Wheat yield prediction and its effects on price risk hedging in Western Australia

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Abstract

Hedging price risk for crops during the season requires information on both price and yield. Information on price risk is available from futures markets, whilst yield risk is more difficult to assess as the farms' yield is not directly observable until harvest. This paper presents a method to predict wheat yield and studies the yield predicting effects on hedged wheat quantity for Western Australian wheat farms. A plant growth simulation model APSIM is used to estimate wheat yields with simulated weather conditions. Historical weather data is used to simulate the evolution of wheat yield expectations during the season. Futures price on Chicago Board of Trade (CBOT) is selected to represent international wheat prices during the season from May to December. Results show that this method can predict wheat yield at least three months before the harvest. With yield prediction information, the representative farm could avoid over hedging wheat yield in dry year and avoid under hedge in the wet year. As demonstrations, in the year 2010, yield prediction protects the farmer from over hedging 80% of wheat yield, while 8% of under hedge in the year of 2011. This method is an effective way to help wheat farmer to achieve the risk minimization objective while hedging through futures contracts.

Keywords: wheat yield prediction, APSIM, yield risk, hedging
1. Introduction

Historically, the Western Australian wheat industry has been exposed to high level of price and yield risk. Price per ton received by growers over 2009 to 2013 varied between $AUD 373 and $AUD 207 and the state average yield varied between 1.08 to 2.14 tons per hectare (ABARE, 2013). In addition, the Wheat Marketing Act 2008 have raised the exposure of supported wheat price to global levels and the increased price volatilities have raised the concern of price risk as well as the risk management (Curwen et al., 2011). Meanwhile, a lot of effort has been put into yield and revenue of crop farms to estimate and predict farm revenues, improve risk management capabilities and protect the farm revenue from catastrophic losses (NRAC, 2012, Islam et al., 2014, Potgieter et al., 2003) Accurate and timely crop yield forecasts would be beneficial to crop producers, state and federal agencies, crop insurance companies, and agricultural marketing agencies (Rijks and Baradas, 2000, Bannayan et al., 2003, Weiss et al., 2000, Quiring and Legates, 2008, Chavas, 2004). This paper presents a method to predict the wheat farm yield before harvest and applies this yield prediction information to adjust the hedged quantity through the futures market.

Weather condition is one of the most important factors that determine crop yield. Previous research has integrated crop simulation system and weather forecast system to make within-season yield predictions. Potential crop yields could be accurately forecasted during the growing season and be evaluated at harvest time (Bannayan et al., 2003, Chipanshi et al., 1997, Jagtap and Jones, 2002, Potgieter et al., 2005, Quiring and Legates, 2008). Quiring and Legates (2008) employed CERES-Maize (Crop Environment Resource Synthesis) to predict rainfed corn yields in Delaware, USA. By combining the observed weather information and forecast weather information, Quiring and Legates (2008) forecasted four times of maize yield before harvest time and proved that with reliable predictions of future weather conditions CERES-Maize can be used to forecast maize yield accurately up to 3 months before harvest. Bannayan et al. (2003) used CERES-Wheat to make within-season wheat yield forecasts at four experimental sites in the United Kingdom. Bannayan et al. (2003) utilized a weather generator to simulate future weather conditions and demonstrated that this approach could provide reliable predictions of wheat yield starting in June, which is around 230 days (7.5 months) after sowing and 60 days (2 months) before harvest. Chipanshi et al. (1997) used CERES-Wheat to make within-season yield forecasts at three locations in Saskatchewan, Canada. Historical weather data was employed to provide historical
information to estimate future weather conditions. Results have proved that CERES-Wheat can provide a reasonable estimate of expected yields 2 months before harvest.

In the Australian environment, the Agricultural Production System Simulator (APSIM) is widely tested and applied to simulate crop yields (Luo et al., 2005, Keating et al., 2003, Asseng et al., 1998, McCown et al., 1996). Asseng et al. (2001a) employed APSIM to simulate the water balance under a wheat crop in the central Western Australian wheatbelt. Keating et al. (2003) summarized the tests of robustness of APSIM on a wheat based farming systems. The close agreement between simulated yields and observed yields for soil water, soil nitrogen, crop biomass and crop yield demonstrated the validity and robustness of APSIM in these circumstances. However, to date, no study has utilized APSIM and weather forecasts to make within-season predictions of crop yields and revenues in Australia. The objective of this research is two-fold. The first objective is to determine if the weather simulation model and crop simulation model can be used to forecast rainfed wheat yield up to 7 months prior to harvest in Western Australia. The second objective is using the forecast wheat yields to guide the farmer to manage the price risk by hedging through futures market to achieve the risk minimization objective.

