An assessment of the value of seasonal forecasting technology for Western Australian farmers[†]

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Abstract

Of the number of seasonal forecasting systems that have been developed of late, none are of practical benefit to Western Australian farmers. This study aims to improve the methodology for assessing the value of forecasting technology *ex ante* to its development, using the Merredin agricultural region of Western Australia as an illustration. Results suggest that a seasonal forecasting technology that provides a 30 per cent decrease in seasonal uncertainty increases annual profits by approximately five per cent. The accumulated annual benefit to farmers in the Merredin region (an area with 754 farm holdings over 35, 500 square kilometres of land) is approximately two million dollars. Hence, support is given for the development of seasonal forecasting techniques in Western Australia.

Keywords: Seasonal forecasting information; seasonal uncertainty; whole-farm modelling; MUDAS

1. Introduction

Australian agricultural producers face high levels of seasonal uncertainty (Scoccimarro et al., 1994). This seasonal uncertainty (both within and between years) significantly reduces the efficiency of their production systems. An accurate seasonal forecast would allow farmers to tailor their management practices to better suit the pending seasonal conditions. This analysis is an assessment of the value of seasonal forecasting technology for Western Australian farmers.

A number of seasonal forecasting systems have been developed of late. Most of these systems use the El Nino Southern Oscillation (ENSO) phenomenon in conjunction with other climate indicators (such as cloud cover, water vapour and agronomic data) (e.g. Hammer (1996), Meinke and Hammer (1997), Orlove et al. (2000), Podbury et al. (1998) and Rimmington and Nicholls (1993)). In Australia, the ENSO phenomenon is strongly associated with droughts that occur throughout Australia suppressing rainfall during the winter, spring and summer months of the southern hemisphere (Podbury et al., 1998). The Southern Oscillation Index (SOI) is a key indicator of ENSO (Coughlan, 1988) and is a measurement of the standardised difference in atmospheric pressure between Tahiti and Darwin. The SOI significantly correlates with rainfall events in subsequent months, a lag that allows it to be valuable as a forecaster of seasonal rainfall (Bureau of Meteorology, 1993). However, the correlation between rainfall and the SOI is strongest in the northern and eastern areas of Australia (up to 0.6 in parts of northern Queensland, New South Wales and Tasmania) but is relatively weaker in the western and central areas of Australia (up to 0.3) (Podbury et al., 1998). Hence, the SOI is of little use as a seasonal forecasting tool for agricultural areas of Western Australia (IOCI, 1999). A relatively new innovation, the Indian Ocean Climate Initiative (IOCI) commenced in 1997 to research the effects of the Indian and Southern Oceans on climate in south-western Australia. While the IOCI have developed seasonal forecasting technologies which show promise, no method offers accurate forecasting skill as yet (IOCI, 1999).

A wealth of literature exists explaining biological impacts of seasonal forecasting on agricultural systems. However, only a small proportion examines the economic impacts of such forecasting information (e.g. Byerlee and Anderson (1982), Fox et al. (1999a), Fox et al. (1999b), Hammer (1996), Marshall et al. (1996), Mazzocco et al. (1992), Mjelde and Cochran (1988), Mjelde et al. (1988) and Mjelde and Dixon (1993)). Two limitations can be identified in those studies that have put an economic value on seasonal forecasting technology. First, some studies have valued improved decision-making from seasonal forecasting for individual farm enterprises with no consideration given to the interdependencies between enterprises in the whole-farm context (e.g. Byerlee and Anderson (1982), Fox et al. (1999b), Hammer (1996), Marshall et al. (1996), Mjelde and Cochran (1988) and Mjelde et al. (1988)). Neglect for interactions between enterprises will cause the valuation of forecast information to be underestimated[1]. The second limitation is the use of a small number of years for which data is compared. For example, Fox et al. (1999a) and Fox et al. (1999b) use only two years of data. Such a limited

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[1] Hammer (1996) notes that further research should extend his study with the whole-farm enterprise mix.

sample of seasons may cause economic values to be over- or under-estimated depending on seasonal conditions and quality of forecasts in those years.

