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Valuing seasonal climate forecasts in a state-contingent manner

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We applied state-contingent theory to climate uncertainty at a farm level to assess the value of seasonal climate forecasts in the Central West region of NSW. We find that modelling uncertainty in a state-contingent manner results in a lower estimate of forecast value than the typical expected value approach. We attribute this finding to a more conservative long-term farm plan in the discrete stochastic programming (DSP) model, which is better balanced for climate uncertainty. Hence, a climate forecast, even though it still revises probabilities held by farmers, does not call forth such large changes in farm plans and associated farm incomes. We then use the DSP model to assess how attributes of a hypothetical forecasting system, particularly its skill and timeliness, as well as attributes of the decision environment, influence its value. Lastly, we assess the value of current operational forecast systems and show that the value derived from seasonal climate forecasts is relatively limited in the case study region largely because of low skill embodied in forecasts at the time when major farm decisions are being made.

Key words: value of information, climate forecasting, R&D evaluation, risk, uncertainty, simulation.

1. Introduction

Improved seasonal climate forecasts are seen as a key technology to help farmers make better decisions in a risky climate. As an information-based technology, the valuation of climate forecasts faces similar challenges to valuing information more generally. These challenges extend beyond methodologies for pricing information to the difficulties in demonstrating that use of seasonal climate forecasts can lead to more-profitable farming strategies. Adoption has been patchy. No doubt concerns about the skill embodied in seasonal climate forecasts have not helped.

Here, our intent is to shed further light on the value of seasonal climate forecasts to mixed farming in the Central West of NSW. We employed the model developed by Crean *et al.* (2013), which uses discrete stochastic programming (DSP) to analyse production uncertainty in a manner consistent with state-contingent theory (Chambers and Quiggin 2000). They

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compared this approach with a traditional stochastic production function approach and found that farm plans generated by the DSP model were more profitable than those from an expected value model and more closely resembled actual land use.

Three key issues are addressed here. First, we assess whether the way in which uncertainty is modelled has an impact on the estimated value of seasonal climate forecasting. Our expectation was that modelling uncertainty in a state-contingent manner would result in a lower estimate of the value than the expected value approach because DSP farm plans are better balanced for uncertainty. Hence, a climate forecast ,even though it still revises probabilities held by farmers, may not call forth such large changes in farm plans and in farm incomes.

Second, we use the DSP model to assess how attributes of a hypothetical forecasting system, particularly its skill and timeliness, as well as attributes of the decision environment, influence its value. Information about the value of skill and timeliness can be used to direct investment in research to improve these qualities.

Third, we assess the value to mixed farming in the Central West of NSW of statistical based seasonal forecast systems provided by the Bureau of Meteorology (BoM) and the Queensland government based around the El Nino Southern Oscillation (ENSO) phenomenon.

2. A state-contingent approach

Chambers and Quiggin (2000) proposed that state-contingent production theory was the best way to think about all problems of uncertainty. 'The crucial insight of Arrow and Debreu was that, if uncertainty is represented by a set of possible states of nature, and uncertain outputs by vectors of state-contingent commodities, production under uncertainty can be represented as a multi-output technology, formally identical to a non-stochastic technology' (Quiggin and Chambers 2006, p.153).

We applied state-contingent theory to climate uncertainty to assess the value of seasonal climate forecasts in Central West NSW, a typical mixed farming area in south-eastern Australia exposed to climate variability. The representative farm of 1,500 ha is engaged in annual winter cropping in rotation with pasture and fallow activities, first-cross lamb production, and merino wool production (Crean *et al*. 2012). Variations in the production environment were represented by nine sets of planting conditions, reflecting different combinations of winter crop planting dates (PD) (early – 20 April; mid – 10 May; and late – 5 June) and starting soil moisture levels (low – 30 mm; average – 60 mm; and high – 100 mm). Rainfall was the uncertain parameter within the model. Three discrete rainfall states were defined based on growing season rainfall (May–October) at Condobolin (s = dry, average or wet) over the period 1902–2006 (105 years). The dry state contained the lowest third of years (growing season rainfall of 0–177 mm); the average state, the middle third (178–249 mm); and the wet state, the upper third (>249 mm). Rotational effects reflecting weeds, crop diseases and soil moisture status were represented on average rather than dynamically.

Applying state-contingent theory in our context recognises that farmers are able to choose from a set of technologies that canvas a number of future seasonal outcomes, not just a single expected season. It allows a broader set of responses to climate risk than traditional expected value approaches, which are only optimal when the 'actual season' coincides with the 'expected season'.

A two-stage DSP model was developed where time was divided into the 'present' and the 'future'. Here, x_1 is a vector of stage 1 decisions, s is the state of nature, and x_2 $(s,\ x_1)$ is a vector of stage 2 decisions, contingent upon earlier stage 1 decisions and the state of nature. The DSP problem maximises state-contingent income over all states and is written as:

$$\operatorname{Max} E[Y] = -C(w, r, p) + \sum_{s=1}^{S} \pi_s r_s. \tag{1}$$

Here, π_s is the probability of state s occurring, r_s is the revenue received in state s, and w and p are input and output prices, respectively.

The objective function (risk neutral) reflects a two-stage decision process that maximises the expected net farm income from crop, pasture and livestock production decisions across three climate states subject to constraints on availability of land, labour and capital, which must be satisfied in each state.

