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RISK ATTITUDE, PLANTING CONDITIONS AND THE VALUE OF SEASONAL FORECASTS TO A DRYLAND WHEAT GROWER*

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The value of a seasonal forecasting system based on phases of the Southern Oscillation was estimated for a representative dryland wheat grower in the vicinity of Goondiwindi. In particular the effects on this estimate of risk attitude and planting conditions were examined. A recursive stochastic programming approach was used to identify the grower's utility-maximising action set in the event of each of the climate patterns over the period 1894-1991 recurring in the imminent season. The approach was repeated with and without use of the forecasts. The choices examined were, at planting, nitrogen application rate and cultivar and, later in the season, choices of proceeding with or abandoning each wheat activity. The value of the forecasting system was estimated as the maximum amount the grower could afford to pay for its use without expected utility being lowered relative to its non-use.

Introduction

Background

The Drought Policy Review Task Force (1990) proposed that the responsibility for managing climate be shifted away from government and onto growers and that drought be accepted as a normal feature of the commercial environment of agriculture. The National Drought Policy (NDP) announced in 1992 aimed to facilitate the shift to farmer self-preparedness by measures including government funding of drought-related research and additional education programs. Seasonal forecasting was identified in particular as a way of enabling farmers to mitigate the adverse financial consequences of drought (White 1994).

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Seasonal forecasting aims to move farmers as far as possible to a situation of certainty regarding future seasonal conditions and to thereby increase the likelihood that good decisions will lead to successful outcomes. As noted by Anderson (1991), however, research into seasonal forecasting is not the only form of research with the potential to reduce climate-related production risk. Plant breeding, for instance, can also reduce production risk by improving crop or pasture performance under climatically-stressed conditions. Indeed, 'a first objective of wheat improvement in Australia was to produce varieties sufficiently drought-resistant to cope with the short seasons and hard finishing conditions' (Callaghan 1973).

Expenditure under the NDP was projected to be $15.1 million over a four year period, including $2.1 million for research into opportunities such as seasonal forecasting (Department of Primary Industry and Energy 1992). This funding is of sufficient magnitude to warrant economic analyses designed to compare returns from seasonal forecasting research with returns from other types of research, such as plant breeding, aiming to increase farmers' self-preparedness in managing climatic variability.

Economic analysis also has a role in identifying where the greatest returns in seasonal forecasting research are likely to lie. Mjelde, Sonka, Dixon and Lamb (1988), for instance, found there were significant potential gains for USA maize producers from making less accurate seasonal forecasts available earlier rather than more accurate forecasts available later.

The Seasonal Forecasting System

A recent development in seasonal forecasting has been identification of 'phases' of the Southern Oscillation (SO) by Stone and Aulicems (1992). The phases relate to trends in the Southern Oscillation Index (SOI) over two consecutive months. The SOI measures atmospheric pressure differences between Tahiti and Darwin. Phase 1 (Phase 2) corresponds with a consistently negative (positive) SOI over that period. Phase 3 (Phase 4) corresponds with a rapidly falling (rising) SOI over that period and Phase 5 corresponds with the SOI being consistently near zero. When past records of rainfall, or temperature, are partitioned into those corresponding to the SOI phases, then frequency distributions for each SOI phase relating to rainfall or temperature in subsequent months can be produced. These frequency distributions can be used as probability distributions in seasonal forecasting (Stone 1994).

Phase 1 or Phase 3 identified in late autumn is associated with a high probability of below average rainfall during the following winter and spring at many locations in eastern Australia, whereas Phase 2 or Phase 4 identified at this time is associated with a high probability of above average rainfall (Stone *et al.* undated). For Goondiwindi in the north-

eastern grain belt, the rainfall probability distribution associated with Phase 5 was found to be similar to that derived using all years in the historical record (Stone and Hammer 1992).

Study Objectives

The primary objective in this study was to contribute information for decision-making with respect to allocation of resources to, and within, seasonal forecasting research by estimating the value to farmers of the seasonal forecasting system based on SO phases. Subsidiary objectives were to examine how the value of the forecasting system is affected by (i) a farmer's attitude to risk; and (ii) planting conditions.

Theory and Previous Studies

Expected Utility Theory

Most studies valuing seasonal forecasts have been cast within an expected utility (EU) theoretical framework and have assumed decision makers process forecasts according to Bayes' Theorem. These include Bacquet *et al.* (1976) who estimated the value to pear orchardists from forecasts issued daily regarding the likelihood of a frost occurring overnight. Byerlee and Anderson (1982) used this approach to value the benefits of rainfall forecast information for fodder conservation. Mjelde *et al.* (1996) also used this approach to explore the effects of government institutions in the USA (e.g., crop insurance and disaster programs) on the value of improved climate forecasts.

Application of EU theory requires that both the prior probability distribution of outcomes and the risk attitude of the decision-maker, encapsulated in a von Neumann-Morgenstern utility function $U(.)$, be precisely specified (Anderson *et al.* 1977). The optimal action according to EU theory is that which maximises expected utility, where the expected utility of an action is given by weighting the utility associated with each outcome by the probability of the outcome occurring. In the special case where a decision maker is risk-indifferent, as was assumed to be the case in Mjelde *et al.* (1988), Mazzocco *et al.* (1992) and Mjelde and Dixon (1993), this criterion is equivalent to maximisation of expected profit.

