REPORT

Analysis of the benefits of improved seasonal climate forecasting for agriculture

Prepared for
Managing Climate Variability Program

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Summary

This report

- In this report the benefits of seasonal forecasting for the agriculture sector and the wider rural community are discussed.
  - The report draws on and complements the companion report – 'Analysis of the benefits of improved seasonal climate forecasting: for sectors outside agriculture' also prepared by the CIE for the Managing Climate Variability Program.
- The available literature on the analysis of the impact of forecasts for agricultural activities is reviewed and the benefits of seasonal climate forecasts are quantified.
  - Two alternative approaches are used to quantify the benefits due to a lack of detailed information for a robust estimate of the value of seasonal forecasting.

Agriculture and climate

- Agriculture is highly sensitive to climate conditions.
  - In their study of the US economy, Lazo et al. (2011) found that the sensitivity of the agriculture sector is 12 per cent, and given the greater extent of climate variability, this is likely to be higher in Australia.
  - Estimates of the impact of recent droughts suggest agricultural output was reduced by up to 30 per cent, and 60 per cent in the case of wheat.
- Many management decisions are affected by weather conditions and may be refined with the use of weather and climate forecasts. These include:
  - careful management of planting times
  - determining the area and crop variety to plant
  - controlling stocking rates
  - pre-empting health issues in livestock
  - managing water and fertiliser applications
  - optimising harvesting times.
- The development of climate forecasts to date in Australia has mostly focused on use by agricultural producers, as there is significant potential for productive use of forecasts in the sector.
  - Agriculture is a well-coordinated sector – industry organisations have channelled considerable effort into ensuring forecasts are relevant to farmers

and made accessible through the development of tools to aid in decision making.

- Farmers are experienced in risk management and making decisions under uncertainty.

Value of forecasts

- Forecasts are likely to be of greatest value in areas of high climate variability and Australia has one of the most variable climates (Hennessy et al. 2008).
- The value of a climate forecast is less than the extent of climate sensitivity.
  - Not all impacts of weather on sectoral output can be eliminated with a climate forecast, no matter how skilful.
  - Any mitigation actions that are adopted must be cost effective.
  - Mitigation actions are not costless and therefore the value of a climate forecast is diminished by the cost of acting on it.
  - Climate forecasts are not perfectly accurate and there are costs associated with incorrect forecasts.
- The value of improved seasonal forecasts for the agriculture sector depends on a wide range of complex and interrelated factors:
  - forecast accuracy – including accuracy at relevant spatial resolution and with appropriate lead times
  - forecast adoption rates
  - risk attitudes
  - seasonal conditions experienced.

Quantifying the benefits

- Due to the lack of detailed information available in the published literature, two different approaches were used to generate estimates of the value of improved seasonal climate forecasts.
  - Based on the assumptions used to value the MCVP, the total value of forecasts to the agriculture industry is estimated to be around A$110m per year.
  - Using a more detailed methodology that incorporates the uncertain nature of improved seasonal climate forecasts and the cost of responding to forecasts, the value of improved seasonal climate forecasts that could be realised through optimising fertiliser application in wheat enterprises in WA is estimated at between A$418m and A$780m per year.
  - Assuming the same parameters hold for all cropping across Australia (an assumption that is necessary due to the lack of further information), improved seasonal forecasts may have a value of between A$800m and A$1491m.
  - There is also very limited information available about the value of forecasts to livestock operations. The value of forecasts for livestock operations is estimated to be in the range of A$158-438m.

   - **Combining the cropping and livestock estimates, provides an estimate of the value of improved seasonal forecasts for the Australian agriculture sector in the order of A$958-1930m.**
- **With increasing climate variability expected under climate change, the value of seasonal forecasts to the agriculture sector is expected to increase in the future.**
- **The potential value of improved seasonal climate forecasts is significant, and much greater than the equivalent value estimated for a range of other sectors in the economy[1]. This holds both in terms of the total value, and as a share of industry value added (see table 1).**

1 Summary of value of forecast for different sectors

Industry	Potential annual value of forecast	Industry value added	Potential value of forecast as share of industry value added
	A$m	A$m	%
Construction	192	79 851	0.20
Electricity	2.3	16 556	0.01
Coal mining	68	20 852	0.33
Oil and gas	93	20 363	0.46
Transport	5	22 824	0.02
Water supply	28	10 550	0.27
Agriculture	1 567	21 429	7.31

Note: All values are given in Australian dollars at 2012 prices

Source: CIE estimates

Rural communities

- **The value that improved seasonal climate forecasts bring to the agriculture sector is likely to have flow on benefits, and multiplier effects for local rural communities.**
   - **An increase in farmer incomes, and a decrease in variability of incomes, is generally beneficial for local communities.**
- **A number of factors have the potential to complicate the distribution of benefits through the community.**
   - **A decrease in expenditure on locally sourced inputs, including hired labour, by farmers as a result of improved forecasts may have negative impacts on the broader non-farming community.**
   - **The increasing number of corporate farms means improved profits flow to headquarters rather than local communities.**

1 A full discussion of the value of improved seasonal climate forecasts for sectors other than agriculture is available in the companion report to this one: 'Analysis of the benefits of improved seasonal climate forecasting: for sectors outside agriculture' (also prepared by The CIE for the Managing Climate Variability Program).

Future work

- **While it is clear the benefits of improved seasonal climate forecasts is significant for the agriculture sector, further work is needed to be able to fully quantify these benefits in a comprehensive manner. Future work should endeavour to fill the gaps in the current literature – particularly the value of seasonal forecasts to livestock operations and a wider range of management practices.**

1 Introduction

The Managing Climate Variability Program (MCVP), and its predecessor the Climate Variability in Agriculture Program, has been investing in improving the knowledge and information available on climate and climate variability. The focus of the program has been on products that help primary industries and natural resource managers manage the risks and opportunities presented by Australia's variable climate.

The MCVP is interested in understanding the possible benefits of further improvements in seasonal climate forecasting for the agriculture sector and rural communities.

In this report the benefits of seasonal forecasting for the agriculture sector and the wider rural community are discussed. The available literature on the analysis of the impact of forecasts for agricultural activities is also reviewed. An estimate of the potential value of improved seasonal forecasts for agriculture is presented using the framework developed in the companion report – 'Analysis of the benefits of improved seasonal climate forecasting: for sectors outside agriculture'.

In the next chapter, some definitional issues relevant to the rest of the report are discussed. In chapter 3 the climate sensitivity of the economy is discussed along with some key areas of consideration in understanding the use and value of climate forecasts. Chapter 4 provides a summary of the literature on the value of climate forecasts. Chapter 5 describes the methodology that was adopted to estimate the value of improved seasonal forecasting for this project. Chapters 6 and 7 discuss specific issues relevant to the agriculture sector, and provide discussions of the value of seasonal forecasts for the sector. In chapter 8 the impacts of seasonal climate forecasts on rural communities is discussed. Finally, chapter 9 summarises the results. Unless otherwise stated, all values given in the report are in Australian dollars at 2012 prices.

2 Context

Managing Climate Variability Program

The Managing Climate Variability Program is a collaborative rural research and development (R&D) program that aims to help primary industries and natural resource managers manage the risks and exploit the opportunities afforded by Australia's variable and changing climate. The MCVP continues the work of the Climate Variability in Agriculture Program which started in 1992.

The Managing Climate Variability Program is funded by the Grains, Rural Industries and Sugar Research and Development Corporations (RDCs), and Meat and Livestock Australia, with possible future support from other rural RDCs. The program invests in projects undertaken by research organisations including the Bureau of Meteorology (BOM) and Commonwealth Scientific and Industrial Research Organisation (CSIRO).

Over the past two phases of the program (2007/08 to 2013/14), MCVP has invested in 28 projects including research, communication and management/administration. A significant part of the work program is being undertaken by BOM aimed at more rapid development of a range of forecasts based on the Predictive Ocean Atmosphere Model for Australia (POAMA), a coupled ocean-atmosphere model. Development of POAMA has been a priority in recent years due to its potential for forming dynamical seasonal forecasts. Statistical forecasts are expected to become less reliable as a result of climate change.

The impact assessment of MCVP phases II and III (2007 to 2013) found that the MCVP investments led to a more rapid uptake of the POAMA products than would have been the case without MCVP investment. The benefit to farm production would be the same regardless of MCVP investment, however the benefits would be realised faster and earlier.

In the next phase of the MCVP, investments will likely be focused on:

- climate forecasting research: such as improving the accuracy of seasonal climate forecasting (on the 2-8 week and 3-6 month timescales) and improving the ease of use of forecasts. The focus will be on investment in POAMA, recognising the benefits of dynamical forecasting
- providing climate forecasting services to help users benefit from forecasts
- developing climate risk management tools and decision support using improved forecasts.

This report

The MCVP seeks to understand and quantify the potential value that may be realised through further investment in improving seasonal forecasting. Consequently, two reports have been prepared for the MCVP. This report looks at the value of seasonal climate forecasts for the agriculture sector and rural communities. A companion report – 'Analysis of the benefits of improved seasonal climate forecasting: for sectors outside agriculture' discusses the benefits that seasonal forecasting may bring to other sectors of the economy. The two reports use the same framework to quantify the potential benefits of improved, but imperfect, seasonal forecasts.

The existing literature on the value of seasonal climate forecasts is somewhat limited, particularly for sectors other than agriculture. This may be due to the following facts.

- There has been very limited use of seasonal climate forecasts by industries other than agriculture.
- Valuation of forecasts generally requires:
  - a model of how users incorporate forecasts into the decision making process
  - a model of how economic outcomes are determined by decisions and the realised state of nature.
- These requirements demonstrate that the value of improved seasonal forecasting is not a simple calculation. It is, in many ways, highly particular and highly contextual.

This report provides a brief documentation of the process undertaken to estimate the value of improved seasonal forecasts, the methodology adopted and the challenges faced. Further details on the methodology and background are provided in the companion report for other sectors.

Climate and weather

The main difference between weather and climate is related to the time period that is being considered. Weather refers to atmospheric conditions observed or expected over a short time frame whereas climate refers to atmospheric conditions, patterns and behaviour over a longer time period. The time frame at which atmospheric conditions are referred to as climate may differ between people, industries and organisations. For example, the US National Aeronautics and Space Administration (NASA) defines weather as short term changes in the atmosphere of periods of between minutes to seasons (Gutro 2005). Climate is defined as average weather conditions observed over longer time periods of up to 30 years. BOM defines climate as the atmospheric conditions over a long period of time and climate generally refers to the normal or mean course of weather (BOM n.d.). It may include the future expectation of weather in the order of weeks, months or years ahead.

