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Using climate information to approximate the value at risk of a forward contracted canola crop

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Abstract. In recent decades farmers have used financial instruments such as cash forward contracts to lock-in a price for increasing proportions of their crop through different stages of the production cycle. Given the high variability of the Australian climate this practice has inherent risk with drought induced crop failure being significantly probable. Under failed crop conditions farmers buy themselves out of the contracted position at prevailing prices thereby compounding the financial burden of crop failure. This paper reports on the role of the relatively recent developments in climate prediction, based on the SOI phase system, to develop crop yield probability distributions using regression approximation and to evaluate the Value at Risk of establishing a forward contracted position. Value at Risk is here defined as the 5% interval of the probability distribution of Enterprise Gross Margin and is used to ascertain the capital adequacy of a business in the face of a worst-case scenario.

Keywords: Canola crop, agricultural risk management

Introduction

Pre-harvest contracting of Canola in the pre- and post-sowing period has been used to varying degrees by Australian farmers over the past few decades to lock in an economically viable price for their crop (Lubulwa et al. 1997). Farmer focus groups and interview results conducted in south-eastern NSW during 2003 indicate that since the 2002 drought in eastern Australia the use of forward contracts has declined and this has been confirmed by interviews with a major commodity trading company. This social research evidence suggests that many farmers had been financially "burnt" by the forward selling decision with drought conditions resulting in crop failure and an inability to fill legally contracted positions that were entered into early in the growing season.

To enable farmers to have some certainty with respect to the final price of their crop however, forward contracts still have an important role to play in fixing farmers' incomes. Certainty of price provides some assurance for financiers and farm operators that adequate cash flow will occur to cover costs of production at the end of the season.

As discussed above, the practice of price fixing has inherent problems. Whether you are a grower or a trader, forward selling or being short in the market is considered a high-risk strategy (Bittman 2001). Selling short is selling something that you don't have based on the view that you will be able to supply it at a later date. Understanding the

downside risk (Nawrocki 1999) of a short trade is important for financial management. With forward physical sales the risk of not fulfilling a contract is attributed to what is known as the washout cost. This cost is the difference between the cash price of Canola at harvest time and the price agreed to in a contract, plus an administration fee (Cottle 2003).

Given recent improvements in climate forecasting methods (Hammer et al 1993; Nicholls 1997) a computer-based bio-economic model has been developed to explore the role of SOI phase-based climate forecasts (Stone et al. 1996) to approximate the probability of achieving a range of Canola yields and Enterprise Gross Margins (EGM) based on forward sold positions. The question to be answered is "what is the value of the risk in a worst-case scenario given expended operating costs, forward prices, known rain, probable future rain and probable harvest-time cash prices at each stage of the growing season?" This paper introduces a model designed to address this question for a Canola enterprise.

Model Development

Most studies undertaken in farm risk have been aimed at finding solutions to minimize variance of income and if necessary at the cost of income (Pannell et al 2000), yet Ortmann et al (1992) report that farmers seek information to assist in defining expected outcomes for tactical decision-making to maximize the opportunity for profit and not necessarily to avoid risk. For Malcolm

(1994) “the elaborate decision analytic methods such as those espoused in the decision theory and systems literature are not much use in practice in the very complex and uncertain situation of the farm business” and he claims the straight forward budget is much more useful as a decision aid.

The aim here then is to enhance the simple tools that are already in use through introducing a stochastic analytic process to identify the range of probable outcomes of a decision to forward sell or not forward sell a proportion of a crop using fixed price contracts.

One measure used to assess the downside risk of a trading position is known as Value at Risk (VaR) (Linsmeier and Pearson 1996). VaR is a measure used to establish whether or not a business has adequate capital to cover a worst-case scenario (Johansson et al. 1999).

Traditional VaR in the finance sector uses a variance-covariance matrix to determine the VaR at a 5% probability for periods of days and months with little extension beyond the year (Best 1998; Johansson et al 1999). In agricultural situations the realization of cropping system output only occurs once per year and in the Australian context is highly variable across the years due to climate variability and global commodity market fluctuations. Under these conditions Manfredo and Leuthold (1999) argue for using a full value approach to VaR. That is a measure that calculates a full probability distribution of gains and losses for a portfolio of assets over extended time periods using the historical record as the dataset. The 5% interval is then used to assess the Value at Risk.