The action satisfying the EU criterion *without* access to a seasonal forecast is the prior optimal action. A seasonal forecast allows a decision-maker's prior probability distribution for outcomes to be revised using Bayes' formula to obtain a posterior probability distribution. The action satisfying the EU criterion *with* access to a particular forecast is the Bayes' action. The set of actions satisfying this criterion for each possible forecast is the Bayes' strategy. The expected utility of the Bayes' strategy is given by the weighted average of the utilities of the Bayes' actions, where the weighting given to the utility

of a particular Bayes' action is the probability that its associated forecast will be issued (Anderson *et al.* 1977).

The monetary value of a forecasting system is given by the maximum amount the decision-maker could afford to pay for its use without expected utility of the resulting Bayes' strategy falling below expected utility of the prior optimal action.

Hilton (1981) found that only characteristics of the system itself (e.g. accuracy and timeliness of forecasts) have a consistent directional effect on the value of information. Changes in factors that are external to the system (e.g. risk attitude and degree of prior uncertainty) will not necessarily exhibit such a consistent effect. Byerlee and Anderson (1982) and Mjelde and Cochran (1988), for instance, each found that the value of seasonal forecasts did not monotonically increase with the level of risk aversion of the decision-maker.

The axioms underlying expected utility (EU) theory have come under challenge (Schoemaker 1982; Buschena and Zilberman 1994). Notwithstanding these challenges, this decision theory has remained the one predominantly used in economic analysis (Machina 1989) since 'it seems that no better operational framework has yet found wide acceptance' (Hardaker *et al.* 1991, p. 9). Although Chavas (1993) has developed a theoretical framework for analysing the value of information which does not require assumptions that decision makers are Bayesian and behave according to EU theory, recent studies of the value of information (e.g., Pannell (1994); Mjelde *et al.* (1996)) have continued to rely on these assumptions.

In all of the studies identified above, the value of seasonal forecasting was estimated for a small set (sometimes of one) of case-study farmers. Byerlee and Anderson (1982) and Mjelde and Cochran (1988), for example, used the case study approach to analyse the impact of changes in risk attitudes on the value of seasonal forecasting, while Bacquet *et al.* (1976), Mjelde *et al.* (1988), Mjelde and Cochran (1988) and Mazzocco *et al.* (1992) used the approach to explore the effect on value of forecasts of varying assumptions regarding the prior probability distributions held by decision-makers. While the case study approach was also adopted in this study, we are cognisant of the difficulty of extrapolating results obtained from a non-statistically chosen sample (Bacquet *et al.* 1976).

Accounting for Risk Attitude

There are four major approaches for dealing with risk attitude: (1) assume risk-indifference and therefore a goal of maximising (minimising) expected monetary gains (losses) (e.g.; Mjelde *et al.* 1988, Mazzocco *et al.* 1992; Mjelde and Dixon 1993); (2) specify a utility function based on previous research (e.g. Byerlee and Anderson 1982); (3) use stochastic efficiency criteria (which satisfy the axioms of EU theory) to avoid the need to specify a particular utility function (e.g.

Mjelde and Cochran 1988); and (4) directly elicit farmers' risk attitudes (e.g. Bacquet *et al.* 1976).

Of the above approaches, the second appears to remain the most popular among decision analysts seeking to account for risk attitudes other than indifference in their models. It avoids the costs of direct elicitation and can, with judicious variation of the risk preference parameter, emulate the third approach in identifying upper and lower bounds on the value of a technology.

Approach (2) requires that the functional form of $U(.)$ be chosen. Forms invoking decreases in risk aversion with increasing wealth, appeal to the intuition of economists (Anderson *et al.* 1977). The quadratic form used by Byerlee and Anderson (1982) involves the counter-intuitive assumption that absolute risk aversion increases with increasing wealth. The negative exponential form which has been popular among agricultural economists in recent years (e.g. Easter and Paris 1983; Kingwell *et al.* 1992; Kingwell and Schilizzi 1994; and Ogisi *et al.* 1994) assumes that absolute risk aversion is unaffected by wealth. In contrast to this constant absolute risk aversion function, the constant relative risk aversion (CRRA) functional form accords more closely with intuition and, furthermore, recent empirical testing by Pope and Just (1991) found that farmer behaviour could be better explained by a CRRA functional form than by the negative exponential form.

Prior Probability

In valuing forecasts, the process is to assess the marginal benefits that accrue from introducing additional information to a situation characterised by some prior knowledge level. In all of the studies surveyed, the prior probability distributions of decision-makers were assumed rather than directly elicited. In the studies by Byerlee and Anderson (1982) and Mjelde and Dixon (1993) the prior probability distributions were assumed to be equivalent to historical climatic frequency distributions. Bacquet *et al.* (1976) also used this assumption as well as an assumption that the decision-maker has no prior information. Mjelde *et al.* (1988), Mjelde and Cochran (1988) and Mazzocco *et al.* (1992) used a historical frequency distribution as well as alternative assumptions that climatic conditions in the imminent season will be (1) identical to those in the previous one; (2) identical to those in the worst of the years in the data set; and (3) identical to those in the best of the years in the data set.

Embedded Risk

In Bacquet *et al.* (1976) and Byerlee and Anderson (1982) it was implicitly assumed that outcomes of climatic risk arise after all decisions have been made. However, most decisions about farming systems are subject to risks which are embedded within the decision process

rather than appearing only after all decisions have been made (Hardaker *et al.* 1991). Trebeck and Hardaker (1972), Hardaker *et al.* (1991) and Dorward (1994) concluded that models of farmer behaviour need to explicitly account for the tactical choices that arise during a season as the outcomes of embedded risk unfold.