This paper adds to the existing literature on seasonal forecasting by assessing the value of a forecasting technology that decreases seasonal uncertainty for farmers in the eastern wheatbelt of Western Australia. The analysis does not suffer the limitations of previous valuations of forcasting technology. The whole-farm context is considered through the use of a whole-farm mathematical programming model, MUDAS (Model of an Uncertain Dryland Agricultural System). MUDAS represents seasonal uncertainty in the farming system with eleven discrete weather-year states, each with an associated probability of occurrence. Each weather-year state was classified using meteorological records from 1907 to 1995, overcoming the data limitations of previous studies. The aim of the study is to improve the methodology for the valuation of climate forecasting technology using a Western Australian farming system as an illustration. Given that no accurate seasonal forecasting technology is available for Western Australia, this analysis shows to what extent the investment of funds into developing such a technology would be beneficial in this context.

The paper proceeds as follows. The second section is a description of MUDAS. The third section demonstrates how the model can be used to value seasonal forecasting technologies and reports on the results of the analysis. The article concludes with a brief summary.

2. The model

This analysis uses MUDAS, a whole-farm discrete stochastic programming model of a mixed cropping system of Western Australia. It is based on the Merredin region of Western Australia, a region approximately 250 kilometres east of Perth and 35, 500 square kilometres in size. Variations in seasonal conditions are reflected in MUDAS through the modelling of the ramifications of eleven weather-years on enterprise yields and management. Seasonal uncertainty is a particular concern in the Merredin region where the variation in wheat yields is the highest in the state (Petersen and Fraser, 1999). Aspects of MUDAS will now be described under the following headings: the objective function (Section 2.1), weather year states (Section 2.2), soil types (Section 2.3), enterprise options (Section 2.4), and tactical adjustments (Section 2.5). For a more detailed exposition on the nature and structure of MUDAS, the readers are referred to Kingwell (1996). A brief discussion of why MUDAS was used will be presented after this description (Section 2.6).

2.1 The objective function

The objective function of MUDAS involves maximisation of expected utility (in the case of risk aversion) or expected profit (in the case of risk neutrality). However, the following analysis is simplified to omit the role of risk aversion. This simplification is justified given that previous studies have found the variance-induced change in farm management from external pressures to be small relative to the expected profit-induced changes, under levels of risk aversion consistent with Merredin levels (e.g. Kingwell (1996)).

The objective function used involves maximisation of expected terminal wealth as follows:

$$MaxE(W_t) = \sum_{t=1}^{n} S_t W_t \qquad (1)$$

where S_t = the probability of occurrence of ending at terminal state t,

W_t = terminal wealth at terminal state t,

n = the number of terminal states i.e. 55 states of nature; 11 weather-year states by 5 price states.

Marshall et al. (1996) define wealth as initial wealth plus annual profit in a decision period. Terminal wealth in MUDAS is specified as initial wealth plus profit in the decision period where initial wealth comprises mostly of the value of the land, cropping machinery and the sheep flock. The maximisation of terminal wealth is achieved through the selection of optimal levels of farm activities. These activities are represented as columns in a data matrix with the constraints or limitations to these activities represented as rows.

2.2 Weather-year states

MUDAS includes the impact of 11 discrete weather states (or seasons) on the farm enterprises. To limit the "curse of dimensionality", defined by Anderson (1991) as "where there are so many aspects to deal with quantitatively that clear analytical insight is difficult" (p. 4), these weather-years are defined as those with potential to affect farm management, in particular the dominant enterprises for the Merredin region: wheat and sheep.