$C(w, r, p)$ is the cost of inputs committed prior to the state of nature being known (eg variable costs of growing wheat) based on the selection of stage 1 activities (x_{1j}), while the $\sum_{s=1}^{S} \pi_s r_s$ term is the probability-weighted sum of state-contingent revenues derived from stage 2 activities (eg harvest and sale of wheat) made possible by that commitment of inputs. Once the optimal stage 1 decisions are determined, inputs committed in stage 1 are the same in every state of nature, whereas the inputs selected in stage 2 are specific to each state.

In stage 1 of the DSP approach, the farmer makes decisions about the areas of crop, pastures and fallow, taking into account the probabilities of future dry, average and wet states. With only the probabilities known, stage 1 decisions must trade off returns across all states in order to be optimal under uncertainty. In stage 2, recourse decisions are taken about the end use of crops (eg sell grain, store grain, graze crops, cut crops for hay) and pastures (eg graze, cut for hay), which are contingent upon both the state of nature and the decisions taken in stage 1. In other words, when making stage 1 decisions, the model looks forward and weighs up the possible consequences in stage 2 of such decisions. This approach attempts to capture the flexibility that farmers have over the choice of production technologies when faced with climate uncertainty.

3. A conceptual model of the value of information

By focussing on states of nature, we can follow Hirshleifer and Riley (1992) in illustrating how information reducing uncertainty has value to decision makers. In a two-state world (s = 1 (dry), 2 (wet)) with three possible acts (x = 1, 2, 3), the expected utilities of the acts, assumed here to be alternative crops, are shown by their respective pay-off lines marked x_1, x_2 and x_3 (Figure 1). The horizontal axis shows the probability of a dry state (π_1) increasing from left to right. The utility of x_1 (eg an irrigated crop) is unaffected by rainfall and is therefore represented by a horizontal line. In contrast, x_2 and x_3 are crops reliant on rainfall. Act x_2 could be a fodder crop that provides high returns due to higher prices in a dry state but lower returns in a wet state, while x_3 is a grain-only crop that performs well in a wet state, but fails in a dry state. The probability of the wet state (π_2) is $1-\pi_1$. Prior to a forecast, the decision about which crops to grow is made on the basis of the prior probability, π. The act with the highest utility, G, is x_1.

Suppose a seasonal climate forecast system **F** can generate two possible forecasts $f = f_1, f_2$. The farmer processes the forecast and forms a revised or posterior probability distribution over the occurrence of states. Applying Bayes' theorem, the posterior probability distribution $\pi_{s|f}$ is:

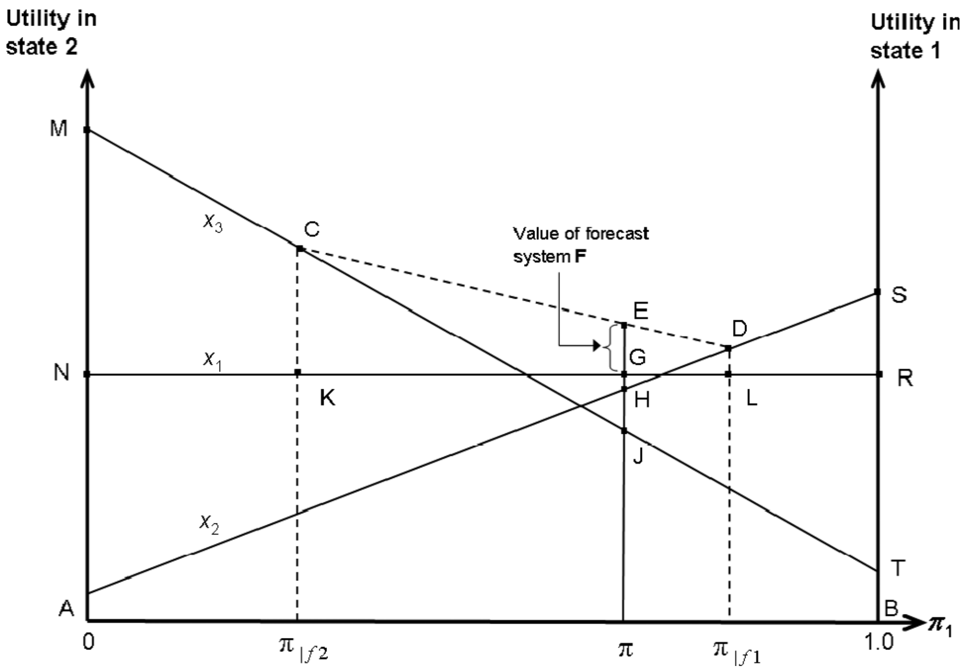

Figure 1 The economic value of climate forecasts in a two-state world. (Source: adapted from Hirshleifer and Riley 1992, p. 182).

$$\pi_{s|f} = \pi_s \frac{q_{f|s}}{\sum_s \pi_s q_{f|s}} \tag{2}$$

where $\pi_{s|f}$ is the posterior probability of state s given forecast f; π_s is the prior probability of s, as before; and $q_{f|s}$ is the conditional probability (or likelihood) of f, given s.

The posterior probabilities are essential to the valuation of forecasts. After a particular forecast f, the decision maker determines the optimal action again using the model represented by (1), but now employing the posterior probabilities $\pi_{s|f}$, rather than the prior probabilities π_s.

