furthermore, at low prices, only three of the 12 decision setting combinations yielded value, while this increased to eight for high prices. These results show that relative crop price is important in realising SCF value. Sensitivity to changes in relative crop price of the other crops (mungbean, cotton and wheat) would similarly modify both the without- and with-forecast decision (i.e. more likely choose the higher valued crop) and potentially the forecast value.

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 Gunnedah region for October to December rainfall is approximately 55%, equating to a skill score used here of just 10%.

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Appendix 1: Industry engagement

Overview:

As part of the project 'Improved Use of Seasonal Forecasting to Increase Farmer Profitability', a case study approach is being used to assess the potential value of seasonal climate forecasts when incorporated into farm management decisions. Within the grains industry and based on the current GRDC boundaries (https://grdc.com.au/About-Us/GRDC-Regional-Panels), a southern, northern and western case study will be evaluated. This workshop was held to explore the northern grains case study on 13 October 2017.

Attendees:

Peter McKenzie (Agricultural Consulting and Extension Services), Doug Richards (Glenmore Rural Services), Robert Freebairn (Robert Freebairn Consultant). David McRae (Scientist, University of Southern Queensland) and Michael Cashew (Research Officer, Climate Applications, NSW Department of Primary Industries) as workshop organisers and presenters.

Representative farm:

Discussions were based on a representative dryland mixed cropping grazing enterprise based in the Gunnedah (Liverpool Plains) region.

At the commencement of the workshop the participants agreed on the key characteristics of the representative farm.

- The total farm area: 1700 ha
- Total capital investment: $ 8 million
- Soil type: Predominately fertile black and grey cracking clays
- Loan equity: 82%
- Proportion of farm under crop: 50% (850 ha) comprising 60% summer and 40% winter cropping
- Proportion of farm under pasture: 50% (850 ha) comprising sheep and cattle

The cropping rotation sequence was based on summer crop (sorghum), winter fallow, summer crop (sorghum), winter crop (wheat), summer fallow, winter fallow. This sequence has historically obtained a 5.4% return on owners' equity.

Summer cropping options include mungbean, cotton, sunflower and sorghum. Winter cropping options include winter cereals such as wheat, barley and dual-purpose cereals for grazing, faba beans, chickpeas and canola. More emphasis was also placed on the summer cropping decision-making with winter cropping considered a secondary decision.

Decision points:

In discussion, the participants identified and agreed on some key drivers of major cropping decisions including:

- Soil water profile (known)
- Commodity prices (taking into account factors such as spot prices and on farm storage with associated input costs)
- Specific crop sequences (driven by disease and weed burdens, nematodes, soil fertility and chemical residual issues etc.)
- Seasonal forecasts (incorporating both rainfall and temperature - shorter term for sowing and longer term for frost risk, disease incidence and increased challenges at harvest)
- Crop knowledge including the availability of machinery and technology (especially for 'new' crops)

- Equity balance (higher equity levels increase the potential to push the boundaries)
- Enterprise 'pillar crop' (what historically has provided the best and most consistent return, balance between summer and winter, etc.).

However for the purpose of this case study, three key decision drivers were identified. These were:

- Soil moisture (low, medium, high)
- Commodity price (low, medium, high)
- Climate forecast (poor, equal chance, wet).

Summer crop area sowing decision example:

Scenarios were proposed based on 'what if' combinations of the key decision drivers with the management response option to sow sorghum, sow cotton, sow mungbean, leave fallow or mix of these options. Through discussion, the following decision matrix was developed (Table 6).

Table 6 Summer crop area sowing matrix

Commodity price	Soil moisture	Climate forecast	Decision
Med	Med	Equal chance	Option includes to focus on 'pillar crop' and well as/or lower cost crop such as mungbean (input costs lower). Could sow sorghum and graze or make hay (considered a baseline decision when nothing is pushing other than finances).
Low	Low	Dry	Fallow entire area to use as moisture accumulation for winter program.
Low	High	Dry	Sow increased area to sorghum.
Low	Low	Wet	Fallow entire area to use as moisture accumulation for increased winter program. Some may sow reduced area of sorghum in case of wetter finish to season.
Low	High	Wet	Either sow lower cost crops or what gives best financial return or what mix best fits the preferred cropping sequence.
High	Low	Dry	Don't sow high cost crops (e.g. cotton). Instead sow either or mix of sorghum, mungbean and/or fallow.
High	High	Dry	Sow high value/best financial return crops.
High	Low	Wet	Sow lower cost crops taking into account best return and best fit rotation.
High	High	Wet	Sow all available area and consider double crop option (e.g. chickpeas) straight into sorghum or wheat into mungbeans.