The decision problems addressed by Mjelde *et al.* (1988), Mjelde and Cochran (1988), Mazzocco *et al.* (1992) and Mjelde and Dixon (1993) involved embedded risk and sequential decision models were accordingly developed to account for tactical choices arising at successive stages distinguished by increasing climate information. The models utilised a stochastic dynamic programming (SDP) framework under which backward recursion endogenously accounted for opportunity costs of decisions at each stage in terms of options precluded in subsequent stages. The approach used by Mjelde and Cochran (1988) seems internally inconsistent, however, since risk aversion was assumed when valuing forecasts while, as noted above, risk indifference was assumed when specifying the objective function of the model used to identify the optimal action for a given decision environment.

Method and Data

The Case-Study Enterprise

Research developing the seasonal forecasting system based on SO phases has largely focussed on its use by farmers in the northern grain belt of eastern Australia. This area extends from Dubbo in northern New South Wales to Emerald in central Queensland. Stone *et al.* (undated, p. 4) characterise wheat growing in this area as follows: 'Rainfall is variable, summer dominant, and limiting, rarely exceeding evaporative demand in any month. Successful wheat cropping has developed by utilising soil water stored during the summer fallow prior to the wheat crop'. Scoccimarro *et al.* (1994, map 2b) found that the coefficient of variation of wheat yield over the period 1978-79 to 1992-93 for most of this region (at greater than 0.53) generally exceeded that for other grain growing regions in Australia.

The native fertility of soils in this region made it suitable for producing wheat of Prime Hard quality, which attracts a significant price premium. However, continuous cropping in the area has depleted this fertility (Dalal and Mayer 1987). Decisions made at planting time regarding application of nitrogen fertiliser have become increasingly important as a result. The optimal planting window for wheat is short due to the desirability of capitalising on a very short optimal window for flowering, which is limited by low radiation receipt and frosting on one side and rapidly rising temperatures and evaporative demand on the other (Woodruff 1992). Choice among cultivars according to their varietal development pattern provides farmers with some control over flowering date despite the stochastic nature of planting opportu-

nities. Choices of planting time, varietal development pattern and fertiliser strategy within this environment thus involve complex decisions (Woodruff 1992).

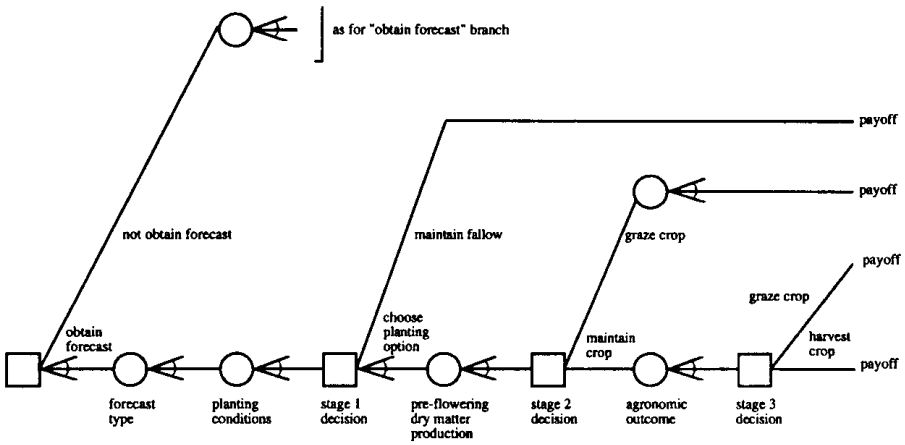
Accounting for this complexity requires in-depth analysis of the situation of individual decision-makers. This study was limited to analysis of one such situation. The case study related to a representative wheat grower in the vicinity of Goondiwindi in the Western Downs/Maranoa district of southern Queensland. The case-study analysis focussed on a farm representative of the 'small wheat area' stratum of wheat growers in this district defined by Smith (1995a,b). Average property size for this group was estimated to be 2,083 hectares (ha). The average area cropped per year over 1990-91 to 1992-93 was 338 ha, of which wheat accounted for 217 ha and other winter crops accounted for 113 ha. Average area of summer crops was only 8 ha (Smith 1995a,b).

The case study focussed on the wheat enterprise of the representative farm. However, the whole-farm consequences of decisions and outcomes within the wheat enterprise were also accounted for as discussed in the following section.

The Grower's Sequential Decision Problem

In this study the value of the seasonal forecasting system was assessed in terms of the benefits it provides for choosing nitrogen application rates and wheat varieties at the time of planting opportunity. A descriptive model of the sequence of decisions relevant to this focus is represented as an outline decision tree in Figure 1. Options branch from decision nodes which are denoted by squares, and states branch from event nodes which are denoted by circles. The decision tree is in outline form insofar as the forks at some of the decision and

FIGURE 1
Outline Decision Tree for the Wheat Enterprise



event nodes (i.e., those with three prongs joined by an arc) symbolically represent a larger number of discrete options or states.