The Decision Problem

A farmer makes a number of input and price management decisions throughout the growing season and at each decision point it is proposed that a portfolio distribution and capital requirement or VaR can be calculated to determine the downside risk of that decision.

It is proposed that the probability distribution of yield is approximated by use of the Southern Oscillation Phase system to determine probable Growing Season Rainfall (GSR) and then, via a Canola yield response model, to determine the probable distributions of Canola yield. The approach is to then use the historical distribution of prices and the approximated distribution of yield to determine the VaR at the 5% probability interval. This approach to downside risk is used to identify and compare the potential loss and therefore the capital required to cover a loss resulting from a worst-case

climate and pricing scenario given a forward trading position.

Yield Risk

The first problem in constructing an analysis of a cropping portfolio is to identify the probable yield of the crop given a climate forecast. Yield uncertainty arises because some input variables are not under the decision maker's control and their levels are not known at the start of the season. With multiple decision variables (X_1, \dots, X_n), predetermined variables (X_{n+1}, \dots, X_k), and uncertain variables (X_{k+1}, \dots, X_m), we have the risky response function

$$Y = f(X_1, \dots, X_n; X_{n+1}, \dots, X_k; X_{k+1}, \dots, X_m; t)$$

With (t) being the time function that recognizes changes from unknown to known variables as the season progresses (Dillon and Anderson 1990).

In this study only the relationship between yield and GSR is analysed with progressive changes in the probable outlook for GSR occurring as the season unfolds.

To develop the GSR response function Statistical Local Area (SLA) (ABS 2001) or farm-level yield response curves to GSR have been calculated through regression of the ABS yield data or farm level historical records against regional or farm-level rainfall records respectively. In general the yield response regression function takes the form of

$$Y = ax^2 + bx + c + E$$

where a, b and c are constants and E is the standard error of the regression.

Static regression models of yield response to environmental variables have been recommended for use in farm scale DSS by authors such as Dillon and Anderson (1990) and used in the development of DSS in wheat protein targeting and marketing in Western Australia by Bowden (1999). With the advent of fast computing facilities and improvements in record keeping and benchmarking through extension programs like Top Crop, it is possible for site specific yield/GSR response curves to be generated and updated on an annual basis for use in generating probable distributions of yield in the upcoming season.

Why not use water use efficiency (WUE) constants for estimating potential yield? The WUE envelope developed by French and Shultz (1984) is a simple linear approach to estimating the potential yield of a crop as a benchmarking activity and more recently as forecasting tools based on climatological probabilities. Examples include potential yield calculator or PYCal (Tennant and Tennant 1996) and Crop Risk (van Rees et al 2000), both crop risk models developed in Australia.

When using the WUE constant to derive probable yield distributions the probable distribution of rainfall is used to calculate a straight-line response to rainfall. This constant response, while providing a theoretical potential, does not reflect historical outcomes that have imbedded in them the impacts of a range of variable responses to limiting factors such as pest, disease, weed and fertility influences that impact on the actual response of a crop to growing season rainfall. While it is agreed here that the regression based model is not a perfect predictor of crop response, the regression approach does provide a more representative response to rainfall than the French and Shultz' (1984) Water Use Efficiency equation without having to perform major calibration as required by a deterministic crop model such as APSIM (McCowan et al. 1996) or PERFECT (Littleboy et al. 1993).

Price Risk

Without active risk management the farmer's probable distribution of unhedged gross revenue $P(R_U)$ is the product of the probable spot price at harvest $P(p_s)$ and the probable farm yield $P(Y)$ given the probable distribution of GSR:

$$P(R_U) = P(p_s) * P(Y | GSR).$$

If a farmer forward sells a proportion of the crop the probable gross revenue $g(R_f)$ is the product of a certain forward price $h(p_f)$ where $h = 1$ times a proportion of the expected crop q plus the remaining expected quantity i ($y - q$) times the probable harvest time cash price $j(p_s)$. Where g , h , i and j are probabilities and t being a recognition of the time step variable where contracts can be taken out progressively through the growing season then:

$$R_f = f(p_f \cdot q + (y - q) p_s; t)$$

The risky profit function can be represented by the sum of the revenues less marketing cost minus the sum of the input costs such that:

$$\Pi = 1/T \sum (R_f - c | Y, p_s, p_f) - \sum (p_i X_{it} | Y) \quad (i=1, 2, \dots, n),$$