If forecast f_1 is received, the posterior probability of a dry season becomes $\pi_{1|f1}$ and the posterior optimal decision (or Bayes strategy) shifts from x_1 to x_2. The expected utility of this decision is D. The expected utility gain over x_1 (V_{f1}) is equal to DL, reflecting the probability-weighted average of the gain SR in state 1 and the loss NA in state 2. Conversely, if forecast f_2 is received, the posterior probability of a wet season becomes $\pi_{2|f2}$ and the optimal decision shifts from x_1 to x_3. Expected utility is indicated by C. The expected utility gain over x_1 (V_{f2}) is equal to CK, reflecting the probability-weighted average of the gain MN in state 2 and the loss RT in state 1.

The value of a specific forecast f within an overall forecast system is

$$V_f = \sum_{s=1}^{3} \pi_{s|f} y^*_{sf} - \sum_{s=1}^{3} \pi_s y^*_{so} \tag{3}$$

where y^*_{sf} denotes farm income in state s from optimal farm plan x^*_{sf} based on forecast f and y^*_{so} denotes farm income in s from optimal farm plan x^*_{so} based on the prior probabilities (assumed to be historical climatology).

So V_f is the expected income from the posterior optimal act less the income from the prior optimal act. Forecast f could have zero value in the event that the posterior probabilities led to no change in the optimal act. The valuation of forecasts in this way correctly attributes value only to improved knowledge about future states and not erroneously to a change in the underlying occurrence of states.

The value of a single forecast (V_f) is important, but as Hirshleifer and Riley (1992) noted, 'one cannot purchase a given message, but only a message service' (p. 180). The true measure of economic value is the value derived from the use of the entire forecast system. A single forecast with high skill might be particularly valuable, but add little to the overall value of a forecast system if issued infrequently.

The value of a forecast system is the value of each forecast within the system weighted by the frequency with which it occurs. If **F** denotes a forecast system and $qf(\sum_f^{q_f=1.0})$ is the frequency with which each forecast occurs, then the value of a forecast system with three possible forecasts is

$$V_{\mathrm{F}} = \sum_{f=1}^{3} q_f V_f. \tag{4}$$

The value of the whole forecast system **F** (V_{F}) is the gain in expected utility, represented by EG in Figure 1, lying above the point π on the horizontal axis.

4. Comparing state-contingent and expected value estimates of the value of seasonal climate forecasts

Crean *et al.* (2013) reported the differences between the optimal farm plans from DSP and expected value models for the Central West of NSW. The DSP plan had a lower stocking rate of 2.66 dse/ha relative to the expected value farm plan of 4.61 dse/ha. The DSP plan also had a smaller crop area (598 ha versus 674 ha), and a smaller proportion of that crop area was based on continuous cropping. In the analysis reported here, these are the long-term farm plans prior to the introduction of a climate forecast system.

To realistically capture forecast value within an annual timeframe, responses to a forecast were bound by the overall levels of crop and livestock reflected in these long-term farm plans. The extent of cropping, for example, could not be expanded beyond the total crop area of the long-term farm plan. With-forecast decisions around livestock were restricted to satisfying feed demands, with no flexibility afforded to changing numbers from one season to the next. Stocking rate decisions in the case study area are taken later in the year, well beyond the forecast issued at the time of crop planting, and are also likely to have long-term consequences, which cannot easily be captured in an annual modelling approach adopted here.

In the DSP model, the climate forecast influences probabilistic perceptions about the likelihood of each state. If the forecast provides new and timely information, the DSP model chooses activities that have higher returns in the more probable state. In the expected value model, a climate forecast influences the expected yields of crops and pastures, which induces some change in the farm plan. A dry forecast lowers yield expectations, while a wet forecast raises them. The critical feature of the expected value model, both with and without a climate forecast, is that activities are chosen in response to a single expected state rather than a separate representation of each state as in the DSP model.

Forecast values from the two approaches are provided for a range of skill levels for both dry (Figure 2a) and wet forecasts (Figure 2b). Here, skill is defined as

$$\sigma = \frac{\pi_{f|s} - \pi_s}{1 - \pi_s} \tag{5}$$

where σ represents skill, $\pi_{f|s}$ is the conditional probability of forecast f given state s and π_s is the prior probability of s based on climatology.

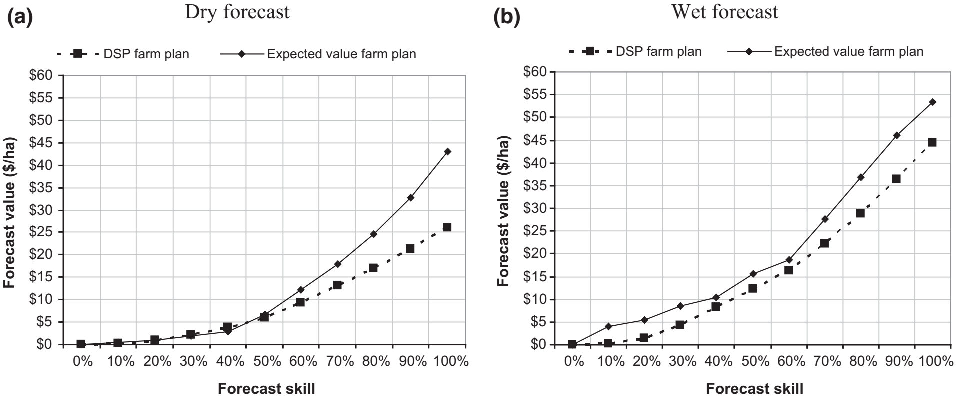

Figure 2 Influence of modelling approach on the estimation of forecast value – 10 May, 60 mm soil moisture. (a) Dry forecast. (b) Wet forecast.