MCVP defines weather as atmospheric conditions for up to 3 days and climate as the conditions for any time period longer than 7 days. Of particular interest to the program for this project is seasonal climate over the time frame of between 2-8 weeks and 3-6 months.

From discussions with various industry leaders, it appears as though most people outside the weather/climate science field, interpret the term climate as being of very long time frames, greater than a year. The term weather is used to describe conditions for periods of up to a year. This differing definition may be the source of some confusion when the climate forecasting products are marketed to different industries.

Climate variability and climate change

The MCVP goals are specifically targeted at issues associated with climate variability rather than climate change. Climate variability refers to short term variations in climate. This may cover periods of seasons, years, or several years. El Niño/La Niña events are also part of climate variability. Climate change refers to the longer term trend of changes in climatic averages, but also incorporates climatic extremes. Despite the focus on climate variability, climate change is important in the context of the MCVP for two main reasons.

- Climate change is expected to lead to an increase in climatic extremes. Therefore the role of the MCVP is likely to increase as the climate becomes more variable.
- Because climate change leads to changes in long term climate averages, statistical forecasting, that has been relied on in the past (based on historical climate observations and averages), is expected to be less reliable in the future. Dynamical forecasts however, are based on physical climate systems and interactions. Dynamical forecasts are expected to have better skill compared to statistical models under climate change, and these forecasts are the focus of the MCVP climate research investments.

3 Understanding the value and use of forecasts

Sensitivity of the economy to climate

Many sectors of the economy are exposed to the impacts of weather or climate conditions, either directly or indirectly. The agriculture sector is clearly an example of a sector whose production is directly impacted by climate. Other sectors face changes to the cost of production or demand for their products because of climatic conditions.

Lazo et al. (2011) estimated climate sensitivity of different economic sectors by examining the extent of inter-annual variation in economic activity in the United States attributable to climate variability. The estimated proportion of gross state product (GSP) for each sector that is sensitive to variation in climate ranged from 14.4 per cent for the mining sector to 2.2 per cent for the wholesale trade sector. The sensitivity estimated for agriculture was 12 per cent.

We applied the percentage sensitivities estimated by Lazo et al. (2011) to selected sectors of the Australian economy as an initial indication of the value of output that may be sensitive to variation in climate (table 3.1). These estimates, however, should not be interpreted as the value that forecasts may have on the various sectors.

Furthermore, these values may not be directly transferable from the US context to Australia. The climate conditions experienced in the US and Australia are quite different. For example, significant proportions of the US experience very cold, icy and snowy conditions through winter months not experienced in Australia. Other areas of the US are prone to hurricanes whereas much of Australia has drier conditions than large areas of the US. Given these differences, the application of the Lazo et al. estimates of climate sensitivity to Australia should be interpreted with caution.

A rule of thumb for the value of information has been estimated to be in the order of 1 per cent of the associated value of output. This applies to information such as forecasts and research. As a starting point, this 1 per cent rule applied to the initial estimate of the value of output sensitive to variation in climate provides a first (and very rough) cut of the value climate forecasts may create.

3.1 Climate sensitivity of economic sectors

Sector	Average GVA 2002-03 to 2011-12	Contribution to GDP (average 2002-03 to 2011-12)	Equivalent U.S. sectoral 70-year climate sensitivity	Sensitivity to climate
	A$m	%	%	A$m
Agriculture	21 429	1.88	12.1	2593
Health care (and social assistance)	61 879	5.43	3.3	2042
Construction	79 851	7.00	4.7	3753
Electricity	16 556	1.45	7.0	1159
Coal mining	20 852	1.83	14.4	3003
Offshore oil and gas (90% of oil and gas extraction)	20 363	1.79	14.4	2932
Retail trade	50 696	4.44	2.3	1166
Transport (road and air)	22 824	2.00	3.5	799
Water (water supply and waste services)	10 550	0.92	7.0	739
Emergency services (public administration and safety)	55 920	4.90	3.3	1845
Financial and insurance services	104 079	9.13	8.1	8430
Tourism [a]	23 761	1.91	3.3	784

[a] Tourism figures are from the Tourism Satellite Account and are based on a 10 year average of 2001-02 to 2010-11

Note: The sensitivity of US sectors to climate has been used here as an initial indicator of the degree of climate sensitivity, however, the climate sensitivity of US and Australian sectors are likely to differ due to the climate conditions faced and the nature of the sectors. These figures should be interpreted considering these caveats.

GVA = gross value added, the sectoral equivalent of gross domestic product (GDP); All values are given in Australian dollars at 2012 prices.

Source: ABS 2012; ABS 2011; Lazo *et al*. 2011

Interaction between sectors

It is important to note that the Lazo et al. results do not account for the economic interactions between sectors. For example, some of the sensitivity of a sector to climate may be a consequence of its interactions with other sectors that are themselves sensitive to climate. Thus, we would expect the climate sensitivity of a particular sector to be a sum of its own direct climate sensitivity and indirect sensitivity through its interactions with other sectors.

To test these interaction effects, we undertook some simulations with the CIE's in-house economywide model[2]. We found that the climate sensitivity in each of these sectors, when combined, would be expected to reduce retail trade output by 8 per cent and insurance output by 7 per cent. Looking at the sensitivities for these sectors in table 3.1

2 For further details see the companion report 'Analysis of the benefits of improved seasonal climate forecasting: for sectors outside agriculture'

shows that these indirect effects could easily explain most of the climate variation for these sectors.

Climate sensitivity and the value of forecasts

While the value of climate sensitivity estimated in the table above places a maximum bound on the value of climate forecasts, it cannot be used as an indicator of the value of climate forecasts to the various sectors. The climate sensitivity measure is an indicator of the extent that the value of output of a sector is affected by climate. The value of a climate forecast is the extent that the impact of weather events can be avoided or reduced using the additional information in the forecast. The value of a climate forecast is less than climate sensitivity due to the following factors.

- Not all impacts of weather on sectoral output can be eliminated with a climate forecast, no matter how skilful. For most industries, there will be some impacts that cannot be eliminated through any degree of investment or preparation to mitigate weather impacts.
- Any mitigation actions that are adopted must be cost effective. There are likely to be some actions that could be taken to protect an industry from the impacts of weather events, however they will only be adopted if they are cost effective. The cost of taking the action should be outweighed by the expected losses avoided by taking such action. This will depend in part on the probability that a particular weather event will occur and the accuracy of the forecasts that are used.
- Mitigation actions are not costless and therefore the value of a climate forecast is diminished by the cost of acting on it.
- Climate forecasts are not perfectly accurate and there are costs associated with incorrect forecasts, both in terms of damage due to missed events and the cost of taking unnecessary mitigation action for false alarms.

Climate forecasts and industry use

Climate forecasts provide indications of the weather conditions that are expected to prevail in the future. Forecasts may provide indications of the expected level or range of temperatures, precipitation, wind, humidity and sunshine. This information may be useful to industries that are exposed to direct or indirect impacts of weather events.

The risk associated with a weather event is a combination of the probability of occurrence of that event and the consequences of the event. Forecasts may enable businesses to take action that would reduce the negative consequences of the event thus reducing the overall risk of a weather event. Forecasts, however are imperfect and inherent uncertainties in forecasts result in false alarms (forecasts that indicate an event will occur but doesn’t eventuate) and missed events (where the forecast does not predict an event that occurs). This uncertainty decreases the potential reduction in risks that forecasts could bring.

Risk of a weather event can be managed or reduced through a range of measures. These may be long term structural or infrastructure-based measures, or they may be shorter term, operational responses.

The ability of an industry or business to respond to forecasts depends on the economic characteristics of the industry and the nature of the climate sensitivity of the activities they undertake. These characteristics include whether activities are seasonal, infrastructure intensive, exposed to weather and extreme events (either directly or indirectly), and the nature of risk management structures in the industry.

The value of improved seasonal forecasting is not a simple calculation. The use of seasonal climate forecasts is highly particular and highly contextual. Optimising the use of seasonal climate forecasts cannot be done independently of establishing a range of pre-conditions. It requires changes in business practices and conceptions of how to undertake risk management (even cognitive understandings of probabilistic forecasts).

Climate sensitive activities in Australia currently have a range of means of dealing with risks associated with seasonal variability. In many cases these have evolved without expecting prospective seasonal (probabilistic) forecasts. Not all climate sensitive activities are able to respond within the time frame of seasonal forecasts — this ability depends crucially on the capital and infrastructure intensity of these activities. On the one hand, capital intensive activities are unable to respond in short time frames. On the other, they often arrange their activities in ways that do not necessarily require good seasonal forecasts. Indeed, much of the trend of modern infrastructure management is concerned with ‘weather proofing’ — finding means of organising daily activities that are optimised across a very long view of climate outcomes rather than finding means of quickly responding to the latest seasonal forecast. (Even this point, of course, is highly contextual and depends on the activity concerned.)

4 The value of seasonal climate forecasts: literature review

A more detailed review of the literature on the value of seasonal climate forecasts is provided in the companion report – 'Analysis of the benefits of improved seasonal climate forecasting: for sectors outside agriculture'. The key points from that review are summarised here.

- Of the relatively limited analysis of the value of seasonal forecasts, most focus on the agriculture sector.
- For forecasts to be of value, they should lead to changes in management decisions that result in different outcomes to those based on business-as-usual decisions. For forecasts to lead to changes in management decisions they need to be relevant and accessible to decision makers.
- There is a difference between the potential value that forecast information may have and the actual effective use of that information. Some of the reasons for this gap include: a lack of spatial, temporal and element specificity, and the way in which information is communicated such as timing, content, phrasing or language.
- The value of forecasts is different from the economic impact of climate conditions as the value of forecasts is only realised through deliberate decision making by the user rather than a natural outcome.
- The application and decision support models that determine outcomes for decision makers from a given set of state of weather and action pairing are complex, data intensive and often site-specific. There are many exogenous factors that are outside the scope of this type of model but still may have significant impacts on results such as plant disease outbreaks, second round impacts on prices and financial market fluctuations. The usual approach to assessing the value of the forecasts assumes a set of actions are taken at the beginning of the season. In reality however, decisions may be continually updated based on evolving conditions and exogenous factors. These adjustments are not incorporated into the decision making framework. Finally, there are difficulties in up-scaling from individual user level to sector level.