The MUDAS weather-years are defined by four classifications as presented in Table 1. The first classification, the amount of summer and early autumn rain, is classified as either "much" or "little". The second classification is time of sowing wheat on clay soil. This classification is defined as either "early" if sowing of wheat on clay soil can commence before May 10, "mid" if sowing can commence between May 10 and early June, or "late" if sowing can commence in June or early July. The third classification is the nature and duration of sowing opportunities. Sowing opportunities for lupins on sandy soils were compared to those for wheat on clay soils. If a large difference was evident then the nature of the sowing opportunity was classed 'patchy'. Where little difference was evident then it was classed 'clean'. The continuation of crop sowing depends on the amount and duration of effective rainfall. A daily time-step simulation model of wheat growth developed by Robinson (1993) was used to classify the duration of sowing opportunities into continuous and discontinuous. Lastly, the timing of spring rains (Coelli, 1990), incidence of waterlogging and frosts (Anderson et al., 1992;

Table 1 Classification of MUDAS weather-year states

	Amount of summer and early autumn rain	Time of sowing wheat on clay soil	Nature and duration of sowing opportunities	Post-sowing weather conditions	Estimate of wheat yield[c] on clay soil (t/ha)	Estimate of what yield[c] on sandy loam soil (t/ha)	Probability
A	much	early	clean, cont[d]	-	2.27	2.18	.067
B	little	early	clean, cont[d]	favourable	1.86	1.94	.124
C	little	early	clean, cont[d]	unfavourable	1.03	1.03	.079
D	much	mid	clean, cont[d]	-	1.90	1.83	.135
E	little	mid	clean, cont	favourable	1.48	1.61	.157
F	little	mid	clean[e], cont	unfavourable	0.49	0.76	.067
G	little	mid	clean[e], discont	-	1.36	1.50	.067
H	much	late	clean[e], cont	-	1.59	1.42	.056
I	little	late	clean, cont	favourable	1.29	1.52	.056
J	little	late	clean, cont	unfavourable	0.33	0.51	.034
K	little	late	patchy, cont[d]	-	0.51	0.82	.157

Source: Kingwell (1996)

[c] Estimate of wheat yield made on first day of sowing; [d] Mostly continuous; [e] Mostly clean

Davidson and Birch, 1978) and temperature (Foulds and Young, 1977) affect crop production. Hence, the fourth classification is post-sowing weather conditions (which includes these factors) and is summarised as either “favourable” or “unfavourable”.

Ignoring weather-year states with low probability of occurrence, or those with a low likelihood of influencing management, resulted in the 11 weather-year states with probabilities of occurrences presented in Table 1. Estimates of wheat yields on clay and sandy loam clays are also presented for each of these weather-year states.

2.3 Soil types

Seven soil types are defined in MUDAS (Table 2). They are based on the soil types that are widely distributed in the Merredin region as described in Department of Agriculture (1991) and Stoneman (1992). These soils display a range of fertility. The acid sandplain soils (S1) are relatively infertile and are usually not suitable for crop production. The other soil types are suitable for crop production with the good sandplain (S2) being the most fertile.

2.4 Enterprise options

The ABS (1997) indicates that the region’s main enterprises are wheat, sheep and lupin production. Hence these three enterprises are represented in MUDAS. Other minor crops (e.g. field peas) and enterprises (e.g. pig production) are excluded from MUDAS as they do not form part of a typical farm.

Table 3 lists the rotation options represented in MUDAS. Lupin production is only possible on the sandy soils while wheat and sheep production is possible on all soil types. Costs associated with crop production on each soil class and weather-year include tillage, sowing, harvest, herbicide, chemical and fertiliser costs. Farmers change their rates of nitrogen application depending on season, expected prices, rotational phase and soil type. Hence, MUDAS incorporates yield-nitrogen response functions for each weather-year, soil type and rotation. To reflect conditions in the Merredin region, sheep are kept for meat and wool production. There are more than 20 classes of sheep in MUDAS, assuming a self-replacing flock. The structure of the flock is dependent on relative prices of wool and live-trade prices for lamb and young wethers, and the husbandry costs associated with each class.