The organization of the paper is as follows: section 2 presents the data and methods, section 3 describes the accuracy of APSIM-Wheat yield forecasts, section 4 estimates the dynamic hedging ratios and evaluate its effects on hedge quantity, and section 5 concludes this paper with a summary of the results and implications.

2. Data and Weather Forecast

2.1 Site and Soils

Located in the middle latitudes (30º to 40º S), Western Australia has a dry summer subtropical climate similar to the Mediterranean basin. Kojonup (33.83º S, 117.16º E, elevation 305 m) in the south of Western Australia was selected to conduct the yield forecast. Kojonup has an average rainfall around 495 mm annually, with 60%-80% (300 mm– 400 mm) of the total rainfall occurs in the winter-spring period (May-October) and 20% to 40% ( 100 mm - 200 mm) of the total rainfall occurs in the summer – autumn period (November - April). The growing season for wheat is around 8 months, which is sowing in the autumn (May) and harvesting in the summer (late November to early December) (Asseng et al., 2001b).
A representative farm in Kojonup was selected to demonstrate the wheat yield prediction simulation. The representative farm only has an acid sandy loam soil type with the PAWC (Plant Available Water-holding Capacity) 90 mm and maximum rooting depth 150 cm. These soil parameters and potential rooting depths were derived from field measurements (Asseng et al., 2001b). Each simulation run commenced on 1 January. After running one simulation, the APSIM was reset into the original statue to ensure each simulation has the same starting condition. The sowing time was controlled by a sowing rule in the module of APSIM. Sowing was set between 5 May and 31 July, but before 5 June sowing will not happen unless at least 25 mm of rainfall had accumulated within the previous 10 days. Full details of wheat yield simulation parameter settings, including the fertilizers utilization, farm manager skills, soil types, are described in Asseng et al. (2001b).

2.2 Weather forecast

In order to feed the APSIM, weather data includes radiation, maximum temperature, minimum temperature, rainfall and evaporation are predicted. The approach to estimate future weather conditions is based on the historical weather data (Duchon, 1986). This approach is taking the weather condition of the coming season has same properties in the previous years as a given condition. And at the predicting date, weather scenarios in previous years have the same probability that could happen in the future. Based on a long period of historical weather dataset, this method does not generate new weather data that never been experienced but use the historical data with equal possibility. To characterize the local weather condition and include the climate changes that has occurred in the Kojonup, 30 years
of historical weather data was used to make weather predictions, from the year 1982 to 2011 (Chipanshi et al., 1997, Quiring and Legates, 2008).

![Figure 2 Weather Forecast Results for 2011](image-url)
Figure 2 illustrates the accumulative rainfall forecast of 2011 as a demonstration of weather simulation. There are eight rainfall simulations, starting from May, June, July, August, September, October, November and December, respectively. Before the starting date, weather data is the actual observation, whilst, after the starting date, 30 years historical weather data are utilized. Each year represents one possible weather scenario in the future. As the season approaching to the end, the cumulative rainfall is increasing and the range of forecast cumulative rainfall is narrowing down. The rainfall forecasts in November and December are getting closer to the actual rainfall observations than forecasts in previous months.

3. Accuracy of APSIM yield forecast

Fed with the simulated weather information, APSIM was used to simulate the bioprocess of wheat growth and predict the possible outcomes of the wheat yield at the harvest time. This range of yield predictions can be used to determine a mean yield prediction and to estimate the probability and uncertainty associated with each yield prediction (Chipanshi et al., 1997).

Simulated weather conditions were made by combining observed weather conditions up until the time of the forecast $t$ with predications of future weather conditions up to $t+l$. $l$ is the forecast lead time and $t+l$ equals to 365 or 366. The prediction of future weather conditions were based on 30 years (1982-2011) of historical data (Quiring and Legates, 2008, Chipanshi et al., 1997). Yield forecasts were made at 8 stages during the growing season, i.e. wheat yield was predicted at each month during the growing period (first day of May, June, July, August, September, October, November, and December). At each forecast date, observed weather data were used up to the forecast date and historical data was appended to create a full growing season of weather data. Thirty different possible weather scenarios (one for each historical weather scenario) were applied for each forecast date and these predictions of final yield are evaluated using the full season simulations.