Approaches to valuing forecasts

Freebairn and Zillman (2002) categorise the various approaches to valuing forecasts into four broad categories:

- **Market prices** – where meteorological services have a private good aspect and have been sold in the market.

- **Normative or prescriptive decision making models** – the most common approach used; models based on simplified optimising decision models are solved under circumstances of imperfect information about weather or climate conditions.
- **Descriptive behavioural response studies** – aim to estimate the value of meteorological services by observing behaviour of actors (individuals, businesses, and government), by using surveys, experiments and regression methods.
- **Contingent valuation methods** – seek to reveal the willingness to pay of individuals or businesses for a particular level of public good by using surveys that set up hypothetical market situations.

Cost-loss model

Most of the studies that estimate the value of climate or weather forecasts used the normative or prescriptive model approach and focused on the agriculture sector (Freebairn and Zillman 2002). The cost-loss model used in many of these prescriptive studies is an application of Bayesian decision theory. It sets out the expected net return of an activity with and without taking action and whether a weather-related event occurs or not. The framework is illustrated in the decision tree (chart 4.2) below. A weather or climate forecast will provide a user with the probability of an adverse weather event occurring on each occasion. Based on this probability the user will decide whether to take action based on their expected returns. That is they will take action if the expected value of taking action is greater than the expected value of not taking action. Using information on the net return from the four possible outcomes (*A,B,C* and *D* in equation 1 and chart 4.2), this decision can be shown to depend on the probability of the event occurring relative to the net returns as shown below:

$$EV_{action} \geq EV_{no\ action}$$

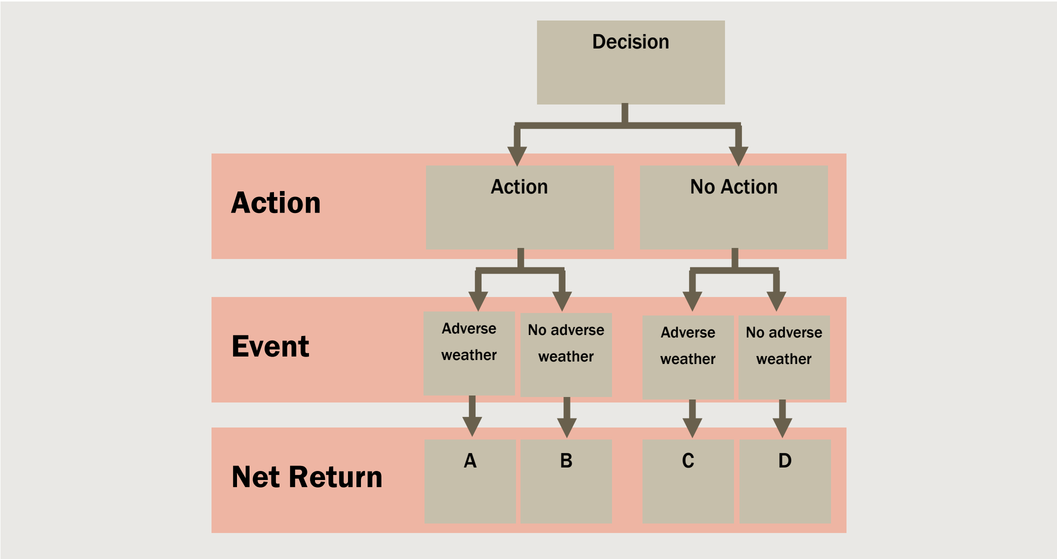
$$pA + (1-p)B \geq pC + (1-p)D$$

$$p \geq \frac{(D-B)}{(D-B)+(A-C)} \qquad (1)$$

Where:

- EV is the expected value or return from taking action or not
- p is the probability of an event occurring
- *A, B, C, D* are the net returns of 4 different possible event/action combinations as shown in chart 4.2.

4.1 Cost-loss framework



Over repeated actions, there will be a total expected return achieved by the user. Comparing this total return with the return that would have been achieved with an alternative forecast yields a measure of the value of forecasts.

The cost-loss framework provides a helpful starting point to considering the value of forecasts, however, it requires detailed information on:

- which weather events will impact on the activity
- what effect those weather events have on the activity
- the cost of weather impacts on the activity
- the actions that can be taken to mitigate the impacts
- the cost of undertaking these actions
- the residual cost of the weather impacts after the mitigating actions.

The cost-loss framework is also a simplification of the decision scenarios most users would face as it examines a binary choice of 'take action' or 'don't take action' and looks at the occurrence of only one weather event. In reality, users of weather and climate forecasts may be interested in a range of different variables and time scales.

The benefit of the Bayesian approach, compared to an approach that estimates the impacts that can be mitigated by the use of forecasts, is that the Bayesian approach incorporates the costs associated with an incorrect forecast. For some industries this cost may be significant.

The cost-loss framework, nonetheless, has limitations. Marzban (2012) argued that the cost-loss framework is not always appropriate as both the value and quality of forecasts are multifaceted, attributes which are not captured in the cost-loss framework. Additionally, as noted previously, returns from forecasts will depend heavily on how forecasts are used.

Despite the drawbacks of the cost-loss framework, the approach to estimating the value of seasonal climate forecasts that has been adopted for this project, outlined in the next chapter, is based on the basic cost-loss model. This is because of the limited availability of alternatives, the ease of understanding and the ability to apply the methodology to multiple sectors.

5 Estimating the value of seasonal climate forecasts in Australia: a methodology

The decision to use forecasts

Climate forecasts are beneficial because they may allow decision makers to gain an understanding of the likelihood that an otherwise random event might occur. By having greater information about the probability of an event occurring the decision maker is better placed to take action to reduce the costs associated with that event.

However, climate forecasts are not perfect and incorrect forecasts may be costly for decision makers that rely on forecasts.

- If a particular weather event is forecast but does not occur (a false alarm) then the forecast user will unnecessarily bear the costs associated with taking mitigating actions.
- Alternatively, if the event is not forecast but does occur (miss) then the full extent of the losses are incurred.

Deciding whether or not to use a forecast will require an assessment of the overall benefits and expected costs. That is the benefits associated with the times when the forecast is accurate compared to the costs incurred when it is incorrect. That will depend on the accuracy of the available forecasts and the relative costs of taking mitigating action and the cost that the weather event may incur. A forecast is more likely to be used if:

- if the forecast has demonstrated skill in the past
- the cost of taking action is low
- the losses from the weather event are expected to be high.

The approach used to value forecasts should incorporate all of these aspects of the decision making process. That is, the framework should include:

- a model of how users incorporate forecasts into decision making (how is the net benefit determined)
- a model of how economic outcomes are determined by the decisions taken and the realised state of nature.

Valuing improved seasonal forecasting is not a simple calculation and is highly particular to an industry or business and also highly contextual. Ideally, specific models of the decision making process and the economic outcomes would be developed for the particular industry, business and location of interest to account for the particular circumstances facing that industry. However, construction of these individual models is beyond the scope of this project. Therefore, a more general framework has been adopted which incorporates the uncertainty aspects of using imperfect forecasts. The approach relies on other sources of information about the losses associated with weather events and the cost of mitigating these losses.

Methodology

The methodology used here, and in the companion report, to estimate the value of improved seasonal forecasts to different sectors is based on Verkade and Werner (2011) and incorporates the trade-offs described above. Verkade and Werner used the concept of relative economic value to determine the benefits of an imperfect forecast (or in this case the improved seasonal forecast) relative to the benefits associated with no forecasts (currently available forecasts) and perfect forecasts. The approach incorporates the reduction in losses due to a weather event, the costs of taking mitigating action and the costs associated with forecast uncertainty.

The methodology can be summarised by equations (2) and (3).

$$B_{seasonal\ forecast} = V\left(EAD_{perfect} - EAD_{current}\right) \quad (2)$$

$$V = \frac{p-(h+f)r-m}{p(1-r)} \quad (3)$$

Where:

- B is the benefit or value of the improved seasonal forecasts
- EAD is the estimated expected annual damage from the weather event under the currently available forecasts and perfect forecasts
- V is the relative economic value
- h is the probability that the forecast correctly forecasts the event (hit, or true positive)
- f is the probability that the event is forecast but does not eventuate (false alarm, or false positive)
- m is the probability that the event occurs but is not forecast (miss, or false negative)
- p is the probability that the weather event occurs (p=h+m)
- r is the cost-loss ratio, that is the ratio of the cost of mitigation action to the losses that could be avoided by that action under a perfect forecast.

Within this framework, the values of the various probabilities (p, h, f and m) are all related as they come from the same possible event chain. Also, they are each constrained by the assumed value of accuracy of the forecasts (a).

The relationships between the values can be summarised in table 5.1 — essentially a matrix setting out the relationships between possible outcomes (event occurs or does not occur) and possible forecasts (correct versus incorrect). The values of h, f, m and q (probability of a true negative occurring) must all sum to 1. By definition, h and m sum to p, and q and f must sum to (1-p).

To implement the model we assume that the overall accuracy the forecast applies equally to circumstances where the event occurs or does not, so the sum of h and q is a.

5.1 The relationships between *h*, *m*, *f*, and *p*

	Correct forecast	Incorrect forecast	Row sum
Event occurs	*h* (hit)	*m* (miss)	*p* (probability of event)
Event does not occur	*q* (true negative)	*f* (false alarm)	*(1-p)* (probability of no event)
Column sum	*a* (accuracy or probability of correct forecast)	*(1-a)* (probability of incorrect forecast)	1

Source: CIE

Benefits of using this method are that:

- it relies on information about the value of two easy-to-consider scenarios (no forecast and perfect forecasts)
- it considers the extent that losses can be mitigated (rather than total climate related losses)
- it incorporates the costs associated with mitigation activities
- it includes the cost of uncertainty and incorrect forecasts.