The figure deals with the decision problem for a single paddock. The first decision is whether to obtain the forecast. If the grower decides to obtain the forecast, one of five forecasts (i.e., SO phases) will be issued at the subsequent event node. Another event node follows relating to the conditions experienced at planting. These conditions are independent of the forecast, which relates to later in the season. If the grower does not obtain the forecast, the event node relating to planting conditions immediately follows the first decision node (in the top section of the decision tree).

The planting conditions modelled were date of planting opportunity (five variants) and soil moisture (percentage of field capacity) (two variants) and soil nitrogen (two variants) as at that date. Twenty sets of planting conditions were considered, composed of all possible combinations of these variants. The planting opportunity dates represented the 10, 30, 50, 70 and 90 percentile values of the historical frequency distribution, while the levels for soil moisture and soil nitrogen were estimated to represent the 10 and 90 percentile values of their respective distributions. Since climatic conditions during a wheat growing season in this region are independent of these types of planting conditions (pers. comm., R. Stone, QDPI/CSIRO Agricultural Production Systems Research Unit, Toowoomba, July 1995), the prior probability distribution of wheat season climatic events was assumed to be equivalent to the historical frequency distribution (derived from the 98-year period 1894 to 1991) regardless of the set of planting conditions being analysed.

Next along each branch is the decision node relating to stage 1 (i.e., planting option) of the wheat growing season. The decision model allowed for choice at this stage among eleven nitrogen application rates and three varieties differing in development pattern. The option of continuing the fallow commenced in summer was also accounted for. It was assumed that twenty per cent of the residual applied nitrogen at grain maturity remains available at the commencement of the following wheat season.

The event node situated to the right of the stage 1 decision node relates to the level of dry matter production prior to flowering. Four classes of pre-flowering dry matter production were distinguished. Next to the right is a decision node relating to options available at flowering (stage 2). The choice at flowering was that of whether a crop planted at stage 1 should be maintained or grazed. A decision to graze avoids the cost of harvesting and provides added feed at a time when fodder reserves such as hay would most likely be distributed to livestock. The net payoff from deciding to graze the crop at this stage was calculated as the cost that would otherwise be incurred in obtaining equivalent feed value by purchasing hay minus the feed value of the

crop stubble remaining after harvest (calculated similarly) if the decision is instead taken to maintain the crop. See Marshall (1996) for further details.

Next to the right is an event node relating to the agronomic outcomes at stage 3 (i.e., which depend on the type of season experienced between flowering and grain maturity). This is followed to the right by a decision node relating to options available at the time of grain maturity in mid to late spring (stage 3). The choice here was whether a crop should be harvested or grazed. The benefits of grazing at stage 3 were of the same type and calculated similarly as described above for grazing at stage 2.

Note that the 'terminal' options from which payoffs arise are 'maintain fallow' (at stage 1), 'graze crop' (at stage 2), 'graze crop' (at stage 3) and 'harvest crop' (at stage 3).

Probability Distributions

Derivation of probabilities for the event nodes shown in Figure 1 following the stage 1 and stage 2 decision nodes assumed that the representative grower is aware of historical climate data as a result of widespread dissemination of climate information following the development of information technology such as the computerised RAINMAN decision support system (Murphy 1993). Thus the value of the seasonal forecasting system arises only from adding information to that already available from a thorough historical knowledge.

The prior probability distribution for the pre-flowering dry matter production event node (representing the without forecast situation) was accordingly derived by assuming that the grower judges that each of the relevant events recorded from 1894 to 1991 is equally likely to recur. Thus the prior probability of the event in a particular past year recurring was assumed to be 1/98.

The posterior probability distribution regarding this event was derived by (a) obtaining 'hindcasts' of which of the five possible forecast types would have been issued in each of the 98 past years (pers. comm., R. Stone, July 1995); (b) partitioning the series of past years according to forecast type; and (c) setting the probability that the pre-flowering event in a particular past year will recur in the imminent season, if that particular SO phase is the one currently identified, equal to the reciprocal of the number of past years associated with that class. For instance, there were 14 past years associated with end-April SO phase 1. The probability that each of the pre-flowering events in these years would recur in the imminent season if this forecast type were issued was thereby calculated to be 1/14.

Regardless of access to a seasonal forecast, information regarding pre-flowering dry matter production becomes available by the time a stage 2 decision is required. The grower's prior probability distribution for stage 3 agronomic outcomes was deduced by simulating the way

the grower would utilise this information to predict agronomic outcomes at stage 3. The method involved calculating, for each of the 98 years, the average of pre-flowering dry matter production over the three varietal types. A cumulative probability distribution was constructed from these data and quartile values were determined. Each of the 98 years was then partitioned into one of four classes bounded by the quartile values. The prior probability that the stage 3 agronomic outcome in a particular past year will recur in the imminent season, if the outcome at flowering falls within the same dry matter class as was the case in that past year, was set equal to the reciprocal of the number of past years associated with that class.

The seasonal forecasting system may also have value for decisions made at stage 2, but this is likely to be a smaller residual value given the length of time since the forecast was issued. The posterior probability distributions for stage 3 agronomic outcomes were assumed equivalent to the prior probability distribution since re-partitioning the years allocated to each dry-matter class according to its associated SO phase would have left too few years per partition to allow adequate representation of these posterior distributions.

It was assumed that outcomes of stage 3 decisions (i.e., whether to harvest or graze) are known by the grower with certainty.