The long-term, without-forecast baseline farm plan from the expected value approach is inherently more exposed to climatic variations than the DSP farm plan. There is a greater possibility for negative outcomes in a dry state and for positive outcomes in a wet state relative to the baseline farm plan from the DSP approach. The costs of uncertainty are minimised in the DSP approach because the possibility of more than one state occurring is explicitly recognised and valued in its without-forecast baseline plan. A reduction in uncertainty, made possible through a skilful climate forecast, is consequently found to be less valuable because farm responses determined by the DSP model are more moderate.

The decisions taken in response to a wet forecast within each model involved the use of higher rates of nitrogen on wheat crops and an expansion in the area of canola at higher forecast skill levels. The value of a wet forecast using the DSP approach was always lower than for the expected value approach. The long-term farm plan from the expected value model had a larger potential crop area and a greater reliance on continuous cropping (which has a greater dependence on in-season rainfall and inputs of nitrogen fertiliser) relative to the long-term farm plan from the DSP model. These differences provide more scope within the expected value model for a wet forecast to influence decisions about crop mix and the use of nitrogen fertiliser.

Decisions taken in response to a dry forecast in both models involved a small reduction in crop area, a shift in the types of crops grown and a reduction in the use of nitrogen fertiliser. In the case of a dry forecast, the value of climate forecasts between the DSP and expected value models did not diverge until skill levels exceeded 50 per cent. When there was greater certainty about the occurrence of a dry state, changes made in the expected value model were more substantial than those made within the DSP model. Again, the larger potential long-term crop area and a greater reliance on continuous cropping provide the basis for greater forecast value.

These findings were generally replicated across other planting conditions involving different combinations of soil moisture and PDs (nine in total).

Our findings can be related to the theory of information value illustrated earlier in Figure 1. A major bearing on the value of information concerns the slope of the pay-off lines associated with different acts under alternative states. Steep pay-off lines provide the necessary conditions for a forecast of those states to have significant value. Because expected value models produce a farm plan (ie acts) for a single expected state, they are unlikely to be optimal across states. In general terms, the solutions of expected value models are likely to produce pay-off lines that are steeper than those of DSP models because the latter explicitly account for a range of states and hence are better placed to deal with climate uncertainty.

Previous studies have shown that the treatment of uncertainty has important implications for the evaluation of technologies (Jones *et al.* 2006). Cost-benefit analyses of technologies can overstate the value of the technology if the 'without technology' scenario underestimates the opportunities facing decision makers. In a similar manner, the expected value approaches may not adequately represent how farmers deal with climate uncertainty and hence overstate the value of seasonal climate forecasts.

5. Determinants of the value of seasonal climate forecasts

The development and extension of climate forecasts are influenced by how attributes of forecasts and attributes of the decision maker's environment affect their value. Hilton (1981) found that only the attributes of the information system itself (such as skill and timeliness) have a consistent effect on the value of information. While attributes of the decision environment (technologies, prices, environmental conditions) can have a large influence on value, their effect is not consistent.

5.1. Value of skill

A skilful climate forecast offers an improvement in predictability over using the climatological record. The economic case for further investment in climate forecasting technologies rests on the extent of benefits flowing to users of forecasts relative to costs associated with improving forecasts. The benefits from improving skill can be illustrated by extending our earlier representation of forecast value to include a new forecast system.

In Figure 3, there are two forecast systems $\mathbf{F}$ and $\hat{\mathrm{F}}$, each producing two forecasts of the climatic state. $\mathbf{F}$ results in posterior probabilities of $\pi_{|f1}$ and $\pi_{|f2}$ (small dash lines). An alternative forecast system $\hat{\mathrm{F}}$ results in posterior probabilities of $\hat{\pi}_{|f1}$ and $\hat{\pi}_{|f2}$ (larger dash lines). $\hat{\mathrm{F}}$ is more skilful because both of its forecasts lie closer to the respective y-axes (where probabilities are one). When the posterior probabilities associated with one forecast system bracket