Some considerations however:

- This approach assumes one decision maker for one type of event; to look at a sector as a whole the results need to be aggregated. The impacts and available methods of mitigating impacts are likely to vary across different areas of the country and for different companies within the sector. These differences should be considered before the results are aggregated to the sector wide level.
- For some sectors the value of forecasts may be achieved through a greater ability to take advantage of favourable weather conditions. In this case, the avoided losses may be substituted for the value of potential gains from optimal reaction to the weather conditions.
- For those sectors that are not directly affected by the weather but rather affected by consumer responses to the weather (for example demand for electricity, health, water and tourism services) there is an added layer of uncertainty associated with understanding consumer responses.
- This method does not consider second or third round effects which may be observed through market adjustments.

Placing bounds on the parameters

The approach described above is useful as it requires consideration of two clear and relatively easy to assess scenarios – the current situation and a perfect, ideal situation.

Understanding the methodology and the logic behind it can be aided by considering the bounds within which the parameters are within.

- The parameters p and r must be between 0 and 1.

  - The probability of a weather event occurring (*p*) is, by definition, between 0 and 1.
  - Logic dictates that the cost-loss ratio (*r*) should be between 0 and 1. A value of *r* greater than one would indicate the costs associated with mitigating the losses were greater than the expected losses and therefore would not be worth undertaking.
- The value of *p* must be greater than that of *r* (*p*>*r*).
  - The logic around this condition is explained by the optimal forecast rule below.
- The value of seasonal forecasts will be positive if *V* is between 0 and 1.
  - For a perfect forecast, *V* has a value of 1 (*m=f=0, h=p*)
  - For the currently available forecast, *V* has a value of 0.
  - A value of *V* less than 0 suggests that the forecast was less useful than the current forecast and therefore would not be used.

Optimal forecast rule

For any given situation, where a weather event is forecast to occur, a decision maker is faced with the choice to either take mitigation actions, at a cost of C, to avoid some of the expected damage or losses associated with the weather event. Of the total expected losses from a weather event, some (L_u) will be unavoidable but some of the losses (L_a) could be avoided by taking the mitigation action.

A forecast will only be acted upon if the total expected costs from acting are less than the expected costs from not acting. That is:

$$C + pL_u < p(L_a + L_u)$$

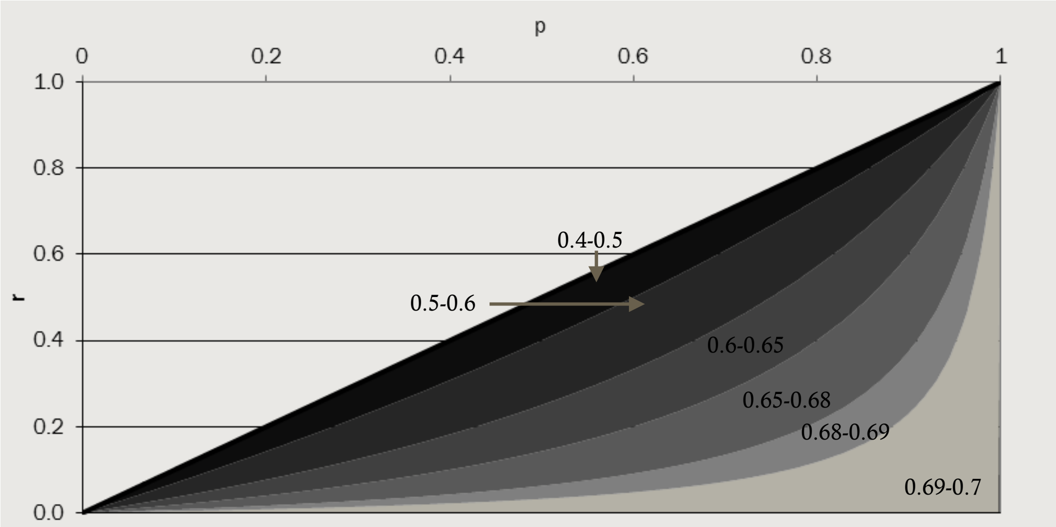
$$p > \frac{C}{L_a} = r \quad (4)$$

This inequality shows that for the forecast to be useful, the cost loss ratio must be less than the probability of the given weather event occurring.

The shaded area in chart 5.2 shows the range of combinations of *r* and *p* that yield positive values of V, and satisfy the optimal forecast rule. The different shading shows combinations of *p* and *r* that provide similar relative economic values (*V*). For an accuracy of 70 per cent[3], the combinations of *r* and *p* in the darkest area towards the centre of the chart return a value of *V* between 0.4 and 0.5. For the lightest area to the bottom right of the chart, the value of *V* is between 0.69 and 0.7.

3 Accuracy of 70% can be interpreted as proportion of true forecasts in total forecasts (that is the sum of true positives and true negatives to total forecasts). It was assumed that this proportion was also the proportion of true positives in the total number of positives and the proportion of true negatives in total number of negatives.

5.2 Combinations of p and r that satisfy the optimal forecast rule



Data source: The CIE

High probability events

There are two clear scenarios in which a forecast is not of value but which not captured in the proposed model illustrated above. These are the specific situations where the cost loss ratio is 0 or where the probability of an event occurring is 1. In each of these situations, basic reasoning shows that mitigation actions should be taken regardless of the forecast. This is because either the mitigation action is costless (*r=0*) or the event is certain to take place (*p=1*).

The idea can be extended to cases where *r* is very low and *p* is high. In these circumstances, taking mitigation regardless of the forecast could be justified to avoid the costs associated with a missed forecast. In the case of high probability events, this logic is demonstrated by the actions of industry. As explained in chapter 3, for events that can be reasonably expected to occur, industries endeavour to 'climate proof' their activities so that they do not necessarily need to adjust their activities in the short term.

6 *Agriculture, climate and forecasts*

Exposure of agriculture to impacts of weather and climate

Output from the agriculture sector is inextricably linked to weather conditions. Climate is the strongest driver of inter-annual variability in agricultural output. A range of climate variables affect agricultural production, including temperature extremes, frosts, sunlight hours and extreme events, however the most significant aspect of climate for agricultural production is rainfall (White 2000). The total volume of rainfall, distribution of rainfall over growing seasons, and timing of rainfall events all impact the growth of crops and livestock feed. White (2000) stated that 'the underlying source of climate variability affecting the Australian economy is the occasional substantial fluctuations in agricultural production due to rainfall variability, notably major droughts'. Wheat production in Australia has varied as much as 60 per cent from year to year due to low rainfall conditions (Howden and Henry n.d.). The 2002 drought reduced Australian agricultural output by 30 per cent, while the 1994-95 drought decreased production by 9.6 per cent (White 2000).

Climate forecasts in agriculture

To date, the agriculture sector has been the foremost user of seasonal climate forecasts. Much of the development of the forecasts has been with the agriculture sector in mind. Agricultural industry bodies have made significant contributions to funding the research in the area and the bodies have also expended significant effort in translating probabilistic forecasts into useable tools and information to provide easily accessible information to individual farmers. Many of the research articles that look at the value of seasonal climate forecasts also focus on the agriculture sector.

Due to the complex links between agriculture and the physical conditions determined by the weather, many management decisions are affected by weather conditions and may be refined with the use of weather and climate forecasts. Farmers can make use of climate forecasts to avoid potential losses, minimise expenditure, maximise yields and returns and also manage environmental impacts of farming operations. These objectives can be achieved through:

- careful management of planting times
- determining the area and crop variety to plant
- controlling stocking rates
- pre-empting health issues in livestock
- managing water and fertiliser applications
- optimising harvesting times.

The particular decisions made by farmers vary with the agricultural industry and the region of operation. For climate forecasts to be useful for improving these decisions, they need to: be available with adequate lead time for farmers to respond; forecast the relevant climate variables; and be of sufficient accuracy for farmers to rely on. Table 6.1 provides some examples of the decisions, and required lead times, for different agricultural industries in Australia.

6.1 Forecast uses for different agricultural enterprises

Agricultural enterprise	Key decision	Forecast lead time	Forecast period
Northern Australia rangelands (beef, summer-dominant rain)	Stocking rate decisions in May (1st round muster) and September (2nd round muster) in relation to pasture growth in the following wet season November – March.	May: 6 months; Sept: 2 months	5 months
Southern Australia rangelands (sheep/wool, winter dominant rain)	Stocking rate decisions in April/May in relation to pasture growth in the following winter June-August and the following summer December-March.	For winter: 1 month; For summer: 8 months	3 months 4 months
Winter-dominant rainfall (wheat, pulses, canola)	Decisions on varieties to plant, fertiliser inputs and planting density in April for the length of the crop season. Decisions on inputs in the middle of the crop growing period (June/July).	1 month 0 months	4-6 months 3 months
Summer-dominant rainfall (wheat, sorghum, cotton)	Decisions to plant in imminent season (April for winter crop and October for summer crop) or deferral of planting to subsequent season, plus choice of crop and variety and adjustment of inputs in relation to rainfall and temperatures.	April: 1 month October: 1 month	4-6 months 4-6 months
Sugar production in irrigation areas in NE Australia	Decisions about whether to use irrigation water supplies in September-December in relation to rainfall occurrence in following summer January-March. Decisions about when to start harvests (June-November) based on the beginning of the rainy season (September-November) are made in around March.	October: 3 months March: 4-5 months	3 months 3 Months
Sugar mill planning in rainfed tropical sugar systems	Mill planning decisions in November-December about harvest period conditions (mainly wetness) in the following June-December, especially late in the harvest in November-December.	November: 7 months	6 months
Agribusiness in cereal-growing regions	Grain storage, transport and fertiliser supply decisions in November in relation to next year's winter grain production.	November: 6 months	4-6 months

Note: Here forecast lead time refers to the period between the date at which the forecast is made and the start of the period being forecast, and forecast period is the actual period over which the forecast runs.