3.1 Yield Forecast Results

This section evaluates the ability of APSIM to provide predictions of wheat yield in Kojonup in Western Australia, using data from three growing seasons of the year 2009, 2010 and 2011. These three years are particularly useful for evaluating model performance because weather
conditions were extremely varied (Table 1). During 2011, rainfall was above the average, which is the major reason that leading to above average yields. Rainfall in 2010 was far below the average level resulting in lower yields than the average level. Rainfall in 2009 is at the average level. Yield forecasts were conducted for eight different forecast dates for growing seasons of 2009, 2010, and 2011. For each forecast date, the observed weather data were used up to the day of the forecast and simulated weather data were used from the time of the forecast until harvest. Thus, 30 different simulations for each month were carried out for each forecast date.

Table 1 Monthly and Annual Rainfalls (mm) in Kojonup in Western Australia (1957-2011)

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>9.8</td>
<td>19.4</td>
<td>19.8</td>
<td>1.6</td>
<td>29.2</td>
<td>395.4</td>
<td>30.4</td>
<td>1.4</td>
<td>507</td>
<td>2.36</td>
</tr>
<tr>
<td>2010</td>
<td>2.4</td>
<td>15.8</td>
<td>41.6</td>
<td>16.4</td>
<td>41.6</td>
<td>117</td>
<td>40.4</td>
<td>12.8</td>
<td>348</td>
<td>1.46</td>
</tr>
<tr>
<td>2011</td>
<td>76.5</td>
<td>7.2</td>
<td>24.6</td>
<td>40.2</td>
<td>41.6</td>
<td>424.8</td>
<td>65.9</td>
<td>52</td>
<td>691.2</td>
<td>3.23</td>
</tr>
<tr>
<td>1957-2011 Mean</td>
<td>16.6</td>
<td>12.2</td>
<td>21.6</td>
<td>31.8</td>
<td>58.9</td>
<td>313.7</td>
<td>26.3</td>
<td>14.3</td>
<td>495.4</td>
<td>2.96</td>
</tr>
</tbody>
</table>

According to the results of wheat yield prediction (Figure 3), the model is able to correctly predict yield during all three years. In 2009, wheat yield in Kojonup was below the average (2.36 t/ha compared to an average yield of 2.96 t/ha between 1982 and 2011 in Table 1). Although rainfall in 2009 (507 mm in Table 1) was slightly above the average level (495.4 mm), the rainfall in May was 50% less than the average level, which caused the lower yield in the 2009 season. In 2010, wheat yield was significantly below average (1.46 t/ha). Rainfall in 2010 is far below the average level especially in the growing period June to October. This lack of precipitation during the critical growth phases resulted in wheat yields that were well below the average level. The 2011 growing season was much wetter than normal with high rainfalls during June and September in Kojonup. These wet conditions resulted in higher than normal yield (3.23 t/ha).

Box plots in Figure 3 summarize the yield predictions (kg/ha) for Kojonup of eight forecasts: May, June, July, August, September, October, November and December for 2009, 2010 and 2011. The line in the center for the box is the median, the top of the box corresponds to the 75th percentile and the bottom of the box corresponds to the 25th percentile. The length of the box is the inter-quartile range. If the baseline yield fallen into the box (the inter-quantile
range), the wheat yield is predictable at this prediction date (Quiring and Legates, 2008, Chipanshi et al., 1997).

Figure 3 Wheat yield predictions and cumulative probabilities of yield predictions.
There was a high variability in the yield forecasts in May and June, shown by the large error bar associated with each forecast in the box plots in Figure 3. This high yield variability shows that at the start of the growing season there is high level of uncertainty associated with wheat yield. When the simulations were conducted closer to harvest with more actual weather records, the error terms decreased and reached the lowest values approximately one month prior to physiological maturity. The yield forecasts conducted a few months prior to harvest resulted in a similar value to the baseline yield, which indicating the accurate yield forecast could be obtained by this method. However, predictability of yield depends on actual weather condition (wet, dry or normal). In the year of 2009, a normal year, wheat yield could be predicted at May but with great heterogeneities. In the year of 2010 (very dry year) and 2011 (very wet year), the wheat yield could not be accurately predicted until 3 months before harvest (October).