Winter crop area sowing decision example:

Scenarios were again proposed based on 'what if' combinations of the key decision drivers with an available management response option of sow wheat, sow chickpeas, sow dual-purpose cereal, sow faba beans, leave fallow or mix of these options. Through discussion, the following decision matrix was developed (Table 7).

Table 7 Winter crop area sowing matrix

Commodity price	Soil moisture	Climate forecast	Decision
Med	Med	Equal chance	Options include: focus on winter 'pillar crop', sow chickpea (lower moisture requirement and more time to fill profile), could consider a dual-purpose cereal depending on livestock prices and existing stocking rate as well as need for groundcover etc. (considered a baseline decision when nothing is pushing other than finances).
Low	Low	Dry	Sow dual-purpose cereals on lighter area, fallow the balance.

Low	High	Dry	Sow entire area to best financial return option and best fit for crop rotation/sequence.
Low	Low	Wet	Sow chickpea (lower moisture requirement and more time to fill profile before peak use), could consider dual-purpose cereals to cover any potential livestock feed gap. Reduce winter cropping area and/or consider barley.
Low	High	Wet	Sow entire area to best return financial option, best fit for crop rotation.
High	Low	Dry	Sow winter area to chickpea (lower moisture requirement and more time to fill profile before peak use), could consider dual-purpose cereals. Reduce winter cropping area planted, consider barley.
High	High	Dry	Sow entire winter cropping area, consider increased plant of duram and chickpeas, fabas and canola a potential option.
High	Low	Wet	If return on chickpea high plant maximum potential area, balance of winter crop area planted with a barley option, add in dual purpose crop, consider sowing configuration to take in any later moisture.
High	High	Wet	Plant full winter cropping area, consider more durum/cereals/faba beans than chickpeas, reduce area planted to barley and consider canola as an option.

General discussion:

General rules regarding crop rotations and balance between the percentages of cropping area available to be planted to specific crops was also discussed. This was considered important as the workshop participants viewed decision-making as more complex than just a ‘plant everything’ to a specific crop ‘or plant nothing’ without taking into account previous cropping decisions.

For example, a higher frequency chickpea rotation than one crop in four years in the same field is considered to be at higher risk of disease. The basic crop rotation rules discussed were:

- Sorghum up to eight consecutive repetitions
- Chickpeas one year in three to four
- Sunflowers, cotton (dryland) and canola one year in four
- Winter cereals sequence not to include wheat on wheat.

While seasonal climate forecasts were identified as an important component of managing risk, in general discussion, a strong emphasis was given to starting soil moisture and commodity pricing. This also reflected a general view that making sowing decisions based on any one factor was high risk.

Appendix 2: Gross margin values

Crop production costs for summer cropping options in this study were based on the NSW DPI Northern Zone East (Figure 13). 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* crop simulation data to determine annual cropping returns. A summary of crop gross margins is provided in Table 8. An example of a relevant gross margin budget detailing practices is reproduced below.