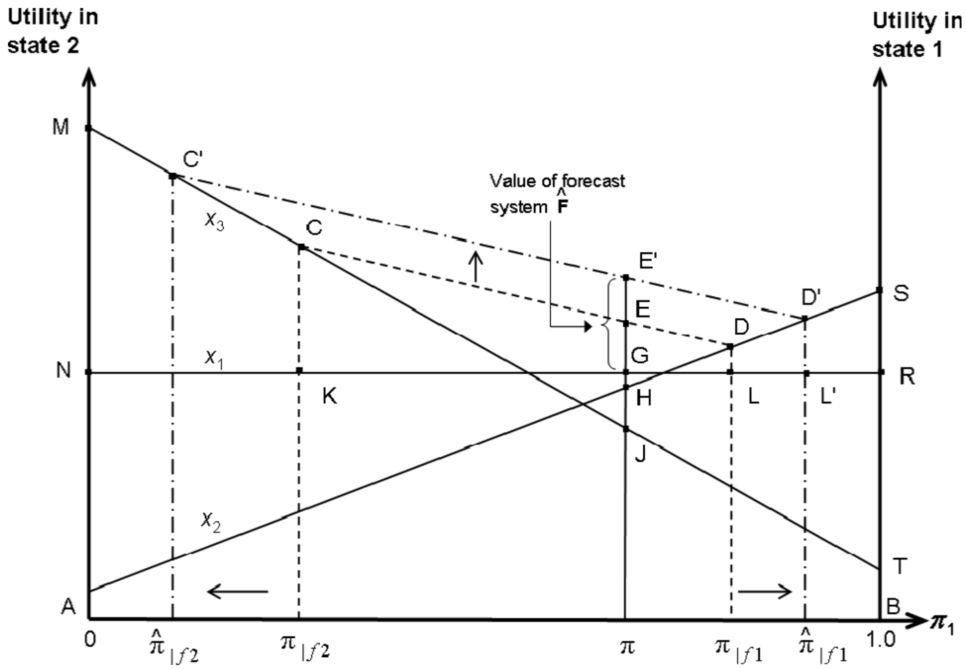

Figure 3 The economic value of a more skilful climate forecast in a two-state world (source: adapted from Hirshleifer and Riley 1992, p. 189).

those of another, such a system can be defined as being 'more conclusive' (Hirshleifer and Riley 1992).

In comparison with the utility derived from the initial forecast system, points C and D, the use of $\hat{\pi}_{|f1}$ leads to the higher utility of D' from a forecast of state 1 and a higher utility of C' from a forecast of state 2. The more skilful climate forecast of $\hat{\text{F}}$ results in expected utility of E', which exceeds the expected utility of forecast system **F** by EE'. This is the expected marginal gain of improved forecast skill.

An important consequence of the bracketing condition is that a more skilful forecast like $\hat{\text{F}}$ leads to a higher expected utility because there is lower risk associated with its use (Hirshleifer and Riley 1992). There are fewer times when $\hat{\text{F}}$ is different from the real state. Hence, there is a smaller risk of posterior error (choosing the wrong action) associated with using the more skilful climate forecast. In the event that a more skilful climate forecast also leads to a further change in a decision, relative to the less skilful climate forecast, then the gain in utility will be even greater.

Estimates of the value of a hypothetical forecast system from the DSP model are aggregated over three forecast types (dry, average and wet) and three levels of starting soil moisture (low, average and high) (Table 1). A full set of results are contained in the Appendix. The value of the forecast is expressed on a per-hectare basis using the farm's long-term crop area as the denominator.

Table 1 Economic value of a hypothetical seasonal climate forecast system ($/ha)

Skill (%)	Planting date			Overall
	20 April	10 May	5 June	
10	$0.38	$0.20	$0.00	$0.20
20	$1.62	$1.08	$0.06	$0.96
30	$4.77	$2.59	$0.51	$2.62
40	$8.80	$4.57	$1.26	$4.80
50	$13.26	$6.58	$2.10	$7.13
60	$17.96	$8.94	$3.00	$9.71
70	$22.68	$11.81	$4.03	$12.58
80	$27.43	$15.16	$5.35	$15.78
90	$32.48	$19.02	$6.87	$19.35
100	$37.83	$23.23	$8.45	$23.18

The first three columns in Table 1 summarising forecast value according to PD were derived by weighting the forecast values under each level of soil moisture by the soil moisture probabilities. The probabilities of low, average and high levels of starting soil moisture (on April 30) were assessed using APSIM (Keating *et al.* 2003) to be 0.25, 0.50 and 0.25, respectively. The last column is the economic value of a forecast system across all PDs, derived by weighting the forecast values achieved under each PD by the PD probabilities.

The annual value of the forecast system, taking into account the probabilities of all planting conditions ranged from $0.20 to $23.18/ha, depending on forecast skill. The relationship between forecast skill and value was positive as expected but not linear. Improvements in skill at lower absolute levels are valued less than improvements in skill at higher absolute levels. An increasingly skilful forecast allows the DSP model to divert more resources towards production in the forecasted state. Farm income in the forecasted state is given greater weighing in the objective function as forecast skill improves. As a consequence, income in the non-forecasted states is increasingly traded off for income in the forecasted state as skill improves. Model restrictions ensure that the overall probability of the occurrence of each climatic state is the same as its historical probability of occurrence (ie the prior probability, π_s).

5.2. The influence of planting time on value

An attribute of the decision environment which did have consistent effect on forecast value was the time of planting. The annual value of seasonal climate forecasts ranged from $0.38 to $37.83/ha for the 20 April PD, from $0.20 to $23.23/ha for the 10 May PD and from $0.00 to $8.45/ha for 5 June PD. Earlier planting opportunities provided the greatest scope for changes in land use and the use of inputs like nitrogen in response to seasonal climate forecasts.

6. The value of operational seasonal climate forecasting systems

6.1. Bureau of meteorology

This BoM 'Seasonal Climate Outlook' is based on sea surface temperatures in the Pacific and Indian Oceans (Drosdowsky and Chambers 2001).[1] Climate outlooks provide information on the state of ENSO and map the probability of exceeding median rainfall in the following 3 months. Crean (2009) estimated that the skill of BoM forecasts at the start of the winter cropping season across six locations in the Central West had an upper bound of around 20 per cent (Eqn 5).[2]

A forecast system with a skill score of 20 per cent was found to have an overall annual economic value of $0.96/ha in the case study region. This is lower than the $3.60/ha found by Marshall *et al.* (1996) for the SOI (Southern Oscillation Index) phase system in respect to wheat production in southern Queensland. However, it is similar to the annual benefits estimated by Petersen and Fraser (2001) of $1.23/ha for a hypothetical forecast in the Merredin agricultural region of Western Australia. Applying an annual $0.96/ha to total crop area in Central West region of 1.776 million ha in 2010–2011 (Australian Bureau of Statistics 2012) gave an annual forecast value of approximately $1.71 million.