Where c is the costs of marketing and given the probable distributions of yield Y , spot price p_s , forward price p_f . Fixed costs are not represented in this model but can be easily incorporated. The empirical distribution is constructed by identifying each contemporaneous realisation of prices and yields with one of the possible states of distribution and assigning it a probability that assumes independence between price and yield.

This model has been extended further to explore the production risk of forward

contracting the crop and the implications of not being able to meet these contractual obligations when drought induces a crop failure. The standard practice for dealing with an inability to honour a forward contract is known as washing out the contract. At the time of writing Grain-Co's (now Graincorp) policy on washing out cash contracts was to charge an administration fee and, if the harvest time market price is greater than the contract price, the farmer pays the difference (Cottle pers. comm. 2003). If however, the harvest price is below the contract price then the farmer only pays the administration fee to close out the contract. Up to 2003 there was no standardized market for trading of forward contracts, however, in practice it seems plausible that a farmer would purchase grain on the open market to fulfil the contract obligation.

Extension to the model requires two scenarios to be addressed. The first is for approximating the expected washout cost when the amount forward contracted is greater than the probable yield. The second is for dealing with the problem of writing the crop off and not harvesting.

To address the issue of partial washout of a forward position a logical IF THEN branching algorithm is required such that when the amount forward sold is greater than the probable harvest, the value of the washout is calculated as part of the enterprise profit/loss function Π . This algorithm is:

If $V_c > (Y_p | GSR, SOI)$ Then

$$\Pi = Y_p P_c - ((V_c - Y_p) P_h - (V_c - Y_p) P_c) - C_a - \sum P_i X_i$$

Where

Y_p = the probable yield given a probable GSR determined by an SOI phase indicator

P_c = the average contract price forward sold

V_c = the volume forward contracted

P_h = the probable harvest spot price

C_a = the administration cost associated with washout of a contract

$\sum P_i X_i$ = the sum of the costs of production

When a rule for not harvesting a crop is reached, e.g. expected GSR of less than 110 mm, then the worst-case scenario is calculated for washing out the whole of the contracted position. The complexity of the situation is further compounded by whether or not the probable harvest price is more or less than the average contract price. A washout cost is only incurred if the probable harvest price is more than the contract price. The following algorithm represents implementation of this rule.

If $GSR \leq 110\text{mm}$ AND $P_h > P_c$ then

$$\text{VaR} = - (V_c \cdot P_h) - (V_c \cdot P_c) - C_a - \sum P_i X_i$$

Input Data

The farm data used are the history of the annual total Canola yield (tn), area sown (ha), farm growing season rainfall (April to October, mm), enterprise variable cost (\$/ha), crop calendar of operations, record of forward selling decisions, farmers' intention of forward selling including the contracted tonnage and price.

Where annual yield data were not available they were supplemented with local statistical area data derived from the ABS annual agricultural census. Rainfall records were also collected from farms or supplemented with RAINMAN (Cleworth et al. 1999) rainfall records for the nearest town.

Historical market data used in the model include the weekly Canola price delivered port (\$/tn) since 1995 when export influences became a significant factor in price determination (Bartholomaeus 2002). These data have been derived from archived newspapers and personal collections. Price data is used to calculate both the frequency and the cumulative probability distribution of harvest time prices.

The model calculates yield distributions using both SOI base forecasts and climatological distributions. It then generates probable enterprise net returns after operating costs for both forward sold positions and uncontracted positions.