Table 2 MUDAS soil types

Soil class	Description	Area (ha)
S1 (Acid sands)	Yellow, loamy or gravelly sands. Native vegetation is wodgil with sheoak and banksia on deep white sands.	500
S2 (Sandplain)	Deep, yellow-brown loamy sands. Native vegetation is gravillea and tamma.	500
S3 (Gravelly sands)	Yellow-brown gravelly sands and sandy gravels. Native vegetation is tamma.	250
S4 (Duplex)	Grey, sandy loams, loamy sands, gravelly sands and sand over white clay with yellow or red mottles. Native vegetation is mallee.	250
S5 (Medium heavy)	Red-brown, sandy loam over clay sub-soil. Native vegetation is salmon gum and tall mallee.	375
S6 (Heavy non-friable)	Dark red-brown sandy clay loams. Native vegetation is gimlet, morrel and salmon gums.	500
S7 (Heavy friable)	S6 soil treated with gypsum.	125

Source: Kingwell (1996)

Because of the biological complexity of the farming system, it is important to include some interdependencies of enterprises. MUDAS includes five main interdependencies. First, pasture phases increase the weed burden of subsequent cropping phases yet can be advantageous to subsequent crops through increased soil nitrification and disease breaks. Second, sheep selectively graze crop stubble that diminishes the stubble burden for tillage equipment. Third, the cropping phases reduce pasture set in the earlier years of a return to pasture production yet provide stubble as sheep feed after harvest in summer and autumn. Fourth, lupin crops are legumes and hence provide a yield boost to subsequent wheat crops due to nitrification of soils. Lupins also provide a disease break and aerate soils through deep root growth. Fifth, lupin seed that remains in the paddock after harvest provides nutritious feed for sheep.

Table 3 Rotation options in MUDAS[f]

Rotations on soil classes S1, S2, S3 and S4	Rotations on soils classes S5, S6 and S7[g]
WL	PPPP
WWL	PPPW
PPPP	PPW
PPPW	PPWW
PPW	PWPW
PPWW	WWWW
PWPW	
WWWW	

Source: Kingwell (1996)

2.5 Tactical adjustments

In reality, farm managers change their farm management as the year unfolds to either minimise losses or capitalise on extra profits (Antle, 1988; Bathgate et al., 1991; Dorward, 1994; Hammer, 1996; Mazzocco et al., 1992; Mjelde and Dixon, 1993; Schroeder and Featherstone, 1990; Stewart, 1991; Taylor, 1993). These tactical adjustments are approximated in MUDAS through the use of discrete stochastic

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[f] The wheat-wheat-pasture (WWP) and wheat-wheat-wheat-pasture (WWWP) rotations are not considered feasible for the Merredin region as, in the absence of re-sowing, pastures do not regenerate after the cropping phases of these rotations.

[g] W = wheat, L = lupins, P = pasture

programming which describes how some management decisions can be made after a state of nature is observed (Hardaker et al., 1991; Hazell and Norton, 1986).

The tactical adjustment options represented in MUDAS can be made at four stages (see Table 4) and relate to enterprise area, machinery and labour usage, seasonal sheep liveweight patterns, sheep agistment, some aspects of pasture and stubble management, lupin feeding and application rates of nitrogenous fertilisers. These options are specific for one or a number of weather-year states. In reality, such options may give ramifications for not only that particular weather-year state but also subsequent states i.e. effects on soil fertility, weed burden and pasture availability. These ramifications are also captured in the model.

Table 4 The four stages in which tactical management decisions are made

Stage	Accumulated knowledge	Management decisions	Actual time of year
1		Determination of initial farm plan to be applied across all weather-years. This plan is adjusted in stages 2 – 4.	Beginning of the year
2	Quantity of summer rain	Feed decisions	March/April
3	Timing and nature of the sowing opportunity	Tactical adjustments concerning crop and pasture areas, deferment of pasture feed, the livestock enterprise, hiring of additional casual labour and rates of application of crop and pasture nitrogenous fertilisers	April – June
4	Growing conditions	Agistment, livestock feeding and harvest labour	July - November