Source: Ash et al. 2007; Everingham et al. 2012

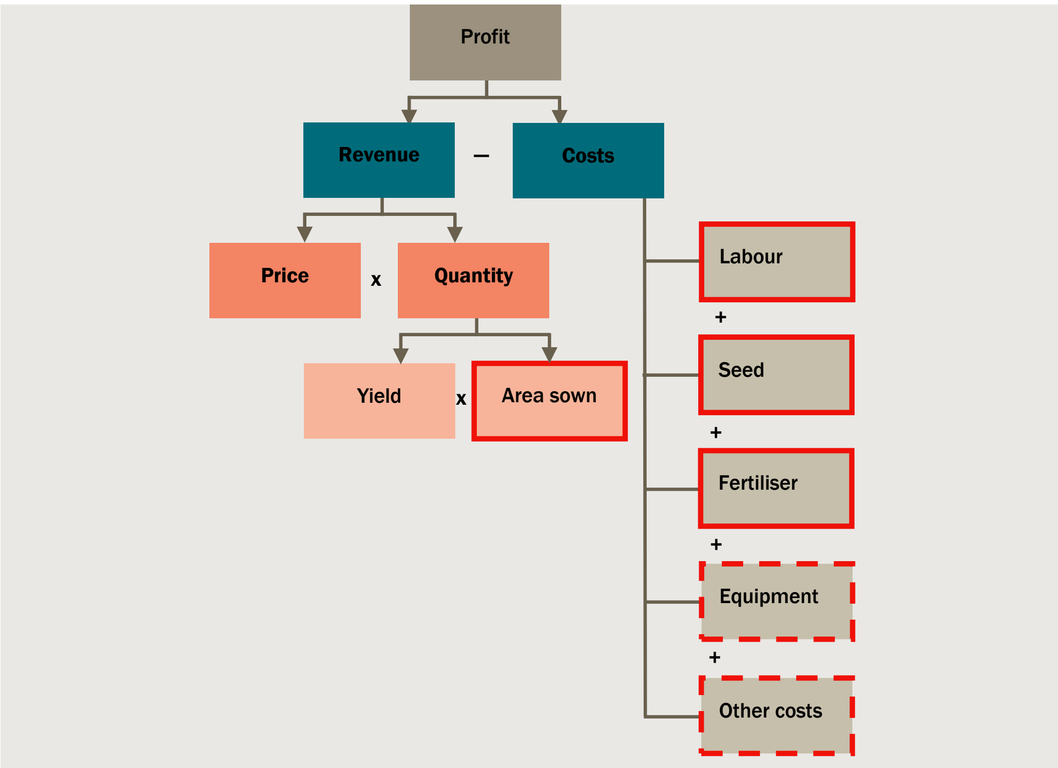
Table 6.1 lists applications of seasonal forecasts for both livestock and cropping industries. The forecasts, however, are likely to have the greatest impact on cropping activities as they operate on an annual cycle and can alter activities to a greater extent based on the expected seasonal conditions. Longer time periods are needed in livestock enterprises to build up stocking rates.

The development of climate forecasts to date in Australia has mostly focused on use by agricultural producers. While generally a diverse, dispersed sector characterised by many small operators, the sector is also well-coordinated. Industry organisations have channelled considerable effort into ensuring forecasts are relevant to farmers and made accessible through the development of tools to aid in decision making. Additionally, farmers are experienced in risk management and making decisions under uncertainty suggesting agricultural enterprises have the potential to make productive use of seasonal climate forecasts.

Farmers' decision making variables

Seasonal climate forecasts derive their value from the changes in decisions driven by information in the forecasts. The ultimate objective of a farmer is to maximise total farm profits. However, profits are determined by the combination of revenue and costs, both of which can be further broken down into a number of variables as outlined below in figure 6.2 (in this example for a cropping enterprise). A farmer has the ability to make decisions about only some of these elements (highlighted with red) – mostly on the cost side.

6.2 Components of farm profit



Data source: The CIE

There is limited opportunity to affect revenues as prices are determined in the market and yields are strongly affected by external factors – particularly weather. This leaves the area sown as the main controllable factor on the revenue side of the profit equation. The costs, however, can be controlled, for the most part, through decisions at the farm and can be adjusted based on information obtained through seasonal weather forecasts. The decisions on the volume of inputs (ie the costs) will have flow on effects to yields and revenues. Variable costs – such as hired labour, seed and fertiliser – are easily adjusted in response to forecasts. Longer term investments – such as equipment and land – are less likely to be changed in response to a particular seasonal forecast.

The value of forecasts for agriculture

The value of improved seasonal forecasts for the agriculture sector depends on a wide range of complex and interrelated factors. The various factors that have been discussed in the literature to varying extents and are reflected in the remainder of this chapter. They include:

- forecast accuracy – including accuracy at relevant spatial resolution and with appropriate lead times
- forecast adoption rates
- risk attitudes
- seasonal conditions experienced.

Accuracy

The accuracy of a forecast depends on, and varies according to, spatial resolution, location, time of the year, weather variable being forecast and lead time of the forecast. The skill of climate prediction models is limited by the chaotic nature of the climate system (National Committee for Earth System Science 2006). Despite this limit, there are still improvements that can be made in the skill of forecasting models. Increasing the accuracy of the forecasts will increase the value of the forecasts provided.

The accuracy of a forecast affects the value of the forecast in two ways. Firstly, it affects the rate of adoption of forecasts. Seasonal forecasts that are believed to be more accurate – at the relevant spatial and time scales – are likely to be more readily adopted by farmers. The more farmers that make use of forecasts, the greater the value to the sector. Secondly, highly accurate forecasts are more valuable as the costs associated with incorrect forecasts are minimised.

Adoption rates

As mentioned above, the rate of uptake of seasonal forecasts is correlated to the perceived value the forecasts can provide farmers. This value varies between different agricultural industries, different regions, different seasons as well as across different individual perceptions of utility.

Surveys conducted in 2000-02 looked at the use of seasonal forecast information by farmers. 77 per cent of farmers were found to be aware of seasonal forecasts but only 45 per cent made use of the forecasts. In Victoria 43 per cent made use of the forecasts. In 2009-11 surveys, the rate of use in Victoria had increased to 69 per cent (White et al. 2013).

Despite the value and benefit that farmers could realise from using seasonal climate forecasts, surveys show that, to date, adoption of forecasts has been limited in some areas and industries. Low uptake may be explained by forecasts that are of low accuracy, lack timeliness or are difficult to understand. The degree of uptake may also be explained by the personal characteristics of the farmer or the nature of the farm business such as the climate variability at the farm location or the degree of risk aversion of the decision maker. For example, the extent to which graziers in north east Queensland use seasonal forecasts was found to depend on their strategic skills, environmental awareness, and social capital (Marshall et al. 2011).

Risk aversion

Risk attitudes affect the value of forecasts by determining the actions farmers take in the face of uncertainty – both under current and improved seasonal climate forecasts.

Some evidence suggests that the value of forecasts increases with increased risk aversion, but decreases at very high levels of risk aversion (Meza et al. 2008). A forecast is still not perfect, and the uncertainty in the forecast may be unacceptable for highly risk averse users.

The value of forecasts between different degrees of risk aversion is also influenced by the weather conditions that are forecast. Forecasts of poor conditions are most useful to near risk neutral farmers and forecasts of favourable conditions of more value to more risk averse farmers (Meza et al. 2008). Highly risk averse farmers are likely to maintain management regimes that protect against poor seasonal conditions. A positive forecast allows these farmers to take advantage of the favourable seasons.

Climate conditions

The value of forecasts varies from year to year depending on the climate conditions that are experienced. For example, Meza et al. (2008) found that forecasts of ENSO phase in Chile were of significant value in warm ENSO phases but zero in the neutral or cold phases.

When determining the value of improved forecasts for the sector, the values need to be determined over a long time period. This will ensure the full range of climate conditions are covered, and also the impact of incorrect forecasts are not overemphasised. As improved forecasts are imperfect, it is inevitable that value will not be realised in every year, and some years acting on incorrect forecasts will lead to negative results. It is the long term impact of forecasts that are of interest.

Forecasts are likely to be of greatest value, and therefore see greater uptake, in areas with high inter-annual rainfall variability. Australia has one of the most variable climates

(Hennessy et al. 2008) and so the potential value of seasonal climate forecasts is greatest in Australia. This is also supported by the literature on the value of forecasts for individual farming enterprises. In a review of studies, Ash et al. (2007) summarised the results from a number of these farm level studies and found that for cropping systems benefits at the farm scale were greatest in Australia. The benefits ranged from:

- 1 to 3 per cent of gross margin or gross benefit in the US
- 2 to 15 per cent in South America
- 3 to 50 per cent in Australia.

Market effects

The relationship between agricultural output and weather are fairly straightforward – low rainfall, or rainfall at poor times, can significantly reduce agricultural output levels. The link to economic returns can be less clear-cut. In times of widespread poor weather, and therefore low output, a shortage of product drives the price of affected agricultural products up, thereby cushioning to some extent the impact of low output on farmers. Ultimately, of concern to farmers are the returns on production. Accordingly, farmers have stated that they would be interested in climate forecasts for the regions other than their own immediate vicinity to enable them to anticipate the market conditions. The use of seasonal climate forecasts for financial management rather than management of physical systems has had little discussion in the literature.

The value of forecasts diminishes as more farmers make use of the forecasts (Meza et al. 2008). Forecasts may allow an individual farmer to increase output in these poor years, but as the supply increases, the prices decline. Therefore, the total market-wide value of forecasts is unlikely to be the sum of individual gains where market interactions are ignored.

Value estimates in the literature

Meza et al. (2008) surveyed the literature about the economic value of seasonal climate forecasts for agriculture – categorising the studies by agricultural system, approaches used and scales of analysis. They found that the picture of the value of seasonal forecasts for agriculture is incomplete, with significant gaps. Existing studies were limited to:

- a narrow range of farming systems and locations
- a restricted set of potential management responses.

Meza et al. reviewed 33 papers and 58 different assessments. Of these, the most common studies were ones that looked at enterprise level effects of forecasts on management of an individual crop. A limited number of studies looked at land allocation at the farm level. Only a few addressed irrigated horticultural crops and only 2 examined the role of forecasts for livestock management.

Our own review of the literature found similar results. The most common studies were those that estimated the potential value of perfect rainfall forecasts for specific agricultural systems. These studies generally make use of detailed agricultural systems models where simulated farm management decisions are modified in response to forecasts, and output is compared to decisions made without forecasts. The benefit of these approaches are that they incorporate many of the complex and interacting factors that influence decisions and outcomes on farm. However, as noted by Meza et al. (2008), the literature did not cover the full range of agricultural operations, and did not incorporate some of the more complex factors such as market interactions and risk aversion. The results of our literature review are summarised in table 6.3.