The BoM's forecast system captured only 4.1 per cent of the value of a perfect forecast system (ie a forecast that perfectly predicted the occurrence of dry, average and wet states) which was $23.18/ha annually (Table 1, 100 per cent skill). The low value associated with the BoM's forecast system is directly related to skill. Low forecast skill means that the posterior probabilities of each state do not differ greatly from prior probabilities. With only a small shift in probabilities, relatively minor changes occurred in optimal farm plans, limiting the economic gains from forecast use.

Advances in climate forecasting are expected to arise from the further development of dynamic climate models (Australian Academy of Science 2006). If this were to lead to a doubling of skill levels (40 per cent), the annual value of a forecast system would increase fivefold to $4.80/ha, a net improvement in forecast value of $3.84/ha annually, or $6.82 million annually for the Central West. Developments in forecasting technologies are likely to benefit a much larger area than Central West NSW.

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[1] The Bureau of Meteorology's official seasonal outlook for Australia changed from a statistical based system to a dynamical (physics based) forecast system in May 2013. The new system is known as the Predictive Climate Ocean Atmosphere Model for Australia (POAMA). This evaluation is based on the former system.

[2] The BoM provides per cent consistent values for their official forecasts using a cross-validated forecast assessment. 'Per cent consistent' refers to the percentage of forecasts that were consistent with either an 'above median' or 'below median' rainfall category later observed. The values reported by the BoM have been calculated using 600 historical forecasts issued from 1950 to 1999.

6.2. Queensland Climate Change Centre of Excellence (QCCCE)

Queensland Climate Change Centre of Excellence forecasts are based on the SOI phase system. The identification of 'phases' in the SOI (Stone and Auliciems 1992) was an important advance in climate forecasting and led to improvements in forecast quality in a number of regions around the world affected by ENSO. The skill of the SOI phase system was assessed using rainfall and SOI data over the 1890–2006 period.

The SOI system obtains its maximum skill level for many areas of eastern Australia in late June and July and has relatively low levels of skill in April and May. Statistical tests of forecast skill confirmed that this was also the case for Central West NSW (Crean 2009). The posterior probabilities of receiving above and below median rainfall were extracted for each phase through hindcasting (Johnson and Holt 1997). The resulting posterior probabilities were then substituted into Equation (5) to determine forecast skill.

To provide an assessment of the value of the SOI phase system, only the SOI-negative and SOI-positive phases were considered, given that they were the only forecasts found to be statistically significant in the case study region. Only forecast information (phase months) available at planting time was valued. Hence, only the phase months 'March–April' and 'April–May' were considered. The SOI-negative forecast lacked skill in these phase months and was disregarded. The SOI-positive phase had a skill score of 11 and 25 per cent for the 'March–April' and 'April–May' phase months, respectively. This provided a conservative assessment of forecast value[3] and avoided ascribing an economic value to forecasts that had artificial skill.

The SOI-positive phase had a probability of occurrence of 23 per cent (29/126 years) for the 'March–April' phase month and 21 per cent (26/126 years) for the 'April–May' phase month (Table 2). Weighting the forecast values reported in Appendix by the probability of each PD and the probability of having a SOI-positive phase placed an annual value on the SOI phase system of just \$0.10/ha.[4]

This low value can be attributed to two factors. First, only two out of the five phases had statistically significant skill and only these phases were assumed to influence decisions. Second, while there was skill in SOI-negative and SOI-positive phases, it was not available at planting time. Hence, it was the timeliness of skill rather than a general lack of skill that was crucial. Moreover, the strong influence of PD on the value of climate forecasts presents a particular challenge. The largest gains from the use of climate forecasts in the case study region occurred under earlier PDs, times

[3] Many studies assess forecast value irrespective of whether the systems have any statistical skill. Only placing a value on forecasts that meet a significance test is conservative because the information contained in the other forecast categories (SOI phases in this case) is disregarded.

[4] 20 April = 0.23 × \$0.59 = \$0.14; 10 May = 0.23 × \$0.46 = \$0.11; 5 June = 0.21 × \$0.22 = \$0.05.

Table 2 Value of SOI-positive phase forecast

Phase month	Skill (%)	Planting date (PD)		
		20 April	10 May	5 June
March–April	11	\$0.59†	\$0.46†	N/A
April–May	25	‡	‡	\$0.22

†Forecast value is determined by rounding the skill score to the closest skill level in Appendix. Reported values are calculated by weighting tabled values by the probability of each soil moisture state. ‡An April–May phase month (ie forecast) becomes known at the end of May and so cannot inform decisions at these PDs.

at which operational statistical forecast systems have particularly low skill levels.

The value of improving the timeliness, taken here to mean the availability of the forecast relative to the timing of decisions, of SOI-negative and positive phase forecasts was assessed by taking the maximum skill scores obtained in July and assuming that this same level of skill was available at each PD. In effect, the skill available later in the season was brought forward to when decisions about crops and input use actually are made.

Improving the timeliness of the SOI-negative phase was valued annually at \$12.95, \$4.74 and \$3.23/ha for the 20 April, 10 May and 5 June PDs (Table 3). Taking into account the probabilities of each PD, the weighted value of improving timeliness was \$6.42/ha annually. Improving the timeliness of the SOI-positive phase forecast was valued at \$17.96, \$12.05 and \$0.79/ha for the 20 April, 10 May and 5 June PDs, respectively. Taking into account the probabilities of each PD, the weighted value of improving timeliness was \$10.71/ha.