2.6 Why MUDAS was chosen for this analysis

MUDAS was used in this study for four reasons. First, it is a whole-farm model that includes the relevant biological complexities and interactions between enterprises in a typical wheatbelt farming system. These complexities and interactions are difficult to capture accurately outside the whole-farm modelling framework, and without them it is likely that the impact of seasonal forecasting technology would be under-estimated (Pannell, 1996). Second, it includes the stochastic nature of production outcomes associated with weather-years allowing the value of seasonal forecasting technology to be analysed. Third, it includes seasonal information from nearly 90 years of observations, providing a comprehensive probability distribution of weather-year states. Finally, MUDAS includes tactical decisions that arise sequentially as the weather-year unfolds. Seasonal forecasting technology would be of less value to the producer if it does not induce tactical changes in farm management. Hence, the full value of this information technology could not be assessed without the modelling of tactical adjustments.

3. Assessment of the value of seasonal forecasting technology for Western Australia farmers

The assessment comprises four parts. First, the methodology for valuing seasonal forecasting technology using MUDAS is presented (Section 3.1). Second, optimal farm management in the absence of seasonal forecasting technology (the standard solution of the model) is described (Section 3.2). The seasonal forecasting technology is then introduced and its long term average impact on farm management and profit is discussed (Section 3.3). Lastly, the aggregated value of the seasonal forecasting technology for the Merredin region is presented with recommendations for directions in future climate research (Section 3.4).

3.1 Simulating increased information through seasonal forecasting technology

The aim of this analysis is to evaluate the economic benefits of a technology that generates seasonal forecasting information for Western Australian farmers. The overall benefit of the forecasting technology is assessed rather than the forecasts themselves. There is potential for confusion over this central aim. If it were the benefits of the forecasts that were being evaluated, a representative sample of forecasts would be determined, and Bayes' Theorem would be used to revise the probabilities for the coming season to reflect information from each forecast. The model would be solved for each forecast and the expected return from these solutions would be weighted by the probability of observing each forecast to find the expected value of the forecasts. This methodology would be suitable if a forecasting technology had already been developed and the precise form of the resulting forecasts was known. However, where such a technology has not been developed a different approach is required. The *ex ante* approach used in this analysis will now be described.

Consider first how the forecasting technology should be specified. The formulation used here is based on that provided by the SOI in the northern and eastern parts of Australia which indicates whether an above average rainfall year is "more likely" or "less likely". This information is given as a once-a-year event, made public at the start of the farm planning period (stage one of decision making).

Now consider the economic impact of the information technology. As Table 1 outlines, the seasons identified in MUDAS have a four-dimensional character which makes it unlikely that the overall impact of any feasible forecasting technology will do more than reduce the general level of seasonal uncertainty faced by Western Australia farmers. Consequently, in what follows the complete forecasting technology is characterised as providing an overall reduction in seasonal uncertainty, but without any change in expected yield. A mean-preserving reduction in uncertainty is specified as this has been the favoured method of representing the value of risk-reducing information since Newbery and Stiglitz (1981). Note that it is straightforward to modify the probabilities in other ways, such as to increase or decrease expected yield. However the approach used in this study can be viewed as representing an “average” assessment of the value of many years of climate forecasts, where sometimes this information would imply increased expected yields and in other cases decreased expected yields, but overall would provide a decrease in seasonal uncertainty.

The new set of weather-year probabilities is calculated assuming the expected yields for each weather-year are those of the standard solution. Table 5 presents the expected yields for each weather-year, the MUDAS standard probabilities and the new set of probabilities. The highest-yielding weather-year, A, and the lowest-yielding weather-years, F and J, are assigned probabilities of zero, and the probabilities of the other weather-years were altered so that the average yield remains at approximately 1.50 t/ha and the coefficient of variation of yield (CV_y) decreases from 24.4 per cent to 17.1 per cent[2]. Note that levels of CV_y of approximately 17 per cent are common for shires in the vicinity of the Merredin region (Petersen and Fraser, 1999).