The study that was found to be the most useful for the current project was by Asseng et al. (2012b). They used a crop simulation model to calculate crop and grain yield responses to fertiliser applications and weather among other variables. The benefits to wheat farms in the Western Australian wheat belt of using the POAMA forecast were calculated based on the difference between gross margins achieved using a fixed nitrogen application rule for all years and the gross margins achieved when nitrogen application is altered based on the POAMA forecast. They found that the benefit of the forecast was on average A$66/ha a year. These results were achieved in areas where the POAMA had forecast skill of around 80 per cent.

6.3 Various estimates of the value of perfect rainfall or ENSO forecasts for agriculture

Study	Benefit	Industry/region	Other information
1	2 per cent of gross margins	Regional scale - Argentina	Perfect knowledge of ENSO
1	10 per cent of income	Grazing in South Africa	Perfect knowledge of ENSO
1	15-27 per cent of profit	Grazing in NE Australia	Imperfect SST and SOI forecast used to adjust stocking rates
1	3-9 per cent of net benefit	Potatoes in Chile	Perfect forecast of SST in Nino region
1	5-10 per cent of net benefit	Spring wheat in Chile	Perfect forecast of SST in Nino region
1	15 per cent of net benefit	Sugarbeet in Chile	Perfect forecast of SST in Nino region
1	14-19 per cent of gross margins	Cotton-sorghum system in Dalby, Australia	SST and SOI forecast
1	3 per cent of gross margins	Winter wheat in Moree, Australia	SST and SOI forecast, fertiliser application rates
1	44-71 per cent of gross margin	Summer cotton (dryland) in Moree, Australia	Imperfect SST and SOI forecast
1	1-2 per cent of total value	US agricultural production (national scale)	Looks at low, moderate and high skill forecasts rather than perfect
1	3-10 per cent of gross margins	Overall, combined estimate for Australia	If adoption rate were 40-50% then value A$70-300m/year
2	A$50/ha of additional gross margin	Wheat in WA	Value of POAMA forecast for nitrogen application, under particular conditions
3	A$66/ha of additional gross	Wheat sheep operations in WA	Average value of POAMA forecast

Study	Benefit	Industry/region	Other information
	margin		for nitrogen application on wheat, under particular conditions
4	0.41 per cent of revenue	Sugarcane in N. Qld	Total value for the Herbert region estimated at A$0.5m (range A$0.1-1.9m)
5	A$26-79/ha of additional gross margin	Wheat in the Murray Darling Basin	Baseline gross margins: A$-20 – 700/ha; higher values realised for areas of higher yield variability.
6	Net returns increased 2.4-132 per cent depending on the model used, price assumptions and grain type	Sorghum and corn in Texas	Looked at nitrogen application rates, crop mix and area planted using single hectare, farm level and aggregate supply models. Models used a range of forecast skill – from historical climate to perfect forecast. The aggregate model used ENSO phase forecasts.
7	US$190/ha or 24 per cent of gross margin	Cropping (maize, wheat, soybean and peanuts) in Argentina	Value of perfect forecasts realised through adjusting a range of farm management practices (crop variety, planting date, planting density, nitrogen fertiliser application).
7	US$3-5/ha, or 0.4-0.6 per cent of gross margin	Cropping in Georgia (maize, wheat, soybean and peanuts), US	As above
8	84 per cent increase in gross margins (or A$208/ha)	Wheat in Birchip, NW Vic	Changes to planting date and nitrogen application in response to a perfect forecast

Sources: 1. Ash et al. 2007; 2. Asseng et al. 2012a; 3. Asseng et al. 2012b; 4. Everingham et al. 2012; 5. Wang et al. 2009; 6. Mjelde and Hill 1999; 7. Jones et al. 2000; 8. McIntosh et al. 2007.

Livestock

Traditionally, cattle farmers have been reactive to climate – responding after climate conditions are experienced. "Ideally, grazers should be able to match stocking rates to seasonal conditions so that animal production is maximized and damage to pasture and land production is minimized" (Jochec et al. 2001).

Jochec et al. (2001) looked at the value of seasonal forecasts for livestock operations in Texas. This is one of very few studies that look in detail at the value of seasonal climate forecasts to livestock enterprises. A biophysical-economic model was used to determine the economic value of forage forecasts when they are used to adjust stocking rates – with and without uncertainty. The results show that under a forecast of above average forage, graziers would increase stocking rates where there is no uncertainty and the past year had above average forage conditions. A below average forecast results in a decrease in stocking rates no matter what the current conditions. The changes in stocking rates based on forecasts were smaller where there was some uncertainty around the forage forecast. The value of the forecast information depended on the price received for destocking cattle relative to the restocking price. Higher destocking prices led to lower expected values of the forecast. The results from this study showed that, even without uncertainty, the forecast information had a positive expected value only when the destocking price was 13-43 per cent lower than the restocking price. The maximum expected value estimated by Jochec et al. was around 37 per cent of the assumed cost per cow cost of restocking. Limitations of the study include the fact that it was a 1-year model, and further gains may be realised if impacts on calving percentages are considered. The model did not incorporate the costs associated with purchasing supplemental feed, the need to purchase feed where there are shortfalls is also expected to impact the value of forecasts to graziers.

7 The value of seasonal climate forecasts for agriculture

Determining an estimate of the value of seasonal climate forecasts for the agriculture sector is not an easy task. As outlined in table 6.1, there is a wide range of potential uses for forecasts in agriculture. The value of the forecast realised through each of the uses differs by location and agricultural industry. Therefore, to obtain a robust estimate of the value of seasonal forecasts, information on the value of each of these uses, locations and industries would be needed. The existing literature does not cover this range of applications.

As outlined in the previous chapter, most of the studies of the value of forecasts for agriculture focus on just a limited set of these industries (mostly cropping – maize and wheat), decisions (fertiliser application and land allocations) and locations (North and South America, Australia) and the predominant forecast type was rainfall level or ENSO phase.

The methodology adopted to estimate the value of forecasts to the sector, outlined in chapter 5, relies on information about the costs and benefits of actions taken in response to weather forecasts. Without detailed information on all aspects of agricultural responses to forecast information, a robust and full estimate of the value of forecasts is difficult.

In an attempt to overcome this shortfall in information, we used two different approaches to provide some idea of the potential value of improved seasonal forecasts for the agriculture sector.

- First, we draw on the economic analysis of the MCVP Phases II and III, which estimates the value of MCVP investments to date.
- Next, we use the methodology proposed in chapter 5, to estimate the value of seasonal forecasts that can be realised through adjustments to fertiliser application rates in WA wheat enterprises. The results of this analysis are relied upon to build up estimates for the value of forecasts for the rest of the Australian agriculture sector.

These approaches are supported by more qualitative information provided in chapter 6.

Value of the Managing Climate Variability Program

The Managing Climate Variability Program has been a significant investor in the development of seasonal climate forecasts, and tools for the use of the forecasts by farmers. In 2013 an economic analysis of the MCVP Phases II and III was undertaken to determine the benefits arising from the MCVP investment (White et al. 2013). The analysis identified the program outputs as:

- improved forecast accuracy, lead-time and ease of use

- increased adoption of seasonal forecasts by farmers
- development of tools and services for managing climate risk.

These benefits were found to primarily accrue to the Australian primary industries, with some spill over public benefits such as improved natural resource management. The analysis did not break down the benefits of the different components of the MCVP program, nor did it provide an overall value of the seasonal climate forecast products that the MCVP had invested in. Rather, the assessment looked at the marginal increase in value that the MCVP investment achieved over and above the value of seasonal forecasting products that would have existed without MCVP investment.

It was assumed that MCVP investment resulted in the forecasting product (the POAMA model) being made available one year earlier than would have been the case without additional investment, and the rate of uptake of the products being faster with MCVP investment. The analysis noted that the actual and potential benefits of the MCVP investment would be driven by the adoption of the products by agricultural industries, but also found that there was little information available on current and likely uptake of the outputs. They concluded that current use of seasonal forecasts may be around 75 per cent.

The use of seasonal forecasts was assumed to lead to a general increase in farm profits and so earlier and faster adoption would lead to benefits in the initial years, but over time the annual value of the forecasting products with and without MCVP investment would converge. The annual marginal value peaked at around A$25 million, in around 2020. The total gross present value of benefits of the investment was estimated at A$95 million over 30 years.

Specifically, the assessment assumed that:

- benefits would be realised 2 years after POAMA become operational
- the investment by MCVP will bring forward the launch of POAMA by one year (from 2014 to 2013)
- there would be a 25 per cent increase in number of farms using seasonal forecasts due to the development of POAMA, the only estimate of current use of seasonal forecasts provided was a rough figure of around 75 per cent of farms.
- it will take 5 years to reach maximum adoption levels with MCVP investment and 7.5 without
- use of POAMA forecasts would lead to an increase of 2 per cent of net value of production for all farms using the forecasts.

The impact analysis, while not valuing seasonal forecasting, provides some context and the assumptions used can be used as inputs into the current task of assessing the overall value of seasonal climate forecasts for agriculture.

A rough back-of-the-envelope calculation using these assumptions shows that the value of improved seasonal forecasts could be in the order of A$110m per year. This calculation assumes that the 2 per cent improvement in the net value of production is an average figure that incorporates the cost associated with incorrect forecasts and all the various different ways the forecasts information can be used. This figure is based on the total net value of farm production averaged over the past 10 years, A$7334m (ABARES 2012), and assumes that the 75 per cent of the farms that use seasonal forecasts are evenly distributed across the size spectrum of farms.

Value of seasonal forecasts

The only study found in the available literature that looked at the value of POAMA forecasts (the BoM's seasonal climate forecasting model) to Australian literature was Asseng et al. (2012b). They found that farmers could gain better returns in wetter seasons when they had access to the POAMA forecast compared to without the forecast. The value of the forecast in wet years for the central and southern wheat belt of WA was up to A$66 per hectare when used to adjust fertiliser application on wheat fields in high rainfall years. No benefit was observed for poor rainfall years.

Much of the literature on the value of seasonal climate forecasts focuses on decision making around fertiliser application in cropping operations. Advance knowledge of a rainfall event (or the amount of rainfall expected) allows farmers to invest in fertiliser application that results in improved yields where there is sufficient soil moisture. The benefits accrue at times of high rainfall as farmers are able to take advantage of the additional water availability through the use of fertiliser.

Due to the availability of information on this application of forecasts, and limited information on alternatives, the results of Asseng et al. (2012b) are used as a base to determine the approximate value of seasonal forecasts for Australian agriculture.