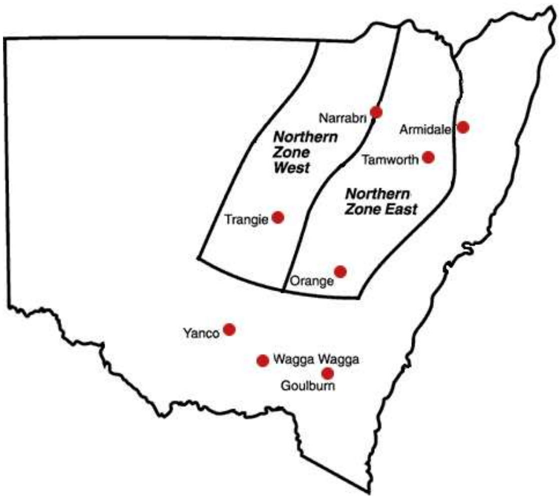


Figure 13 Crop production zones in NSW

Table 8 Gross margin summary – North East NSW

	SORGHUM	**MUNGBEANS**	**COTTON**	**WHEAT**
INCOME				
Yield 1	4.5 t/ha @ 270/t	1.06 t @ $850/t	3.60 bales/ha @$466	2.5 t/ha @ $275/t
Yield 2 (Cottonseed/Gradings)		0.14 t/ha @ $160/t	0.90 t/ha @$300 (less $25/bale discount)	
A. Total Income	**$1,215.00**	**$920.64**	**$1,858.00**	**$687.50**
VARIABLE COSTS[4]				
Fallow management	$0.00	$0.00	$93.00	$0.00
Sowing/Planting	$44.25	$64.56	$100.00	$55.05
Crop protection, app, licence	$0.00	$0.00	$347.00	$0.00
Fertiliser & application	$124.02	$51.00	$41.00	$186.11
Herbicide & application	$230.77	$31.73	$0.00	$54.95
Insecticide & application	$67.00	$11.03	$0.00	$0.68
Fungicide & application	$0.00	$0.00	$0.00	$24.58
Defoliation	$0.00	$0.00	$109.00	$0.00
Harvesting	$84.93	$74.93	$602.00	$64.93
Levies and insurance	$68.65	$9.39	$0.00	$21.10
Grading & bagging	$0.00	$108.00	$0.00	$0.00
Farming: Post-crop	$0.00	$0.00	$45.00	$0.00
B. Total Variable Costs	**$619.62**	**$350.65**	**$1,377.00**	**$407.40**
C. Gross Margin (A-B)	**$595.38**	**$569.99**	**$481.00**	**$280.10**
Source	*NSW DPI*	*NSW DPI*	*Ag Econ/CottonInfo*	*NSW DPI*

[4] 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.

DRYLAND MUNGBEANS (No-till, Double-crop)

Farm Enterprise Budget Series - North-East NSW

Summer 2017-2018

GROSS MARGIN BUDGET:		Sample Budget $/ha	Your Budget $/ha
INCOME:			
Yield	1.20 tonnes/ha		
1.06 tonnes/ha at	$850.00 /tonne (clean seed, processing grade).......	$897.60	
0.14 tonnes/ha at	$160.00 /tonne (gradings)......................................	$23.04	

Crop prices were correct at the time of writing (November 2017), world market volatility makes estimation of future pricing impractical.

A grading percentage of 12% is assumed, but it will vary according to crop and harvest conditions.

	Sample Budget $/ha	Your Budget $/ha
A. TOTAL INCOME $/ha:	**$920.64**	

VARIABLE COSTS:

see following page(s) for details

	Sample Budget $/ha	Your Budget $/ha
Sowing...	$64.56	
Fertiliser & application...	$51.00	
Herbicide & application...	$31.73	
Insecticide & application...	$11.03	
Harvesting..	$74.93	
Levies and insurance...	$9.39	
Grading & bagging..	$108.00	
A. TOTAL VARIABLE COSTS $/ha:	**$350.65**	
B. GROSS MARGIN (A-B) $/ha:	**$569.99**	

2. EFFECT OF YIELD AND PRICE ON GROSS MARGIN PER HECTARE: SENSITIVITY TABLE

YIELD t/ha		**Price**					
gradings		$140 /t	$150 /t	$160 /t	$170 /t	$180 /t	$190 /t
	clean seed	$750 /t	$800 /t	**$850 /t**	$900 /t	$950 /t	$1,000 /t
0.08	0.62	$173	$204	**$235**	$267	$298	$329
0.11	0.79	$289	$329	$369	$409	$450	$490
0.13	0.92	$376	$423	$470	$517	$564	$611
0.14	**1.06**	$463	$516	**$570**	$624	$677	$731
0.17	1.23	$579	$641	$704	$766	$829	$892
0.19	1.41	$695	$766	$838	$909	$981	$1,052
0.20	1.50	$753	$829	**$905**	$981	$1,057	$1,133