This approach raises the issue of reliability, on which the value of the information technology is conditional. First, the (approximately 30%) reduction in seasonal uncertainty is specified such that a coefficient of variation of yield common for shires in the vicinity of the Merredin region is produced. This specification is viewed as a minimum standard for the information advantages of a forecasting technology, and therefore will produce conservative estimates of benefits. Second, the benefits for farmers of improved seasonal information are generated by reduced losses in “poor” years and enhanced gains in “good” years. The approach taken here is a mean-preserving reduction in the coefficient of variation of yield which means that although the results capture the benefits of reduced losses with better information about the likelihood of “bad” years, the benefits of enhanced gains with better information about the likelihood

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[2] Note that MUDAS is an ideal tool for evaluating the benefits of forecasting technology as it includes weather information based on nearly 90 years of observations, and therefore its probability distribution of weather years can reasonably be treated as the "actual" distribution rather than one that farmers are "learning" (as in the Bayesian approach). We are grateful to an anonymous referee for helping us to clarify this point.

of "good" years is underestimated. Nevertheless, the approach supports the impact of the previous specification of "reliability" to produce a lower bound estimate of benefits.

Table 5 Probability distributions for the standard model and the model with decreased seasonal uncertainty

Weather-year	$\bar{y}$ for each weather-year (t/ha)	Standard probabilities	Probabilities for model with decreased seasonal uncertainty
A	2.08	0.067	0.000
B	1.70	0.124	0.146
C	1.62	0.079	0.079
D	1.77	0.135	0.157
E	1.68	0.157	0.179
F	0.81	0.067	0.000
G	1.61	0.067	0.067
H	1.47	0.056	0.056
I	1.32	0.056	0.107
J	0.63	0.034	0.000
K	1.07	0.157	0.208
	Average yield (t/ha)	1.49	1.50
	CV_y (%)	24.4	17.1

It is conceded that this *ex ante* approach will not provide as accurate an evaluation of the benefits of a forecasting technology as would be the case if the precise nature of the technology were known. However, it is arguable that it at least provides a lower bound estimate of these benefits that may be of use in a research evaluation context.

3.2 Optimal farm management in the absence of seasonal forecasting technology

The standard MUDAS solution in the absence of seasonal forecasting technology is presented in this section. Recall that a grower determines an initial farm plan but then makes tactical adjustments to this plan as the weather-year unfolds. Overall, Table 6 indicates that average land use is fairly evenly divided between crop (48 per cent) and pasture (52 per cent) production, with wheat being the dominant crop. Tactical adjustments of land-use are made in relatively moderate (i.e. H) and high (i.e. A and D) yielding weather-years where wheat areas and stocking rates are increased as potential wheat and pasture yields are relatively high. However, in poor-yielding weather-years (i.e. I, J and K), no adjustments are made as prospective yields are low and pasture production is expected to be inadequate to sustain higher stocking rates.

Table 6 Average land use in the absence of seasonal forecasting technology

Land Use	Area	
	ha	%
Total crop	1211	48
Wheat	822	33
Lupins	389	16
Pasture	1289	52

Average nitrogen application rate and the corresponding average wheat yield are presented in Table 7. In relatively high-yielding weather-years (i.e. A and D), levels of $\overline{N}$ are very high as the capacity of the plant to utilise nitrogen to increase yield is high. On the other hand, in relatively poor-yielding weather-years (i.e. J and K), levels of $\overline{N}$ are relatively low as the level and timing of rainfall events are such that the plant has limited capacity to utilise the fertiliser to increase yield.

Table 7 also gives sheep enterprise management information. The sheep enterprise is a self-replacing, ewe-dominant flock with the primary focus of producing young sheep. Young sheep are lucrative as they attract higher prices than older sheep (ABARE, 1999). Also, young sheep produce finer wool than older sheep, and finer wool attracts a higher price than broader wool (ABARE, 1999).