As Mjelde et al (1988) point out, methods for the analysis of the value of information sources can be limited to accuracy of the forecast and comparison of profit functions given probable futures. In the context of comparing enterprise VaR using alternate climate forecasts, assessment of accuracy is based on the incidence of violation of the risk frontier (Jorion 2001) and value is based on comparison of returns at the 5% interval and is similar to the stochastic dominance analysis described by Anderson et al (1977) and used by Prentis and Cox (1995) in similar studies. This model was tested using independent data from six case study farms over a two-year cropping period. Using the 2003 cropping season the model provided a good fit to the seasonal outcome. In 2002, however, the output was not satisfactory. In the following case study the results of VaR of forward selling strategies using alternate seasonal climate information, are compared against a normal or mean GSR in order to monitor variance from the mean as the 2002 drought year progresses. Problems with the model are discussed.

Example case study

The farm used in this case study is located to the northwest of Young, NSW. The farm business would normally crop around 550 ha Canola with the farmer's yield expectations between 1.6 and 1.8 t/ha. A regression analysis of the farm's yield response of Canola to seasonal variations in rainfall for the growing season April to October is presented in Figure 1 (see Appendix). Standard error for this distribution was 0.22 t/ha.

The selling strategy used in this farm business in 2002 was to follow a program of forward sales throughout the season so that up to 60% of the crop would be sold by October. Soil moisture monitoring and price data are the main data used for deciding on pricing tactics on this farm.

The following is a progressive analysis of the projected yield response to GSR given recorded rain, climatological and SOI based GSR forecasts and financial risk results from alternate selling strategies during the drought situation experienced in 2002.

At the start of the season no rain had been recorded and the model does not take account of stored soil moisture that has accumulated through the fallow. Using GSR data derived from Rainman, probable yield distributions were generated (Figure 2, see Appendix), using the above yield response curve. At the start of the 2002 growing season expected yield was calculated at 1.8t/ha based on median expected rainfall for the total growing season, so the expected outcome is 990 t.

The SOI Negative phase in April has a KW/KS³ probability of 0.542. This indicates insignificant correlation between the SOI Phase and the long-term seasonal outlook. In contrast the climatological forecast shows a significant KW/KS probability of 0.914, i.e. there is a good correlation between climatological forecast and whole of season expectations.

Prior to sowing the farmer had taken a forward sold position of 150 t. Analysis of this financial profile shows only a marginal difference in the risk profile for this farm's Canola enterprise (Figure 3, see Appendix) with or without a forward sold position. Based on climatological information the approximate VaR at the 5% interval at the start of every season is to break even with a 1% chance of losing the expended costs of production. The forward sold position indicated some protection in a combined collapse of both the market and production components, given both the SOI phase negative and climatological forecast.

At the 1st July 2002 expected yield had dropped to 1.41 t/ha using received rain (87 mm) and expected median rain for the rest of the season of 233 mm. Overall the yield probability distribution was showing a significant downward trend from a climatically normally base year (i.e. the long-term average growing season).

The SOI Negative phase recorded for this region in May-June 2002 has a KW/KS probability of 0.999 for the four-month prediction to October. In contrast to the climatologic forecast, the SOI based prediction indicated only 13% chance of yield above 1.5 t/ha with the 50-percentile yield at 0.92 t/ha (Figure 4, see Appendix).

Based on received rain and soil moisture the farm manager had, however, continued to forward sell his crop based on the management strategy of following a set program plus the temptation of higher than average prices for Canola.

When comparing the VaR of the selling strategies using alternate climate forecast in July 2002 the SOI Negative forecast with or without a forward sales position was showing a worse scenario than that of the climatological distribution. When comparing selling strategies under the worst case scenario, the VaR of a strategy with forward sales indicated smaller losses than those indicated by a strategy with no forward sold positions.

By the beginning of October 2002 agronomic conditions had improved slightly with 222 mm rain recorded for the period April to the end of September. While the overall outlook for the season was still well below average (Figure 6, see Appendix), the climatological outlook showed a 50% chance of achieving 1.00 t/ha using climatological information and a 45% chance of achieving the same yield with a Negative SOI phase for the preceding two months (KW/KS probability of 0.996).

Financially the SOI forecast in October was showing a VaR at the 5% interval for the uncontracted position of negative \$46,000 with contracted positions showing break even or better.

The reality of the 2002 drought year was that both climatic and price conditions were outside the range of past experiences incorporated into the data that were used to formulate this analysis. At the beginning of October 2002 the model indicated an expected (50 percentile) yield of 1.00 t/ha and local agronomists in the Young region concurred with this estimation.