DRYLAND MUNGBEANS (No-till, Double-crop)

Farm Enterprise Budget Series - North-East

NSW Summer 2017-2018

CALENDAR OF OPERATIONS:		Machinery			Inputs			Total
			Cost	Total		Cost	Total	Cost
Operation	Month	hrs /ha	$/hour	$/ha	Rate/ha	$	$/ha	$/ha
harvest winter cereal crop	Nov							
Herbicide - ground spray, 450 g/L glyph	Nov	0.05	44.32	2.22	1.6 L	7.23	11.57	**13.78**
Wetter - non-ionic surfactant		with above			0.2 L	6.60	1.32	**1.32**
Sowing: Seed +inoculum	Dec	0.20	60.32	12.06	25 kg	2.10	52.50	**64.56**
Fertiliser - Granulock SuPreme Z	Dec	with above			50 kg	1.02	51.00	**51.00**
Herbicide - haloxyfop-R 520 g/L	Jan	0.05	44.32	2.22	0.15 L	55.00	8.25	**10.47**
Uptake oil	Jan	with above			0.50 L	6.68	3.34	**3.34**
Crop insurance **	Jan			0.00%				**0.00**
Insecticide - indoxacarb	Jan	0.05	44.32	2.22	0.4 L	8.00	3.20	**5.42**
Insecticide - alpha cypermethrin 100g/L	Feb	0.05	44.32	2.22	0.4 L	8.50	3.40	**5.62**
Desiccant- Roundup Attack™ 570 g/L	Mar	0.05	44.32	2.22	1.6 L	0.38	0.61	**2.82**
Harvest	Mar	contract		74.93	per ha incl fuel			**74.93**
Grains Research Levy				1.02%	of farm gate value			**9.39**
Grading & bagging	May	contract		$90 /t				**108.00**

AGRONOMIC NOTES:

Mungbeans can be an ideal opportunity double crop following winter cereals. Soil moisture profiles must be replenished if satisfactory yields of high quality beans are to be produced. Best suited to heavier soils.
Weeds: Select a paddock free of broadleaf weeds. Good weed control is essential. To reduce the likelihood of herbicide resistance, rotate herbicide groups and weed management techniques. Ensure weed escapes are controlled before they can set seed.
Pests: Closely monitor crops for thrips, mirids (from pre-budding and flowering), heliothis and green vegetable bug. **Fertiliser:** If applying phosphate fertiliser, use a fertiliser that contains good levels of sulfur as well, e.g. single superphosphate. Fertiliser requirements should be based on paddock records and soil tests.
Desiccation: Usually required to even up crop maturity across a paddock and to prevent additional flowering.
Harvest: Use air assist headers to reduce losses at harvest. Harvest costs based on $70/ha for a crop up to 2.5 t/ha. Communicate with your buyer throughout the season and have storage options available.
Insurance: ** Varies with Local Government Area and postcode, check with your insurer.
For further information, refer to the NSW DPI "Summer Crop Production Guide", "Mungbean management Guide 2011" https://www.daf.qld.gov.au/plants/field-crops-and-pastures/broadacre-field-crops/mungbeans and the Australian Mungbean Association http://www.mungbean.org.au/best-management-guide.html

Always read chemical labels and follow directions, as it is your legal responsibility to do so. Use of a particular brand name does NOT imply recommendation of that brand by NSW DPI.

PRICE: - The price given is for processing grade mungbeans at the time of writing.
Consult marketing sources for more up to date price information.

LABOUR REQUIREMENTS: - labour is not costed in this budget. If labour costs $25.20 /hr, total labour cost would be $12.60, reducing the gross margin to $557 /ha.