Table 7 **C**rop and sheep enterprise management in the absence of seasonal forecasting technology

Average yield (t/ha)	1.53
Coefficient of variation of yield (CV_y) (%)	24.8
Average nitrogen application rate (kg urea / ha)	61.4
Average number of sheep in winter	4012
Average number of sheep in winter less agistment	3985
Average stocking rate in winter (DSE / pasture ha)	3.09
Average level of supplementary feeding (tonnes of lupins fed)	109

The main tactical adjustments made to the sheep enterprise are agistment and supplementary feeding levels. Most agistment occurs in weather-years F and J, where pasture production is very low and it is cheaper to agist then supplementary feed them with purchased or retained lupin feed. As may be expected, supplementary feeding occurs in relatively poor-yielding weather-years (i.e. F, J, K) where pasture production is limited.

Average financial outcomes of the model are presented in Table 8. Expected terminal wealth, $E(W_t)$, comprises initial wealth plus expected profit, $E(\pi)$. Initial wealth comprises initial equity and land, land improvements (e.g. dams and fences), buildings, plant, equipment and cropping machinery. As initial wealth does not depend on outcomes in wheat and wool prices, changes in terminal wealth are dependent on changes in $E(\pi)$. In the absence of the seasonal forecasting technology, $E(W_t)$ is equal to \$856, 555 and $E(\pi)$ is equal to \$61, 727. The variation of profit, $Var(\pi)$, across weather-years is equal to 1.14×10^{10}, hence the coefficient of variation of terminal wealth, CV_{W_t}, across weather-year states is equal to approximately 12 per cent and the coefficient of variation of profit, CV_π, is equal to 173 per cent.

Table 8 Financial information in the absence of seasonal forecasting technology

$E(W_t)$ (\$)	856, 555
$E(\pi)$ (\$)	61, 727
$Var(\pi)$	1.14×10^{10}
CV_{W_t} (%)	12.44
CV_π (%)	172.65

3.3 Long term average impact of seasonal forecasting technology on farm management and profit

The previous section investigated optimal farm management in the absence of seasonal forecasting technology. This section analyses the long term average impact of forecasting technology on farm management and profit. The probability of occurrence of each weather-year has been altered according to Table 5. Forecasting technology is of value to a grower both because of reduced seasonal uncertainty and because it induces changes in management that cause farm profits to increase. The broad effect of the information technology on land use is a relatively small increase in wheat area planted at the expense of lupins and pasture (Table 9). Associated with this is an increase in average wheat yields due to an increase in average nitrogen application rate (Table 10). Average levels of agistment and supplementary feeding decrease due to a decrease in average sheep numbers (Table 10). Overall, a grower's supply response to seasonal forecasting technology is an increase in wheat area planted and average nitrogen application rates for wheat. Table 11 demonstrates that the long term impact of the seasonal forecasting technology on a grower's income stream is an increase in $E(\pi)$ of approximately 5 per cent and a decrease in $Var(\pi)$ of approximately 26 per cent[3]. CV_π is decreased due to the changes in both $E(\pi)$ and $Var(\pi)$.

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[3] The probabilities of weather-year occurrence were altered such that wheat yield variability decreased by 30 per cent. However, as nitrogen application rates increased (a risk increasing input (Regev *et al.*, 1997)), $Var(\pi)$ did not decrease proportionately.

Table 9 The impact of seasonal forecasting technology on average land use

Land Use	No seasonal forecasting technology		With seasonal forecasting technology	
	ha	%	ha	%
Total crop	1211	48	1214	49
Wheat	822	33	829	33
Lupins	389	16	385	15
Pasture	1289	52	1286	51

Table 10 The impact of seasonal forecasting technology on crop and sheep enterprise management

	No seasonal forecasting technology	With seasonal forecasting technology
Average yield (t/ha)	1.53	1.58
CV_y (%)	24.8	17.4
Average nitrogen application rate (kg urea / ha)	61.4	71.7
Average number of sheep in winter	4012	3980
Average number of sheep in winter less agistment	3985	3980
Average stocking rate in winter (DSE / pasture ha)	3.09	3.09
Average level of supplementary feeding (tonnes of lupins fed)	109	94

Table 11 The impact of seasonal forecasting technology on a grower's income stream (per cent change in brackets)