The general methodology outlined in chapter 5 is refined slightly here to apply to the case of fertiliser application. The cost of the fertiliser (and application), denoted by C, is assumed to be incurred when forecast rainfall over the growing period is greater than a threshold level. If fertiliser is applied and the forecast level of rainfall occurs, then additional yields to the value of Y are realised. However, if either the rainfall does not fall to the degree forecast, and/or no fertiliser is applied, then the additional gains are not realised. This specification of the problem is outlined in the matrix below. The primary difference between this problem and the one set out for other sectors is that here, there are no costs associated with a missed (or false negative) forecast. Despite this, the final formula remains the same as used for the other sectors. However, r, is now technically a cost-benefit ratio and is defined as $\frac{C}{Y}$. All the other definitions, conditions and bounds that apply in the general case outlined in chapter 5 apply here.

7.1 Specification of costs and benefits under different action/state of the world combinations

	High rainfall season	Not a high rainfall season
Fertiliser	C-Y	C
No fertiliser	0	0

Source: The CIE

Cost benefit ratio of applying nitrogen fertiliser

BCG (n.d.) provide a discussion of the relationship between optimal potential yields determined by water availability and nitrogen fertiliser demand to achieve the potential yields. Based on that discussion, it was clear that the cost benefit ratio of applying additional fertiliser in response to an increase in expected water availability (or rainfall) is simply the ratio of expenditure on nitrogen fertiliser (per hectare) to the price received for grain (per hectare[4]). So assuming a wheat price of A$280, yields of 1.59 t/ha (ABARES 2012), and average expenditure on nitrogen fertiliser of A$69 per hectare (based on ABARES 2013), the cost benefit ratio used for the analysis is 0.16.

Probability

The probability of a year with high rainfall relative to historical experience, can be anything less than 50 per cent, and will depend on the degree to which rainfall is above historical levels. A range of probabilities were used to estimate a range for the value of forecasts: 40 per cent, 30 per cent, 20 per cent and 16 per cent (probabilities lower than 16 per cent result in a violation of the optimal forecast rule). Higher probabilities are associated with smaller increases above historical rainfall levels.

The following example explains how these probabilities should be interpreted. If from historical experience farmers generally expect seasonal rainfall of 100mm, then they will tend to plan their farming operations and fertiliser applications based on this rainfall experience. Also from historical information we may know, for example, that rainfall of 120mm occurs 40 per cent of the time, 130mm 30 per cent of the time and so on. Therefore, when we say the probability of a high rainfall event is 30 per cent, in this example, we are referring to a rainfall event of 130mm. The actual levels of rainfall for the various probabilities, however, will depend on the region.

The cost-benefit ratio of applying additional fertiliser is independent of the extent of additional rainfall, so long as the application of fertiliser matches the expected level of rainfall.

Value of seasonal climate forecasts

Based on the value of A$66/ha estimated by Asseng et al., the value, on average, that POAMA forecasts could bring to the central and south wheat belt of WA is in the order of A$144m per year if it were adopted by all wheat farms in the region.

We can use the estimate achieved for the WA wheat belt to infer results for the rest of the country. We build up the results by region, starting with the value of seasonal forecasts to wheat farms in WA, then wheat farms in Australia and then extend this to all cropping operations in Australia. For each step to larger coverage, the Asseng et al. results become slightly less relevant. The results therefore have an increasing degree of ambiguity and should therefore be interpreted with care. This approach was used to provide an illustration of the potential scale that seasonal forecasts could have for Australian

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4 Calculated as the product of the grain price per tonne and the yield in tonnes per hectare.

agriculture and was restricted due to the paucity of available information on the value of forecasts for different industries and regions.

Based on the framework outlined in in chapter 5 and above, the information required to estimate the value of seasonal climate forecasts is outlined here.

- The probability of a high rainfall event. The underlying probability that an event will occur is needed to value the benefit of a forecast of that event. We chose a number of probabilities to provide a range of results. These are described in more detail earlier in this chapter.
- The accuracy of the forecasts. The accuracy of POAMA in the WA southern wheat belt used to generate the study results was 80 per cent. The accuracy of the POAMA forecasts is not 80 per cent across the country, or even for the WA northern wheat belt. Overall the accuracy of POAMA is expected to be around 70 per cent.
- The area of land planted. The data for each of the areas of interest (area planted to wheat in WA, area planted to wheat in Australia and area cropped in Australia) were taken from ABARE farm surveys and averaged over the past 10 years.
- The cost-benefit ratio. This was assumed to be 0.16, as explained above.
- The relative economic value (the relationship between the value of perfect and imperfect forecasts). These were calculated based on the accuracy and cost benefit ratio for each of the probabilities included in the analysis. The calculations gave a relative economic value of between 0.7 and 0.4.
- The value of a perfect forecast[5]. In this case we had information about the value of an imperfect forecast in the central and southern wheat belt of WA (A$66/ha/year). Using this and the other information outlined here, we were able to calculate that the value of a perfect forecast, per hectare, would be in the range of A$88 to A$110 per hectare depending on the probability of high rainfall.

Due to the uncertainty around these estimates, for each of the probabilities a range of values for the perfect forecast were adopted (20 per cent higher and lower than the central case). This is used as form of sensitivity analysis to demonstrate the effect of the assumption on the results.

Table 7.2 shows the results for all wheat farms in WA. The value to wheat producers across WA is almost double that of the value to producers in the central and southern wheat belt. The analysis is extended further to all wheat production in Australia in table 7.3 and all cropping in Australia in table 7.4.

5 A perfect forecast is taken to mean a forecast with 100 per cent accuracy.

7.2 Estimated value of improved seasonal forecasts to Western Australian wheat

Probability of a high rainfall season compared to historical experience	Low case – assuming the value of a perfect forecast is 20% lower than the central case	Central case	High case – assuming the value of a perfect forecast is 20% higher than the central case
%	A$m	A$m	A$m
40	198	247	297
30	191	239	286
20	175	219	263
16	159	199	239

Note: All values are given in Australian dollars at 2012 prices

Source: The CIE

7.3 Estimated value of improved seasonal forecasts to Australian wheat

Probability of a high rainfall season compared to historical experience	Low case – assuming the value of a perfect forecast is 20% lower than the central case	Central case	High case – assuming the value of a perfect forecast is 20% higher than the central case
%	A$m	A$m	A$m
40	520	650	780
30	502	628	753
20	461	576	691
16	418	523	628

Note: All values are given in Australian dollars at 2012 prices

Source: The CIE

7.4 Estimated value of improved seasonal forecasts to Australian cropping

Probability of a high rainfall season compared to historical experience	Low case – assuming the value of a perfect forecast is 20% lower than the central case	Central case	High case – assuming the value of a perfect forecast is 20% higher than the central case
%	A$m	A$m	A$m
40	994	1243	1491
30	960	1200	1440
20	881	1101	1321
16	800	1000	1200

Note: All values are given in Australian dollars at 2012 prices

Source: The CIE

There is very limited information about the use of seasonal forecasts by livestock enterprises. The information in the literature suggests that stocking rates can be optimised for the expected level of forage in the coming season. The only Australian study on the value of seasonal forecasts for livestock was mentioned by Ash et al. (2007), where the forecasts were estimated to increase income by 15-27 per cent.

To provide a rough estimate of the value on an aggregate scale using the same approach as used for the cropping enterprises, we assumed that livestock had the same relative economic value of forecasts as for wheat, and that a perfect forecast may increase farm cash income by 15, 20 and 27 per cent for the low, mid and high cases respectively. The estimated values of improved seasonal forecasts for the livestock sector are shown in table 7.5, and the results for total agriculture (livestock and cropping combined) are in table 7.6.

7.5 Estimated value of improved seasonal forecasts to Australian livestock

Probability of a high rainfall season compared to historical experience, leading to increased forage	Low case (assumes a perfect forecast would increase farm cash income by 15%)	Central case (assumes a perfect forecast would increase farm cash income by 20%)	High case (assumes a perfect forecast would increase farm cash income by 27%)
%	A$m	A$m	A$m
40	244	325	438
30	225	300	406
20	189	252	340
16	158	210	284

Note: All values are given in Australian dollars at 2012 prices

Source: The CIE

7.6 Estimated value of improved seasonal forecasts to Australian agriculture

Probability of a high rainfall season compared to historical experience	Low case	Central case	High case
%	A$m	A$m	A$m
40	1238	1567	1930
30	1185	1500	1845
20	1070	1353	1661
16	958	1210	1484

Note: All values are given in Australian dollars at 2012 prices

Source: The CIE

7.7 Worked example: the value of improved seasonal forecasts for fertiliser application

In this box, we work through the calculation of the value of improved seasonal forecasts for an assumed probability of 40 per cent, and the central case where perfect forecasts are assumed to increase farm income by A$88/ha in WA (this corresponds to the top left cell in table 7.2).

We use equation 3 outlined in chapter 5:

$$V = \frac{p - (h + f)r - m}{p(1 - r)}$$

The value of accuracy (*a*) of the forecast is assumed to be 0.7; and the probability (*p*) is 0.4. Based on the relationships between *a*, *p*, *h*, *f* and *m* set out in table 5.1, we know that: *h=0.28*, *f=0.18* and *m=0.12*. The value of *r* is given in the text as being 0.16. Inputting these assumptions into the equation gives a value for *V* of 0.62.

And equation 2 given in chapter 5 is then used to calculate the value of improved seasonal forecasts:

$$B_{seasonal\ forecast} = V\left(EAD_{perfect} - EAD_{current}\right)$$

The term in the brackets is effectively a dollar measure of the difference between income under currently available forecasts and under perfect forecasts. This value has been found to be A$88/ha. Therefore, the value of the improved, but imperfect, seasonal forecast would be A$55/ha. The number of hectares sown to wheat in WA (average over 10 years) is 4.52m. Therefore, the value of the seasonal forecast to WA wheat production is A$247m.

8 Rural Communities

The value that improved seasonal climate forecasts bring to the agriculture sector is likely to have flow on benefits to rural communities around the country. An increase in farmer incomes, and a decrease in variability of incomes, is beneficial to the communities in which the farmers live and spend their incomes. If all the additional income that farmers can realise by using seasonal climate forecasts are spent in rural communities, there may be a multiplier effect whereby the additional income (or gross regional product) or the region is greater than the aggregate increase in income to farmers.