Net Payoffs

The next step in applying the case-study approach was to identify, for every combination of event outcomes, the monetary consequence (or net payoff) of each option available at the decision nodes for stages 1 to 3. Where an option was a terminal option this required only straightforward budgeting. However, for precursor options this also involved identifying the 'follow-on' options that would be chosen in the subsequent stage/s.

Identifying the follow-on options that would subsequently be chosen if a particular option were chosen at a given stage involved applying backward induction or 'averaging out and folding back' (Anderson *et al.* 1977, p. 125) to the decision tree represented in Figure 1. A detailed description of how this was performed is provided in Marshall (1996).

Prices received after harvest for the various grades of wheat grain were assumed to be known by the grower with certainty at the time of planting opportunity. This approach follows that in previous studies of the value of climate forecasting and can be justified as reasonable for a grower who customarily enters a forward contract at planting. Due to the neglect of price risk in the model, however, care is required in generalising the findings of this study to other categories of growers.

The benchmark farm-gate return for ASW quality wheat (minimum of 10 per cent protein) was assumed to be $125/t. Benchmark farm-gate returns for the Prime Hard (min. 13 per cent protein), Australian Hard

(min. 11.5 per cent protein) and Feed grades of \$175/t, \$140/t and \$80/t respectively were chosen as representative of the returns that might be expected on average in the foreseeable future. For each grade other than Feed grade, an adjustment of \$5 per one percentage point deviation in protein above the grade benchmark and, in the case only of ASW wheat, below the benchmark, also applied. The three varieties with differing development patterns available at each planting opportunity were assumed to be equally eligible for classification of their grain as Prime Hard or Australian Hard.

Calculation of the net payoff from an option under particular climatic conditions required simulation of the agronomic consequences of those conditions. This was performed by staff of the Agricultural Production Systems Research Unit (APSRU) at Toowoomba using the wheat module of the Agricultural Production Simulation Model (McCown *et al.* 1996). Simulations were performed for each of the 20 different combinations of planting conditions. Simulation data included grain yield and grain protein content and in-crop dry matter at flowering and grain maturity. As the model was unable to account for residual soil moisture in a particularly wet season carrying over to the following wheat crop, this effect was not captured in this study. The simulation also did not account for effects of frosts on grain yield and quality. The effect on grain protein of grain yield losses due to frost damage was assumed to be as reported in Woodruff (1992). The fact that the financial impact of a loss of grain yield due to frost damage could be offset to some extent by a corresponding increase in grain protein was thereby accounted for in this study. See Marshall (1996) for further details.

Risk Attitude

The grower's risk attitude was represented using the CRRA functional form detailed in equation 1:

$$(1) \qquad U = \pi^{1-R_r} / (1 - R_r) \qquad R_r > 0, R_r \neq 1$$

where π is some measure of financial performance and $R_r = RW$ is the coefficient of relative risk aversion, with R being the coefficient of absolute risk aversion and W being wealth (Hey 1979).

To test the effect of increasing risk aversion on the value of the forecasting system, sensitivity testing was performed using two alternative 'risk-averse' settings for R_r. Anderson and Dillon (1992, p. 55) noted that 'speculations as to likely values of (R_r) have ranged from about unity to two' but that 'values as small as 0.5 might be presumed if an individual were regarded as hardly concerned at all with risk'. Accordingly a value for R_r of 1.5 was chosen in this study to represent the attitude of a typically risk-averse grower and a value of 0.75 to represent a grower who is less risk-averse than typical. To value the

forecasting system for a risk-indifferent grower, the forecasting system was also valued with R_r set equal to zero.

The argument of the utility function was terminal wealth, W, where $W = W_0 + P$, W_0 is initial wealth apportioned to the wheat enterprise and P is annual profit from the wheat enterprise. W_0 was estimated as described in Marshall (1996) to be $225,073. The coefficient of absolute risk aversion, R, corresponding with this level of W_o when R_r = 0.75 is 3.3×10^{-6}. For $R_r = 1.5$ the corresponding value of R is 6.7×10^{-6}. This range corresponds closely with the range of 2×10^{-6} to 6×10^{-6} used in Patten *et al.* (1988), with the range of 3×10^{-6} to 5×10^{-6} used in Kingwell (1994b) and with the point value of 3×10^{-6} used in Kingwell and Schilizzi (1994).

Identifying the Prior Optimal Action and Bayes' Strategy

Identification of the prior optimal action and the Bayes' strategy given a particular set of planting conditions and a particular risk attitude was achieved by means of a sequential decision model illustrated in Figure 2. The model was composed of three mathematical programs (MPs), each representing one of the three stages of the decision process illustrated in Figure 1. Each MP was designed to identify, for the relevant decision stage, the options that would maximise expected utility in the imminent season.

The DEMP mathematical programming framework of Lambert and McCarl (1985) was used for each of the three MPs since (a) it is consistent with EU theory; (b) the only restriction on the form of the utility function is that it be concave or quasi-concave; and (c) probability distributions for option net payoffs can be directly represented using data sampled from the historical record, thereby (i) avoiding the need to assume a distributional form; and (ii) implicitly capturing correlations among net payoffs of the various options.