What then happened was that extreme heat and zero rain conditions were experienced in October and the farm ultimately yielded 0.2

t/ha. At the same time harvest time prices peaked at over \$550/t. This was over \$100 higher than previous peaks in Canola prices.

Given the contracted position entered into, this farm business incurred washout costs of \$37 000 for the forward sold position, thereby compounding the overall loss resulting from lost production costs to equal \$181 000. This outcome violated the risk profile for the forward sold position for both the SOI based forecast and the climatological forecast.

Consistent with Tversky and Kahneman's (1982) theories of psychological anchoring this extreme situation had considerable impact on the farmer. As a consequence no forward positions were taken in the following year (2003), even though seasonal conditions were favourable, average yields were predicted by this model, and the standard forward selling strategy would have returned better than harvest cash prices received.

Discussion

For effective risk management, understanding the mean yield and price levels are insufficient since it is the extreme events that occur with low probability, which can bankrupt a farm business.

A bio-economic Canola model has been developed to test whether or not climate information could be used to evaluate the risk of a forward sold position for Australian farmers. The basic assumption in developing this model is that farmers are interested in information that allows them to assess the implication of tactical decisions and not necessarily optimal solutions that minimise risk. Given this situation, an historical VaR method of risk assessment has been used to evaluate the downside risk of a forward sold position given a climate forecast.

Using the above system it can be seen that the SOI phase system under some circumstances shows deviation in the risk profile of an enterprise and could be used in conjunction with other agronomic information to inform decisions about pricing a crop. This is especially so where adequate records are kept to enable formulation of farm specific GSR response models. Likewise monitoring the probable distribution of the financial status of an enterprise is possible, as is calculating the VaR given the influence of seasonal rainfall and a seasonal climate outlook. The main value is in comparing probable distribution against a standard or mean year and observing deviations from this.

There are however many limitations to the model presented. The usefulness of any system is dependent on the datasets used to formulate prior probabilities. The case study

above shows clearly that problems arise when conditions occur that are outside the datasets for both rainfall and price. While Hayman and Fawcett (2003) have shown that climate forecasts based on the SOI phase system have relevance to the southeastern cropping zones of Australia, the 2002 season showed that circumstances at the extremes of historical distributions test the efficacy of these systems of forecasting. It is doubtful that even complex models such as APSIM would have formulated the probable outcome that occurred in 2002. Independence between local yield and price may also be thrown into question by the situation in 2002. Supply and demand factors for global oilseed markets were such that shortages in Canola supplies compounded competition for local seed. Under these conditions local buyers were paying a premium on international Canola prices. This forced domestic prices to historical highs and outside the dataset used to construct the price distribution series. Yet it is these exact circumstances that decision makers need to monitor in order to minimise the impact of exceptional circumstances arising from yield and price extremes.

Where to now? The aim of the research was to test ideas around joining the key areas of price and yield risk using contemporary information sources and methods of analysis. Season climate forecasting systems have improved considerably, and methods such as VaR for monitoring risk positions are relatively simple yet important tools to aid in decision-making. To assess the full downside risk of a farm business would require a summing of the total downside risk of each enterprise using a similar methodology, however, sensitivity testing at the tail end needs further work as does the development of risk management strategies. To pursue this, plans are on the table to incorporate Monte-Carlo generated price distributions, simulating conditions beyond known extremes. In conjunction with this the model described above will be expanded to explore the role of futures and options contracts in reducing the downside risk of a cropping enterprise given extreme yield and price conditions.

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Appendix

Figure 1 Farm base regression analysis of canola response to growing season rainfall, Young, NSW

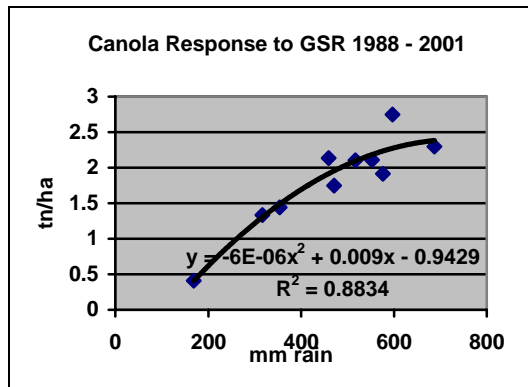


Figure 2 Approximated yield expectations in April 2002 based on climatological and SOI phase GSR forecasts