In reality, a number of effects may distort the link between farmer income and rural communities. The distribution of the benefits may be complex and depends on the nature of the farming business and the actions taken by farmers in response to the forecasts. In addition to farmer-owned operations, other key sources of employment and income in rural communities is hired-labour on farms, and supply of inputs to farms.

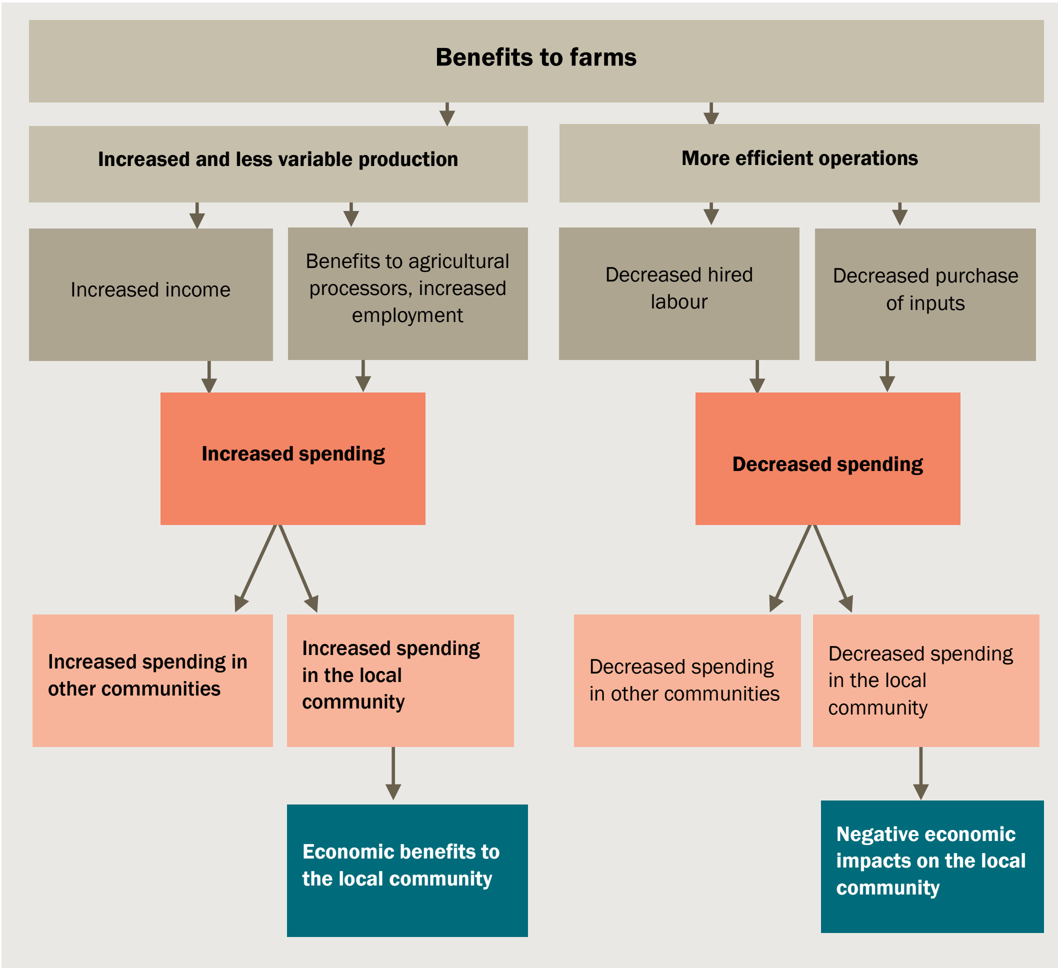
Depending on the farm business circumstances and the forecast conditions, seasonal forecasts may allow farmers to reduce their expenditure on hired labour through more efficient farm operations. This is captured as a benefit at the farm level as the farmer is able to decrease costs and increase profits. There is evidence that past improvements in technologies and efficiency in farm operation has led to a reduced demand for full-time farm labour (Garnett and Lewis 2002). The effect of this to the wider community is less clear, and may be negative.

The use of other inputs may have similar effects. Where inputs are purchased locally, an increase in the use of inputs as a result of the forecast would be expected to have positive flow on benefits for the community. A decrease in the need of inputs may have a negative effect. If farmers source their inputs directly from manufacturers, without the use of local agents or suppliers, the link between farmer input use and rural community incomes is broken.

A further complication in the link between farmer incomes and rural community economic activity, is whether the owner of the farm operations is located, and spends their income, in the local rural community. There is an increasing number of corporate farms where the benefits of forecasts realised on these farms accrue to the corporate headquarters – not necessarily in rural communities. Corporate farms are more likely to be able to take advantage of the information generated by seasonal climate forecasts. These farms have professional managers that may be able to make better use of probabilistic forecasts. They also have multiple farm operations and so are able to optimise their activities over regionally dispersed farms – taking advantage of the climatic conditions in each area. Edwards et al. (2007) discuss the contrasting roles of family farms and corporate farms on rural communities. They found that there is widespread support for the hypothesis that a family farms generally support more vibrant rural communities compared to corporate farms.

Lastly, the use of seasonal climate forecasts by agricultural producers may have flow on effects to downstream processing activities. Many of these activities are located in regional locations – although often different locations to the agricultural producers. Where seasonal climate forecasts allow farmers to maintain more consistent production levels, and overall higher output, these benefits flow through to the processing activities. Processing facilities may be able to hire more staff – leading to flow through effects to the community.

8.1 Possible flow on consequences of benefits to farms from improved seasonal climate forecasts



Data source: The CIE

Quantifying the benefits for rural communities

The spillover benefits from the adoption of improved seasonal forecasts have been estimated using a regional computable general equilibrium model – CIE-REGIONS. The model captures the linkages that exist in the economy between different sectors and regions.

An increase in the efficiency of fertiliser use in the wheat sector was simulated using the model. The results show us that for each dollar of additional value added realised in the wheat sector due to the improved fertiliser use, value added in the rest of the region increases, by between and 16 and 45 cents (for major wheat producing regions).

The results of this analysis are shown in table 8.1. These results build on the assumptions and results of the previous section. The first column shows the value of improved seasonal climate forecasts for the wheat industry in each of the regions. This uses the same 'per-hectare of wheat sown' results determined in the previous section for the central case, and assuming the probability of a high rainfall season (compared to historical experience) of 40 per cent.

The second column applies the spillover factor for each region to determine the value of benefits that the rest of the regional economy would gain as a result of the value that the wheat producers get from the improved seasonal climate forecasts.

8.2 Regional and spillover benefits from improvements to the wheat sector

	Regional wheat sector	Rest of regional economy	Total regional economy
	A$m	A$m	A$m
Central NSW	55	25	80
Riverina NSW	61	26	87
Mallee VIC	40	11	51
Wimmera VIC	18	4	22
Central north VIC	10	3	13
Darling Downs QLD	31	12	43
Eyre SA	50	15	65
Murray and York SA	49	17	66
Central and South WA	119	31	150
North and East WA	122	20	142

Source: CIE estimates

9 Conclusion

Estimating the value of improved seasonal forecasts to the agriculture sector is by no means an easy task. The sector is so diverse and so interconnected with climate conditions it makes analysis of the potential for use of seasonal climate forecasts complicated. The current literature on use of forecasts does not comprehensively cover the various agricultural industries, or the many sets of decisions that operators in these industries could make based on seasonal climate forecasts.

The potential for value to be realised by the agriculture sector is significant:

- Overall, the agriculture sector accounts for around 2 per cent of GDP. The gross value added of the sector averaged A$21.4b over the past 10 years (ABS 2012) and the net value of farm production in 2011-12 was A$11.5b (ABARES 2012).
- Agriculture is highly sensitive to climate conditions. In their study of the US economy, Lazo et al. (2011) found that the sensitivity of the agriculture sector 12 per cent, given the greater extent of climate variability this is likely to be higher in Australia. Estimates of the impact of recent droughts suggest agricultural output was reduced by up to 30 per cent, and 60 per cent in the case of wheat.
- There are a range of actions that farmers can take to respond to, and take advantage of, forecast climate conditions. With reasonably accurate forecasts of rainfall patterns, timing of frosts and temperatures, farmers can optimise their planting, harvesting, water and fertiliser decisions and stocking rates.

Due to the lack of detailed information available in the published literature, two different approaches were used to generate estimates of the value of improved seasonal climate forecasts.

- Based on the assumptions used to value the MCVP, the total value of forecasts to the agriculture industry is estimated to be around A$110m per year.
- Using a more detailed methodology that incorporates the uncertain nature of improved seasonal climate forecasts and the cost of responding to forecasts, the value of improved seasonal climate forecasts that could be realised through optimising fertiliser application in wheat enterprises in WA is estimated at between A$418m and A$780m per year.
- Assuming the same parameters hold for all cropping across Australia (an assumption that is necessary due to the lack of further information), improved seasonal forecasts may have a value of between A$800m and A$1491m.
- There is also very limited information available about the value of forecasts to livestock operations. The value of forecasts for livestock operations is estimated to be in the range of A$158-438m.

- Combining the cropping and livestock estimates, provides an estimate of the value of improved seasonal forecasts for the Australian agriculture sector in the order of A$958m to A$1930m
- With increasing climate variability expected under climate change, the value of seasonal forecasts to the agriculture sector is expected to increase in the future.

The full range of estimates (A$110-1930m) is equivalent to 0.51-9.01 per cent of the gross value added for the agriculture sector. The value of seasonal forecasts varies by industry, season and location. The greatest value can be realised in locations that experience the greatest climate variability, and by farms that are able to adjust their activities in response to the forecasts. Australia has a highly variable climate and therefore is likely to realise significant benefits from seasonal climate forecasts. With increasing climate variability expected under climate change, the value of seasonal forecasts to the agriculture sector is expected to increase in the future.

While it is clear the benefits of improved seasonal climate forecasts is significant for the agriculture sector, further work is needed to be able to fully quantify these benefits in a comprehensive manner. Future work should endeavour to fill the gaps in the current literature – particularly the value of seasonal forecasts to livestock operations and a wider range of management practices. Currently it is unclear whether the management decisions that have been studied are those that are most relevant, or those that are easiest to model using the available tools (Meza et al. 2008).

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