The DEMP framework applied for each of the three MPs was:

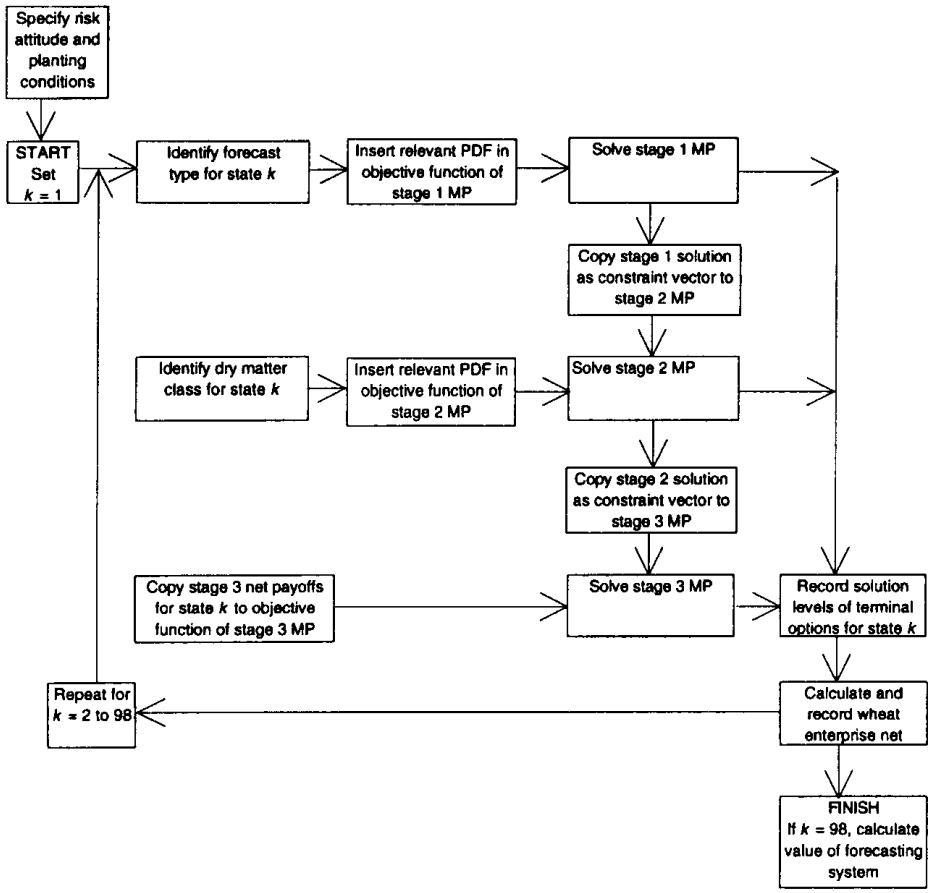
$$\underset{\underline{A}b}{\text{Max}} \sum_{k=1}^{n} P(\theta_{kb})\, U(W_0 + \underline{a}_{kb}\, \underline{A}_b)$$

Subject to:

$$\underline{T}_b\, \underline{A}_b \leq \underline{l}_{kb}$$
$$\underline{A}_b \geq 0$$

where there are n states of nature (i.e., climatic conditions associated with previous years) that may recur in the imminent season, $P(\theta_k)$ is the probability of the climatic conditions associated with the kth previous year recurring in the imminent season, W_0 is initial wealth, $\underline{A}_b$ is a vector of the options available at stage b, $\underline{a}_{kb}$ is the vector of net payoffs per unit of $\underline{A}_b$ under the kth state of nature, $\underline{T}_b$ is the matrix of

FIGURE 2
The Process of Modelling Sequential Decisions and Valuing the Forecasting System



technical coefficients and $\underline{l}_{kb}$ is the vector of constraint limits applying at stage b under the kth state of nature.

As noted previously, $U(.)$ was specified using a CRRA functional form. This form is concave and is therefore consistent with the DEMP framework. Its use necessitated solution by a non-linear programming algorithm.

The EU criterion may lead to diversification among options if the grower is risk-averse and the consequences of alternative options are not perfectly correlated (Anderson *et al.* 1977). It is therefore necessary to distinguish an action, which involves choosing one or more options at each stage, and an option. A grower's flexibility to diversify among available options is characteristically limited, however, by paddock sizes and by the demands on management of running multiple crops with differing requirements. The area of 210 ha assumed to be available for wheat cropping was accordingly assumed to be composed of three

70 ha paddocks. The grower was thus limited to choosing a maximum of three options at any particular stage. This was enforced in the MPs by restricting option levels to integer values relating to 70 ha paddocks.

The level of the land use constraint in the stage 1 MP was accordingly set at three paddocks. The constraint sets of the three MPs related only to land use.

As shown in Figure 2, stage 2 land use constraint limits were recursively determined by optimal stage 1 option levels. If the optimal stage 1 decision is to plant the three paddocks to the early variety with 80 kg per ha of nitrogen fertiliser, for instance, land use constraints would be inserted in the stage 2 MP such that maintaining or grazing a crop planted in this way are the only two available options. Similarly, stage 3 land use constraint limits were recursively determined by optimal stage 2 option levels.

This recursive stochastic programming (RSP) approach is an alternative to the stochastic dynamic programming (SDP) approach used in Mjelde *et al.* (1988) and Mjelde *et al.* (1996). Whereas the backward recursion algorithm for SDP endogenously accounts for opportunity costs of decisions at each stage in terms of options precluded in subsequent stages, solution of an RSP model requires that these opportunity costs be calculated exogenously. As noted above, opportunity costs of decisions at a particular stage were accounted for in the RSP model developed for this study through a process of 'averaging out and folding back'. The resulting loss of accuracy using RSP compared with the SDP approach was considered to be minor and outweighed by the practical advantage of being able to use mathematical programming software and spreadsheet macros rather than the specialised programming language required for the latter approach.