MACHINERY ASSUMPTIONS:

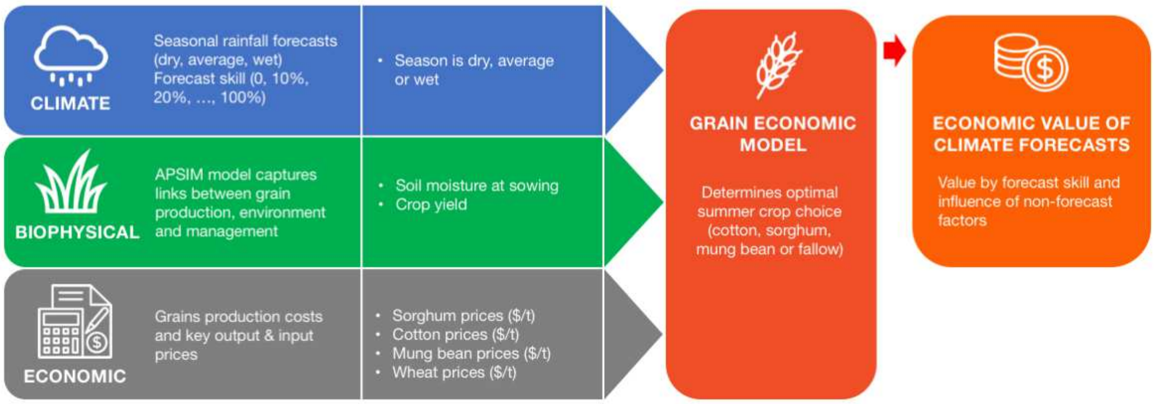
Tractor: 130-140 KW PTO (173-180 HP)

Machinery costs refer to variable costs of: fuel, oil, filters, tyres, batteries and repairs.
You may need to add overhead costs as well, please refer to the Tractor and Implement Costs Guide

Appendix 3: Economic model

1 Overview of the modelling approach

NORTHERN GRAINS



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. sorghum, mungbeans, cotton 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 soil moisture 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).

A two-stage discrete stochastic programming (DSP) model was developed for the northern cropping case study where time was divided into the 'present' and the 'future'. A standard linear programming model was developed into a DSP model by introducing a second period decision. The $x \rightarrow s$ format of static linear programming changes to $x_1 \rightarrow s \rightarrow x_2\ (s, x_1)$ in the DSP case. Here x_1 represents Stage 1 decisions (crop options – sorghum, mungbeans, 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 (tonnes of grain or 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.

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

$$y_s = \sum_{j=}^{Jy} y\ \ cy_j\ xy_j + \sum_{n=}^{N} c_{2nsy} x_{2nsy} \qquad \text{[Equ 2]}$$

subject to:

Land, labour and capital constraints

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

Use of crop outputs

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

Where model parameters are:

π_s probability of state *s*

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

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

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

c_{2ns} the net revenue or cost from activity *n* in state *s* (crop price less yield dependent costs related to harvest, levies, freight 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 summer crops) based on the selection of Stage 1 activities (x_{1j}), while the right-hand term reflects state-contingent revenue derived from Stage 2 activities (x_{2ns}) (harvest and sale of crops). The inputs committed through Stage 1 decisions are the same in every state of nature, while outputs in Stage 2 are specific to each state. While production is state-contingent, as per the outputs from the biophysical model, the prices of inputs and outputs (e.g. sorghum 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 summer cropping. This is set at a level of 510 ha based on the available summer crop area for a typical farm in North East New South Wales.

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 sorghum in Stage 1, combined with the intervening rainfall state, leads to sorghum 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 sorghum 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 crop decisions in each state. This is an important feature when considering the value of imperfect forecasts. Second, the modelling reflects the ability of farmers to consider state-contingent responses, something readily observed in practice. Third, with operational forecasts being probabilistic in nature, rational farmers will interpret probabilistic forecasts as a shift in the odds. This can be readily reflected in a DSP model through the assignment of posterior probabilities to each state based on forecast skill.

2.1 Valuing the forecast system

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

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

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

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

where:

y^*_{sf}	denotes the net return in state *s* resulting from implementing the optimal crop choice x^*_{sf} based on forecast *f*; and
y^*_{so}	denotes net return in state *s* resulting from implementing the optimal crop choice x^*_{so} based on the prior probabilities (assumed to be historical climatology).

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

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

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