Because the SOI-negative and SOI-positive phases are just two of the five phases possible, the economic value derived from their use was weighted by their probability of occurrence. The SOI-negative phase occurred in 22 of 126 years (17 per cent), while the SOI-positive phase occurred in 28 of 126 years (22 per cent). Accordingly, if improved timeliness of both phases could be achieved, and assuming that none of the other phases provide useful information, the annual value of the SOI system was found to increase by a total of \$3.45/ha.[5]

These findings support other empirical work on the importance of forecast timeliness and reinforce evidence from surveys of users in Australia that have highlighted timeliness as a key impediment to forecast use (URS Australia 2001). For mixed farms in Central West NSW, an improvement in the timeliness of operational seasonal climate forecasts provides more value than improving the skill of forecasts provided later in the winter cropping season.

As is the case in Australia, seasonal climate forecasting is increasingly drawing on the use dynamic climate models rather than statistical based

[5] $0.17 \times \$6.42$ (SOI-negative) + $0.22 \times \$10.71$ (SOI-positive) = \$3.45/ha

Table 3 Value of improved timeliness of SOI-negative and SOI-positive phases

	Planting date (PD)			Weighted economic value
	20 April	10 May	5 June	
SOI-negative (dry forecast)				
Skill at PD	0%†	0%†	0%	
Skill at July	44%	44%	44%	
Value of skill at PD‡	\$0.00	\$0.00	\$0.00	\$0.00
Value of July skill at PD‡	\$12.95	\$4.74	\$3.23	\$6.42
Net value of timeliness	\$12.95	\$4.74	\$3.23	**\$6.42**
SOI-positive (wet forecast)				
Skill at PD	11%	11%	25%	
Skill at July	48%	48%	48%	
Value of skill at PD	\$0.59	\$0.46	\$0.22	\$0.43
Value of July skill at PD	\$18.55	\$12.51	\$1.00	\$11.14
Net value of timeliness	\$17.96	\$12.05	\$0.79	**\$10.71**

†A negative skill score existed for March/April phase month. This was set to zero on the basis that it would be irrational for any farmer to knowingly use a forecast with negative skill. ‡Forecast value is determined by rounding the skill score to the closest skill level in Appendix. Single values calculated by weighting tabled values by the probability of each soil moisture state.
Bold text signifies the key result for each forecast.

systems. Dynamic climate models have the potential to provide longer lead-time (ie the time between when the forecast is issued and the response in relevant climatic variables) and provide a better understanding of climate systems and the limits to predictability (Australian Academy of Science 2006).

7. Conclusions

We have examined the implications for valuing an information-based technology, seasonal climate forecasting, from representing uncertainty in a state-contingent manner. We found that the state-contingent approach generally valued climate forecasts less than did expected value approaches. This result arose because the long-term farm plan from the DSP model is better balanced for uncertainty, and hence, a climate forecast does not call forth such large changes in farm plans.

We explored how the attributes of a forecast system and attributes of the decision environment affect forecast value. As expected, forecast skill is strongly related to value, but the relationship is not linear. The overall value of the forecast system, taking into account the probabilities of all planting conditions (PD and soil moisture levels), ranged from an annual value of \$0.20 to \$23.18/ha, depending on forecast skill. One aspect of the decision environment that had an important influence on forecast value was the available PD. The annual value of the forecast at different PDs ranged from \$0.38 to \$37.83/ha for the 20 April PD, from \$0.20 to \$23.23/ha for the 10 May PD and from \$0.00 to \$8.45/ha for 5 June PD. Earlier planting opportunities provided the greatest scope for land use change and to profitably change the use of inputs like nitrogen.

The BoM's statistical based forecast system has a skill score of 20 per cent in the Central West of NSW, which the DSP model valued at \$0.96/ha or approximately \$1.71 million annually for the total crop area in the Central West. The BoM's forecast system captured approximately 4.1 per cent of the value of a perfect forecast system. The low value associated with the BoM's statistical based forecast system is directly related to skill. Doubling of current skill levels (ie to 40 per cent) would increase the value of a forecast system by fivefold to \$4.80/ha. This offers a net improvement in forecast value of \$3.84/ha annually. The economic value of an improvement in skill of this magnitude in the Central West alone would be \$6.82 million annually.

Turning to the SOI phase forecasting system, only two SOI phases were found to have statistically significant skill in predicting growing season rainfall for Condobolin – the 'SOI-negative' phase, associated with below median rainfall, and the 'SOI-positive' phase, associated with above median rainfall. Only forecast information (phase months) that becomes available at the time decisions are made was valued, which meant that in the case study region, we only valued the SOI-positive phase that had a skill score of 11 and 25 per cent for the 'March–April' and 'April–May' phase months, respectively. We estimated an annual value on the SOI phase system of just \$0.10/ha for the case study region.

Poor timeliness is a major contributor to the low value of the SOI phase system. While there is some skill in SOI-negative and SOI-positive phases, most skill is apparent in forecasts released later in the season after major farm decisions have been made. If the same level of skill could be realised much earlier, the SOI phase system would be more valuable to farmers. The value of the SOI phase system was found to increase by \$3.45/ha if improved timeliness of both phases could be achieved.