Valuing the Seasonal Forecasting System for the Wheat Enterprise

The data derived and parameters assumed as detailed in earlier sections were used to find the value of the seasonal forecasting system for each combination of planting conditions and risk attitude. As noted earlier, this value is given by the maximum amount the grower could afford to pay to use the system without the expected utility of the Bayes' strategy falling below expected utility of the prior optimal action.

In order to calculate the net payoff outcome of a prior optimal action it was necessary to (a) identify the net payoffs for the associated terminal prior optimal options as calculated at the decision stage at which termination occurs; (b) deduct from these net payoffs those costs which are sunk costs from the standpoint of the termination stage but are nevertheless costs that need to be considered in determining the effect on the gross margin of the wheat growing enterprise; (c) sum the adjusted net payoff values relating to each of the terminal options in order to determine the gross margin obtained from the wheat enter-

prise; and (d) deduct the fixed cost of the wheat enterprise from its gross margin. This fixed cost was estimated as described in Marshall (1996) to be $33,395 per year. The corresponding wealth outcome was calculated by adding the profit outcome to initial wealth.

An analogous process was required to determine the outcome of a particular Bayes' strategy.

Results

Value of the Seasonal Forecasting System

Estimates of the value of the forecasting system under various sets of planting conditions are presented in Tables 1, 2 and 3 for the cases where the representative grower was assumed to be risk-indifferent ($R_r = 0$), to demonstrate a 'lower than typical' level of risk aversion ($R_r = 0.75$) and to demonstrate a 'typical' level of risk aversion ($R_r = 1.5$), respectively.

The probability of each of the (a) five dates of planting opportunity occurring is approximately the same; (b) two levels of initial soil nitrogen occurring is approximately the same; and (c) two levels of initial soil moisture occurring is approximately the same. Hence the expected value of the forecasting system given a particular risk attitude can be obtained as the mean of the sample of forecasting system values corresponding with the set of 20 combinations of planting conditions analysed. Expected values for the three alternative risk attitudes are shown in Table 4. It is evident that the relationship between degree of risk aversion and mean value of the forecasting system is not consistent in direction.

With 20 possible combinations of planting and three alternative grower risk attitudes, the seasonal forecasting system was evaluated under 60 distinct scenarios. The value of the forecasting system was estimated to be positive in all but three of these scenarios, when it was zero. The estimated value of seasonal forecasting varied considerably according to grower risk attitude and planting conditions. The highest estimated value was $11.27/ha/yr (i.e., $2,367/yr for the 210 ha wheat growing area of the representative farm).

The results demonstrate the following predominant tendencies: (1) the value of forecasting tends to increase as planting opportunity becomes earlier (three exceptions out of the 60 scenarios); (2) the value of forecasting tends to be greater when soil moisture at planting is at the higher level (four exceptions); and (3) the value of forecasting tends to be higher when mineralised soil nitrogen at planting is at the higher level (four exceptions). These tendencies indicate that seasonal forecasts will usually benefit the wheat grower more when planting conditions are relatively good than when they are relatively poor.

TABLE 1
Value of Seasonal Forecasting Under Various Planting Conditions when R_r equals 0

Initial Soil Nitrogen	Initial Soil Moisture	Date of Planting Opportunity				
		15 May	26 May	3 June	15 June	28 June
		$/ha	$/ha	$/ha	$/ha	$/ha
40 kg/ha	50%	6.30	4.75	2.51	1.04	0.00
	80%	11.27	5.75	3.39	2.80	1.84
70 kg/ha	50%	7.42	4.74	3.21	1.28	0.28
	80%	2.53	6.01	4.20	2.88	1.87

TABLE 2
Value of Seasonal Forecasting Under Various Planting Conditions when R_r equals 0.75

Initial Soil Nitrogen	Initial Soil Moisture	Date of Planting Opportunity				
		15 May	26 May	3 June	15 June	28 June
		$/ha	$/ha	$/ha	$/ha	$/ha
40 kg/ha	50%	6.97	4.66	2.16	0.97	0.00
	80%	4.34	6.14	3.22	2.94	1.64
70 kg/ha	50%	7.83	4.90	2.84	1.16	0.12
	80%	5.14	6.26	4.23	2.86	1.94

TABLE 3
Value of Seasonal Forecasting Under Various Planting Conditions when R_r equals 1.5

Initial Soil Nitrogen	Initial Soil Moisture	Date of Planting Opportunity				
		15 May	26 May	3 June	15 June	28 June
		$/ha	$/ha	$/ha	$/ha	$/ha
40 kg/ha	50%	7.30	4.58	1.88	0.90	0.00
	80%	7.36	6.24	3.62	3.10	1.47
70 kg/ha	50%	8.21	4.81	2.49	1.05	0.03
	80%	7.79	6.29	4.55	2.92	2.02

TABLE 4
Effect of Risk Attitude on the Mean Value of the Seasonal Forecasting System

Class of Risk Attitude	R_r	Mean Value of Forecasting System ($ per ha available for wheat growing)
Risk-indifferent	0.00	3.70
Less risk-averse than typical	0.75	3.52
Typically risk-averse	1.50	3.83

The data included in Tables 1 to 3 were reconfigured in Tables A1.1 to A1.4 (Appendix 1) to be in a form more suitable for exploring the effect on the value of forecasting of increasing aversion to risk. It is apparent from these tables that there is no general relationship to the effect that the value of the seasonal forecasting system to the representative grower consistently increases (or decreases) as s/he becomes more risk-averse. Byerlee and Anderson (1982) and Mjelde and Cochran (1988) made similar findings. However, a few tendencies can be noted. Namely, the relationship between system value and risk aversion is more likely to be positive (a) the earlier a planting opportunity occurs; (b) the higher the level of soil nitrogen at planting; and (c) the higher the level of soil moisture at planting. In short, the relationship between the value of seasonal forecasting and the representative grower's degree of risk aversion is more likely to be positive the more optimal are planting conditions.