Since 30 time simulations were performed for each of the eight forecasts, it is possible to use the range of yield predictions to calculate the probability of obtaining a given yield (cumulative probability plots in Figure 3). Because the yield forecasts are most uncertain at the beginning of the growing season, the probability curves are flatter for the early forecast months of a growing season (e.g. May, June and July). However, as the season progresses, the probability curves become steeper indicating that there is an increasing certainty in the yield predictions. Despite the varied moisture conditions during the grow season, model-predicted yields were accurate during all 3 years. Therefore, it can be concluded that APSIM wheat is a suitable tool for predicating Kojonup yields (Keating et al., 2003, Robertson et al., 2002, Asseng et al., 1998, McCown et al., 1996).

4. Yield Prediction Effects on Hedged Wheat Quantities

Yield prediction effects on hedged wheat quantities are estimated in two scenarios: static hedging and dynamic hedging. A representative farmer is assumed to make all yield and marketing decisions at the beginning of the season, whereas all uncertainty is resolved at the harvest. The farmer produces wheat only and faces production and price uncertainties during the season. By static hedging, the farmer hedges wheat yield according to the first month dynamic hedging ratio and hold the position until harvest. By dynamic hedging, the farmer hedges wheat and adjusts the position every month to achieve the risk minimization objective. The farmer predicts the wheat yield based on average yield of previous years and predicts
price at May based on the information from the futures market. However, both the exact yield and price are unknown at the beginning of the season.

### 4.1 Hedging Ratio Estimation

Minimizing the variance of the hedged portfolio is one of the most popular methods to estimate the optimal hedge ratio (Johnson, 1959, Baillie and Myers, 1991, Dawson et al., 2000, Kuwornu et al., 2005). Under the mean-variance framework, using minimum variance (MV) hedge ratio, farmers are assumed to be infinitely risk averse.

The dynamic hedging ratio is estimated according to spot and futures prices information, while the hedged quantity is calculated by hedging ratio and wheat yield prediction. One way to calculate the MV dynamic hedging ratio involves the Constant Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroscedasticity (CCC-MGARCH) model (Bollerslev et al., 1988, Baillie and Myers, 1991, Dawson et al., 2000, White and Dawson, 2005). This technique will allow the hedge ratio to be updated during the hedging period. Specifically, in this research the CCC-MGARCH can be written as (Bollerslev, 1990):

\[ r_t = C x_t + \varepsilon_t \]  \hspace{1cm} (1)

\[ \varepsilon_t = H_t^{1/2} v_t \]  \hspace{1cm} (2)

where \( r_t \) is a \( 2 \times 1 \) vector of returns of spot and futures prices; \( C \) is a \( 2 \times 2 \) matrix of parameters; \( x_t \) is a \( 2 \times 1 \) vector of independent variables, which contains lags of \( r_t \); \( \varepsilon_t \) is a \( 2 \times 1 \) vector of errors; \( H_t^{1/2} \) is the Cholesky factor of the time-varying conditional covariance matrix \( H_t \); \( v_t \) is a \( 2 \times 1 \) vector of zero-mean, uni-variance, and independent and identically distributed innovations.

In the general multivariate GARCH (MGARCH) model, \( H_t \) is a matrix generalization of univariate GARCH models. The general MGARCH is also known as the VECH model, in which the \( H_t \) could be expressed as follows:

\[ \text{vech}(H_t) = s + A \cdot \text{vech}(\varepsilon_{t-1} \varepsilon_{t-1}') + B \cdot \text{vech}(H_{t-1}) \]  \hspace{1cm} (3)

where \text{vech()} stacks the unique elements that lie on or below the main diagonal in a symmetric matrix into a vector, \( s \) is a vector of parameters, and \( A \) and \( B \) are matrices of parameters. The CCC-MGARCH model reduces the number of parameters, in which the correlation matrix is time invariant (Bollerslev, 1990). CCC-MGARCH(1,1) is the general
CCC-MGARCH model with one ARCH term and one GARCH term and each element of $H_t$ is modeled by:

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} \cdot h_{jj,t}}$$  \hspace{1cm} (4)

where the diagonal elements $h_{ii,t}$ and $h_{jj,t}$ follow univariate GARCH processes and $\rho_{ij}$ is a time-invariant weight interpreted as a conditional correlation. The dynamic hedging ratio at time $t$ is estimated by

$$h_t^* = h_{12,t}/h_{22,t}$$  \hspace{1cm} (5)

### 4.2 Wheat Price

Crop price projections are linked to the product and its market chain (Münch et al., 2013). Historically, most of Western Australia wheat yields were largely exported into overseas market, therefore crop failures or bumper crops harvested in major exporting countries anywhere in the world govern the price in Australian markets. A good harvest at the farm level can coincide with high prices, as was the case for wheat in 2007 (Gilbert, 2010, Schnep, 2008). And the opposite situation may also occur, which would lead to low farm revenue. The soft wheat price on the Chicago Board of Trade (CBOT) was taken to represent wheat price on the global market because of popularity of CBOT used by wheat trading countries for price risk hedging as well as the large trading volumes being transferred (Williams, 2013). Nominal price is used to show the importance of price risk hedging.

![Figure 4 Wheat prices 2009-2011 (AUD/t)](image-url)
The co-movement of WA wheat daily spot price and CBOT wheat daily futures price is illustrated in Figure 4. Casual observation suggests that WA spot price and CBOT futures price tend to move together over time, which is confirmed by cointegration techniques in Table 4. Table 3 summarizes the descriptive statistics of log price changes for WA spot price and CBOT futures price. It shows that both price changes exhibit statistically insignificant means, which suggests WA spot prices and CBOT futures prices have zero returns. The variance of CBOT futures price is greater than WA spot price, which indicates that CBOT market incorporates information at a faster speed than WA spot market, assuming the variances related to information directly (Ross, 1989). And, these two markets are incorporating different information (Geoffrey Booth et al., 1998).

Table 3. Descriptive Statistics of log Price Changes

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>ADF test</th>
<th>PP test</th>
<th>LM test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spot Changes*100</td>
<td>-0.033</td>
<td>1.775</td>
<td>-0.347</td>
<td>16.015</td>
<td>-30.227</td>
<td>-30.125</td>
<td>48.657</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Futures Changes*100</td>
<td>-0.044</td>
<td>2.577</td>
<td>0.214</td>
<td>4.369</td>
<td>-30.494</td>
<td>-30.508</td>
<td>13.399</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Notes: The 1% critical value of ADF test and PP test is -3.430, LM test is the Lagrange-multiplier test for ARCH effects, which was presented by Johansen (1995). P-value is in parentheses.

Figure 5 shows the returns of WA spot price. As expected, wheat returns are characterized by periods of little movement followed by high volatility. In 2010 and 2011, wheat returns have greater volatility than returns in 2009. In the Table 3, the augmented Dickey-Fuller (ADF) (Dickey and Pantula, 1987, Dickey and Fuller, 1981) tests and the Phillips-Perron (PP)
(Phillips and Perron, 1988) tests indicate that both prices follow an \( I(1) \) process. In particular, the significant results for Engle's (1982) Lagrange Multiplier (LM) ARCH test suggest that both spot price and futures price follow ARCH-type process.

### Table 4. Johansen Cointegration Tests

<table>
<thead>
<tr>
<th>( H_0 )</th>
<th>( \lambda_{\text{Trace}} )</th>
<th>( \lambda_{\text{max}} )</th>
<th>Critical Values</th>
<th>( \lambda_{\text{Trace}} )</th>
<th>( \lambda_{\text{max}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>1%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Cointegrating Vector</td>
<td></td>
<td></td>
<td>1%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>( r \leq 0 )</td>
<td>236.73</td>
<td>138.61</td>
<td>20.04</td>
<td>15.41</td>
<td>18.65</td>
</tr>
<tr>
<td>( r \leq 1 )</td>
<td>98.12</td>
<td>98.12</td>
<td>6.65</td>
<td>3.76</td>
<td>6.65</td>
</tr>
</tbody>
</table>

Notes: Six lags chosen by the AIC are used in Johansen test. Critical values are obtained from Osterwaldlenum (1992).