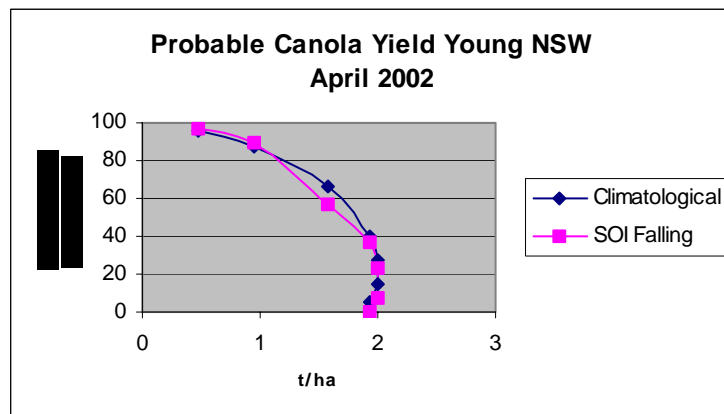


Figure 3 Value at Risk profiles for canola based on alternate climate information and selling strategies April 2002

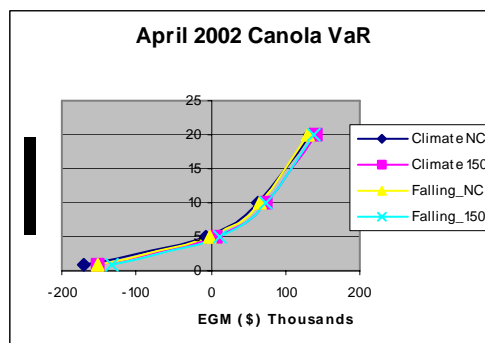


Figure 4 Comparison of probable canola yield using alternate GSR forecasts

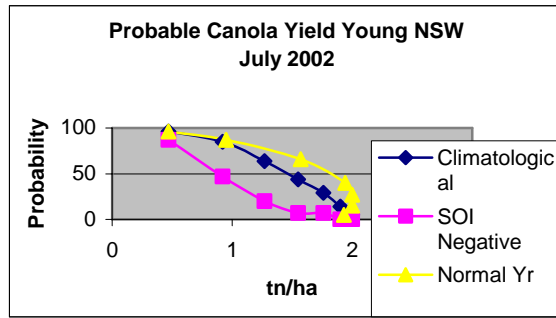


Figure 5 Comparison of VaR using alternate climate information and strategies (350 tn forward sold), July 2002

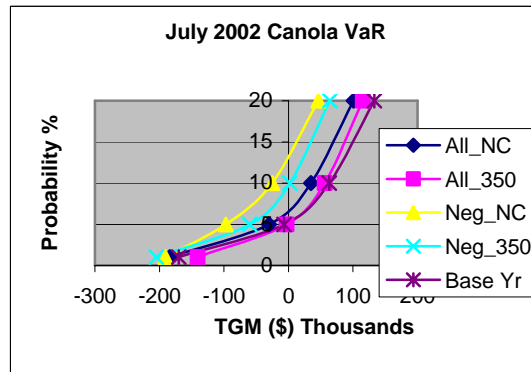


Figure 6 Comparison of probable canola yield using alternate climate forecast, Oct 2002

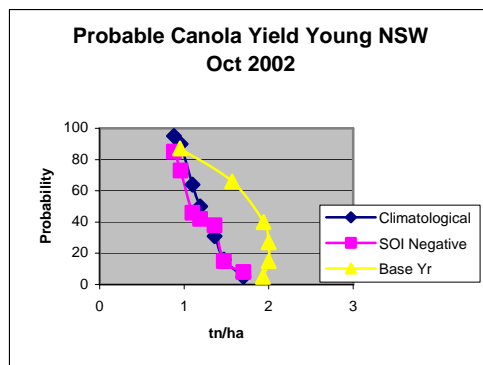


Figure 7 Comparison of VaR using alternate climate information and strategies (450 tn forward sold) Oct. 2002