Attempts to discern reasons for the above tendencies, and the exceptions to them, highlighted the practical relevance of Hilton's (1981) observation that tendencies observed in the value of an information system are the result of a complex interplay of factors internal (e.g., accuracy of the system) and external to the system and that, therefore, variation in external factors, such as planting conditions and risk attitude, should not necessarily be expected to have a consistent directional effect on its value. Reasons for the relative magnitude of the value of the forecasting system given particular planting conditions and risk attitude therefore need to be sought on a case-by-case basis. Although such a task was beyond the scope of this particular study, it remains an important area for further research.[1]

1 The interested reader may refer to Tables 4.8 to 4.34 in Marshall (1996) in which some of the data relevant to this task is presented.

Summary and Conclusions

In this study the value of a particular seasonal forecasting system for wheat growing by a representative grower in the vicinity of Goondiwindi was estimated across a range of decision environments. The decision environments differed both in terms of the grower's risk attitude and in terms of planting conditions.

The system was found to have value in all but three of the 60 decision environments analysed. The mean value of the forecasting system across the various sets of planting conditions analysed was estimated to lie within the range of $3.52 to $3.83 per hectare available for wheat growing (the range due to the range of risk attitudes assumed).

One possible benchmark for assessing the relative significance of the above values is the estimate by Brennan (1989) that on average the release of a new wheat variety provides yield and quality benefits to growers of $3.38/t. For an average Goondiwindi wheat yield of 1.4 t/ha (Lawrence 1993), this is equivalent to a farm-level benefit of $4.73/ha/yr. Hence the mean annual benefit to the representative grower from the development of the forecasting system is lower than that from the development of an average new wheat variety. Assessment of the relative economic merits of the two types of research project, however, would require that the costs of each also be accounted for.

The estimated value of the forecasting system varied considerably according to grower risk attitude and planting conditions. It is not possible to conclude that the value of the forecasting system will invariably be higher (a) the earlier a planting opportunity occurs; (b) the higher the level of initial soil nitrogen; (c) the higher the level of initial soil moisture; or (d) the more risk-averse the grower; nor that it will be invariably lower. However, the results indicate that as planting conditions become more optimal the value of the forecasting system to the representative grower (a) will *usually* increase; and (b) is *more likely* to increase with increasing risk-aversion.

The approach used in this study could be adapted to value seasonal forecasting systems other than the one addressed herein. Prospects for progress in climatological research of relevance to seasonal forecasting (Nicholls 1994; Hunt 1994) suggest that seasonal forecasting systems, like other agricultural inputs, will be subject to innovation in coming years.

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APPENDIX 1
Effect of Risk Attitude on Value of Seasonal Forecasting

TABLE A1.1
Effect of Risk Attitude on Value of Seasonal Forecasting when Soil Nitrogen = 40 kg/ha and Soil Moisture = 50%

R_r	Date of Planting Opportunity				
	15 May	26 May	3 June	15 June	28 June
	$/ha	$/ha	$/ha	$/ha	$/ha
0	6.30	4.75	2.51	1.04	0.00
0.75	6.97	4.66	2.16	0.97	0.00
1.5	7.30	4.58	1.88	0.90	0.00

TABLE A1.2
Effect of Risk Attitude on Value of Seasonal Forecasting when Soil Nitrogen = 40 kg/ha and Soil Moisture = 80%

R_r	Date of Planting Opportunity				
	15 May	26 May	3 June	15 June	28 June
	$/ha	$/ha	$/ha	$/ha	$/ha
0	11.27	5.75	3.39	2.80	1.84
0.75	4.34	6.14	3.22	2.94	1.64
1.5	7.36	6.24	3.62	3.10	1.47

TABLE A1.3
Effect of Risk Attitude on Value of Seasonal Forecasting when Soil Nitrogen = 70 kg/ha and Soil Moisture = 50%

R_r	Date of Planting Opportunity				
	15 May	26 May	3 June	15 June	28 June
	$/ha	$/ha	$/ha	$/ha	$/ha
0	7.42	4.74	3.21	1.28	0.28
0.75	7.83	4.90	2.84	1.16	0.12
1.5	8.21	4.81	2.49	1.05	0.03

TABLE A1.4
Effect of Risk Attitude on Value of Seasonal Forecasting when Soil Nitrogen = 70 kg/ha and Soil Moisture = 80%

R_r	Date of Planting Opportunity				
	15 May	26 May	3 June	15 June	28 June
	$/ha	$/ha	$/ha	$/ha	$/ha
0	2.53	6.01	4.20	2.88	1.87
0.75	5.14	6.26	4.23	2.86	1.94
1.5	7.79	6.29	4.55	2.92	2.02