Table 4 reports the cointegration results given by the Johansen test (Johansen, 1991). Both the \( \lambda_{\text{Trace}} \) and \( \lambda_{\text{max}} \) statistics show that the WA spot prices and CBOT futures price are cointegrated (Juhl et al., 2012). That means that although the WA and CBOT wheat prices are non-stationary and drift apart in short run, they will move together in the long run. This is also significant in previous findings (Zhibo Guo, 2013). Therefore, based on this finding, the price information on WA spot mark is effectively connected with information on CBOT futures market. Hence, it’s appropriate to hedge WA wheat price risk through CBOT futures market.

#### 4.2 CCC-MGARCH Results

The estimation results for the CCC-MGARCH models with normal and student-t distribution assumption are presented in Table 5. As expected, the correlations between the spot and futures returns are statistically significant. From Table 5 it can be seen that \( c_{12} \) is greater than \( c_{11} \), indicating WA spot returns depend more on CBOT returns than itself. The insignificant of \( c_{21} \) and significant of \( c_{22} \) indicate that returns of CBOT futures price has strong self-regression effects. Parameters of matrix \( C \) in Table 5 show that CBOT futures market transfers information into WA spot market, while WA spot market’s impact on CBOT futures market is not significant. Parameters of matrix \( A \) and \( B \) in Table 5 show that both WA spot price and CBOT futures price exhibit strong persistence in volatility, while WA spot price has greater persistence than CBOT futures price. Degree of freedom parameters, \( \nu \), for
student-t distribution are statistically significant, which indicating that crop portfolio returns have excess kurtosis, inconsistent with the results in Table 1. Based on the Log Likelihood ratio, CCC MARCH with student-t distributed errors is preferred.

### Table 5. Results of GARCH Models

<table>
<thead>
<tr>
<th>Parameters</th>
<th>CCC-GARCH (Normal)</th>
<th>CCC-GARCH (Student-t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_{11}$</td>
<td>-0.138* (0.000)</td>
<td>-0.065* (0.044)</td>
</tr>
<tr>
<td>$c_{12}$</td>
<td>0.354* (0.000)</td>
<td>0.318* (0.000)</td>
</tr>
<tr>
<td>$c_{21}$</td>
<td>-0.001 (0.981)</td>
<td>0.028 (0.578)</td>
</tr>
<tr>
<td>$c_{22}$</td>
<td>-0.143* (0.001)</td>
<td>-0.152* (0.000)</td>
</tr>
<tr>
<td>$s_1$</td>
<td>0.022 (0.141)</td>
<td>0.264 (0.076)</td>
</tr>
<tr>
<td>$s_2$</td>
<td>0.925* (0.000)</td>
<td>12.014* (0.003)</td>
</tr>
<tr>
<td>$a_{11}$</td>
<td>6.195* (0.004)</td>
<td>0.137* (0.010)</td>
</tr>
<tr>
<td>$a_{22}$</td>
<td>0.070* (0.001)</td>
<td>0.033 (0.483)</td>
</tr>
<tr>
<td>$b_{11}$</td>
<td>0.111* (0.012)</td>
<td>0.715* (0.000)</td>
</tr>
<tr>
<td>$b_{22}$</td>
<td>-0.067* (0.836)</td>
<td>-0.642 (0.193)</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.095* (0.012)</td>
<td>0.091* (0.031)</td>
</tr>
<tr>
<td>$\nu$</td>
<td>-</td>
<td>4.521* (0.000)</td>
</tr>
</tbody>
</table>

Log Likelihood: -2792.622 -2722.126

Note: Standard errors in parentheses. $\nu$ is the degree of freedom of student-t distribution. Parameters significant at 95% confidence are marked with *.

### 4.3 Yield Prediction Effects on Hedged Quantities

To demonstrate the yield prediction effects on hedged wheat quantities, two scenarios are assumed for the representative farmer. Scenario 1, with updated yield predictions, the farmer is assumed to make the hedging decision at May and adjusts the hedged quantity according to the dynamic hedging ratios and the yield predictions from APSIM. Scenario 2, without updated yield prediction, the farmer makes hedging decision at May and adjusts the hedged quantity only according to the dynamic hedging ratios. In both scenarios, the farmer closes the futures market position at December.
Table 6. Static and Dynamic Optimal Hedging Ratios