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Appendix

Table A1 Forecast value ($/ha). (a) 20 April PD; (b) 10 May PD; (c) 5 June PD

Skill	30 mm soil moisture				60 mm soil moisture				100 mm soil moisture				Overall
	Dry	Avg	Wet	All	Dry	Avg	Wet	All	Dry	Avg	Wet	All	
(a)													
10%	$0.00	$0.00	$0.63	$0.21	$0.94	$0.15	$0.87	$0.65	$0.00	$0.00	$0.00	$0.00	$0.38
20%	$0.04	$0.00	$6.10	$2.05	$3.04	$0.39	$2.88	$2.10	$0.22	$0.00	$0.44	$0.22	$1.62
30%	$3.27	$0.00	$13.76	$5.68	$9.92	$0.74	$6.55	$5.74	$2.49	$0.00	$3.27	$1.92	$4.77
40%	$7.58	$0.00	$21.97	$9.85	$17.00	$1.08	$11.50	$9.86	$10.23	$0.00	$6.67	$5.63	$8.80
50%	$11.89	$0.00	$30.18	$14.02	$25.49	$1.43	$16.45	$14.46	$19.17	$0.00	$11.13	$10.10	$13.26
60%	$16.20	$0.00	$38.38	$18.19	$34.73	$1.80	$21.40	$19.31	$28.10	$0.00	$16.98	$15.03	$17.96
70%	$20.51	$0.00	$46.59	$22.37	$44.01	$2.17	$26.35	$24.18	$37.04	$0.00	$22.90	$19.98	$22.68
80%	$24.82	$0.00	$54.87	$26.57	$53.30	$2.68	$31.30	$29.10	$46.08	$0.00	$28.81	$24.96	$27.43
90%	$30.37	$0.00	$63.54	$31.31	$62.59	$3.20	$37.03	$34.27	$55.17	$0.00	$35.01	$30.06	$32.48
100%	$38.12	$0.00	$72.21	$36.78	$71.87	$3.71	$43.27	$39.62	$64.27	$0.00	$41.71	$35.33	$37.83
(b)													
10%	$0.12	$0.00	$0.24	$0.12	$0.25	$0.00	$0.27	$0.17	$0.00	$0.00	$1.04	$0.35	$0.20
20%	$1.43	$0.00	$2.86	$1.43	$0.86	$0.00	$1.48	$0.78	$0.00	$0.00	$3.98	$1.33	$1.08
30%	$4.78	$0.00	$6.06	$3.61	$2.04	$0.00	$4.30	$2.11	$0.57	$0.00	$7.05	$2.54	$2.59
40%	$9.06	$0.00	$9.26	$6.10	$3.93	$0.00	$8.25	$4.06	$2.07	$0.00	$10.12	$4.06	$4.57
50%	$13.33	$0.00	$12.46	$8.60	$5.96	$0.01	$12.19	$6.05	$3.68	$0.00	$13.19	$5.62	$6.58
60%	$17.61	$0.00	$16.56	$11.39	$9.38	$0.07	$16.29	$8.58	$5.32	$0.00	$16.26	$7.19	$8.94
70%	$21.88	$0.00	$21.89	$14.59	$13.23	$0.13	$22.15	$11.84	$7.22	$0.00	$19.65	$8.96	$11.81
80%	$26.51	$0.00	$27.44	$17.98	$17.09	$0.19	$28.93	$15.41	$9.76	$0.00	$25.81	$11.86	$15.16
90%	$33.09	$0.00	$33.45	$22.18	$21.38	$0.25	$36.49	$19.38	$12.76	$0.00	$32.73	$15.16	$19.02
100%	$41.87	$0.00	$40.27	$27.38	$25.95	$0.32	$44.29	$23.52	$15.82	$0.00	$39.64	$18.49	$23.23
(c)													
10%	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
20%	$0.07	$0.00	$0.00	$0.02	$0.30	$0.00	$0.00	$0.10	$0.00	$0.00	$0.00	$0.00	$0.06
30%	$2.75	$0.00	$0.86	$1.21	$1.26	$0.00	$0.00	$0.42	$0.00	$0.00	$0.00	$0.00	$0.51
40%	$6.11	$0.00	$2.15	$2.75	$3.26	$0.00	$0.00	$1.09	$0.29	$0.00	$0.00	$0.10	$1.26
50%	$9.46	$0.00	$4.01	$4.49	$5.29	$0.00	$0.00	$1.76	$1.13	$0.00	$0.00	$0.38	$2.10
60%	$12.82	$0.00	$6.32	$6.38	$7.41	$0.00	$0.00	$2.47	$2.10	$0.00	$0.00	$0.70	$3.00
70%	$16.27	$0.00	$8.63	$8.30	$10.19	$0.00	$0.00	$3.40	$3.06	$0.00	$0.00	$1.02	$4.03
80%	$22.10	$0.00	$10.94	$11.01	$13.42	$0.00	$0.00	$4.47	$4.29	$0.00	$0.00	$1.43	$5.35
90%	$29.92	$0.00	$13.25	$14.39	$16.64	$0.00	$0.00	$5.55	$5.95	$0.00	$0.00	$1.98	$6.87
100%	$37.83	$0.00	$15.56	$17.79	$20.03	$0.00	$0.00	$6.68	$7.97	$0.00	$0.00	$2.66	$8.45

PD, planting date; All = economic value weighted across forecasts; Overall = economic value weighted across forecasts and soil moisture levels.