	No seasonal forecasting technology	With seasonal forecasting technology
$E(\pi)$ ($)	61, 727	64, 809 (4.76)
$Var(\pi)$	1.14×10^{10}	9.07×10^{9} (-25.69)
CV_π (%)	172.65	146.96 (-17.48)

3.4 The aggregated value of seasonal forecasting technology for the Merredin region.

It is estimated that the long term impact on farmers in the Merredin region of Western Australia of seasonal forecasting technology that decreases seasonal uncertainty by 30 per cent is an increase of profits of approximately 5 per cent ($1.23/ha). It should be recognised that this value is low compared with previous studies. For example, Hammer (1996) and Marshall et al. (1996) found that tactical adjustments due to improved information derived from seasonal forecasting for wheat crop management in the Queensland grain belt increased profit by approximately $10/ha and $3.60/ha respectively. However, it is expected that seasonal forecasting technology would be more valuable in Queensland where seasonal uncertainty is relatively high compared with Western Australia (Scoccimarro et al., 1994). In addition, Fox et al. (1999b) valued precipitation forecast technology for wheat crop management in Ontario, Canada. An average value of $100/ha per year was obtained, although this value varied significantly between the years studied (1994 and 1995). Again, higher values are expected for this region than for Western Australia due to higher levels of seasonal uncertainty and productivity (average Ontario wheat yield is 4.25t/ha compared with 1.5t/ha for the Merredin region). In addition, Fox et al. (1999b) considered the value of seasonal forecasting technology in years where the forecast is of particular benefit (i.e. mean crop yields are increased). This contrasts with the approach taken in this paper which represents an “average” assessment of the value of many years of climate forecasts (i.e. the technology not the forecasts themselves are assessed).

A 1996 survey counted 754 farm holdings in the Merredin region. Hence, the aggregated annual value of seasonal forecasting technology for the region is approximately two million dollars[4]. It should be noted that it is likely that climate forecasting information developed by an agency such as the IOCI would be applicable to a larger area of the

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[4] It is likely that the number of holdings in the Merredin region has decreased since 1996, however, the average size of the holdings would have increased as a result. Hence, the change in holding number is unlikely to significantly affect the results.

south-west agricultural region of Western Australia than the Merredin region. Consequently, a more broadly applicable seasonal forecasting technology would provide substantial benefits for farmers in Western Australia giving support for the allocation of funds to climate forecasting research.

4. Conclusions

At present, accurate seasonal forecasting techniques do not exist for Western Australia, although the Indian Ocean Climate Initiative has developed systems which show promise. This analysis provides an assessment of the value of seasonal forecasting technology for crop-livestock farmers in the Merredin region of Western Australia, the region with greatest seasonal uncertainty in the Western Australian agricultural zone. A whole-farm, discrete stochastic programming model, MUDAS, is used. The model represents the uncertain production environment with eleven discrete weather-year states, each with an associated probability of occurrence. The weather-years states were defined using meteorological records from 1907 to 1995. By using MUDAS, the assessment does not suffer limitations evident in other valuations of seasonal forecasting information where enterprises are considered in isolation from the whole-farm context, and a limited number of years is used.

The overall benefit of the information technology is assessed not the forecasts themselves. It is assumed that the forecasting technology decreases the uncertainty of possible yield outcomes by 30 per cent (to a level common for shires in the vicinity of the Merredin region) while preserving the average yield. This represents the average impact of many years of climate forecasts, some of which may forecast increased, and others decreased, expected yields. A five percent increase in expected profits is observed. The value of seasonal forecasting technology elicited in this study is low compared with estimates of other studies. However, a lower value is expected as the uncertainty and productivity of the Merredin farming system is much lower than those of the other studies. Considering the number of farm holdings in the area, the accumulated annual benefit of seasonal forecasting technology for the region is approximately two million dollars. Moreover, it should be noted that the benefits of an accurate seasonal forecasting tool are likely to be applicable to a larger area than just the Merredin region. Hence, support is given for the allocation of funds to climate forecasting research in Western Australia.

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