<table>
<thead>
<tr>
<th></th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic Optimal Hedging Ratio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>2.8%</td>
<td>3.0%</td>
<td>4.4%</td>
</tr>
<tr>
<td>June</td>
<td>2.9%</td>
<td>3.2%</td>
<td>4.0%</td>
</tr>
<tr>
<td>July</td>
<td>2.9%</td>
<td>4.0%</td>
<td>3.6%</td>
</tr>
<tr>
<td>August</td>
<td>3.2%</td>
<td>6.1%</td>
<td>4.6%</td>
</tr>
<tr>
<td>September</td>
<td>3.1%</td>
<td>3.2%</td>
<td>3.4%</td>
</tr>
<tr>
<td>October</td>
<td>2.8%</td>
<td>4.0%</td>
<td>5.1%</td>
</tr>
<tr>
<td>November</td>
<td>2.9%</td>
<td>3.3%</td>
<td>3.1%</td>
</tr>
<tr>
<td>December</td>
<td>2.8%</td>
<td>5.0%</td>
<td>4.0%</td>
</tr>
<tr>
<td>Static Hedging Ratio</td>
<td>2.8%</td>
<td>3.0%</td>
<td>4.4%</td>
</tr>
</tbody>
</table>

Table 6 shows the optimal dynamic hedging ratios and static hedging ratios for wheat growing seasons from 2009 to 2011. It can be seen that the hedging ratios in 2009 is relatively stable than hedging ratios in 2010 and 2011. The volatilities of the hedging ratio in 2010 and 2011 are mainly caused by the suddenly increased price changes, which can be seen from Figure 4 and Figure 5.

Figure 6 demonstrates hedging quantity changes during the season. Affected by the yield prediction and dynamic hedging ratios, the hedged quantities during the season are drifted apart after August, especially for the season has the extreme weather condition. In the average year (i.e. 2009), hedging with yield predictions has similar hedged quantities with hedging without yield prediction. However, for the dry year (i.e. 2010), hedging without yield prediction leads to an over hedged quantities, while in the wet year (i.e. 2011) hedging without yield prediction leads an under hedged quantities.

For the year 2010, when sowing the wheat seed into the soil at May, the yield prediction is 2.7 t/ha and the optimal hedging ratio is 3.0%, which lead to hedged quantity of 0.081 t/ha. Without updated yield predictions, the farmer hedges 0.135 t/ha of wheat as the hedging ratio for December is 5.0%. However, with the updated yield prediction, the farmer should only hedge 0.075 t/ha of wheat, as the yield prediction at December is 1.5 t/ha. This case shows for a very dry year without yield prediction, the farmer will over hedge wheat yield by 80%
(over hedged 0.06 t/ha). For the year 2011, the situation is in the opposite of 2010. Without yield predictions, for a very wet year, the wheat yield will be under hedged by 8%, which is 0.01 t/ha.

![Figure 6 Monthly Hedged Quantities Comparison for 2009-2011 (t/ha)](image)

5. Conclusion

This paper studied the wheat yield prediction using APSIM and applies the yield prediction to assess its effects on dynamic hedged quantities during the season. Wheat yield predictions were estimated for a representative farm in Kojonup in WA. In line with Quiring and Legates (2008), results show that under three different weather conditions, our method was able to forecast wheat yield before the harvest. In 2009, with normal rainfall, our method is able to forecast the wheat yield at planting time (May). In 2010 (with extremely low rainfall) and 2011 (with extremely high rainfall), this method is not able to forecast wheat yields accurately until 3 months before harvest (October).

With the predicted yield, the representative farmer could adjust the hedged quantity during the season not only according to the dynamic hedging ratios, but also the updated yield information. Without the yield prediction, the farmer may have similar hedged quantity in the average season. However, for the dry season, hedging without yield prediction leads to over hedged wheat yield, whilst the wet season will end with under hedged quantity. Over hedge and under hedge of the wheat yield compromise the risk minimizing objective of hedging.
Therefore, for risk adverse farmer, updated information should be employed together with futures contract to minimize the price risk.

The basic modeling approach utilized in this study can be adapted for economic analysis of wheat yield and hedging in other regions of Australia. The primary adjustments which would have to be made would be to apply the weather generator to forecast the weather condition in the coming season and consider the transaction fee while hedging price risk, including the direct hedging cost and cross hedging cost. Economic analysis of yield and revenue predictions for other crops in WA, such as barley and canola, could also be conducted with the basic model structure by simulating future possible weather conditions and utilizing the price information in the futures market.

References


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