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Quantifying the extent to which enterprise mix diversification can mitigate economic risk in rainfed agriculture

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Abstract

Climate variability can induce uncertainty in yields, and threaten long term economic viability of rainfed agricultural enterprises in the absence of effective adaptation strategies. Enterprise mix diversification has been found to be an effective adaptation strategy for mitigating multiple sources of farm business risk in some contexts. The extent to which enterprise mix diversification can mitigate climate induced variability in long term net returns from rainfed agriculture is assessed in this paper. Building on APSIM modelling, the assessment applies Monte Carlo simulation, probability theory, and finance techniques, to assess the potential for enterprise mix diversification to mitigate climate-induced variability in long term economic returns from rainfed agriculture. Five alternative farm enterprise types comprising three non-diversified farm enterprises and two diversified farm enterprises consisting of a correlated mix of rainfed agricultural activities were considered. The decision to switch from a non-diversified agricultural enterprise with the highest expected return to a diversified agricultural enterprise consisting of a mix of agricultural enterprises was analysed. Correlation analysis showed that yields were not perfectly correlated (i.e. are less than 1) indicating that changes in climate variables cause non-proportional impacts on yields. Results show that whilst diversification can reduce the standard deviation of net returns by up to A\$122ha^{-1} and increase the worst probable net loss by A\$99ha^{-1}, diversification can reduce the expected net returns by up to A\$96ha^{-1} and reduce the maximum probable net gain by up to A\$602ha^{-1}. Further, under non-diversified enterprises, the likelihood of realising net losses higher than the maximum probable net loss under the diversified enterprise was estimated at up to 6%. Conversely, under the non-diversified enterprise, the likelihood of realising net gains higher than the maximum probable net gain under diversified enterprises was estimated at up to 16%.

Keywords: climate variability; yield uncertainty; economic returns; rainfed agricultural enterprise, risk, Monte Carlo

1. Introduction

Australia's major agricultural regions are characterised by uncertain and variable climatic conditions including temperature and rainfall (Furuya and Kobayashi, 2009; Wang *et al.,* 2009a). Climate variability is an important source of risk affecting long term economic viability of rainfed agricultural systems (Marton *et al.,* 2007; Iglesias and Quiroga, 2007; Lotze-Campen and Schellnhuber, 2009). Climate models predict an increase in future climate variability and a significant increase in the frequency in major agricultural regions in Australia (IPCC 2007; Suppiah *et al.,* 2006). This is likely to increase the uncertainty and variability in agricultural yields and economic returns (John *et al.,* 2005; Wang *et al.,* 2009b). In the absence of effective adaptation strategies, this is likely to increase variability in farm incomes in the long run.

To mitigate the extent of the impact of climate variability on farm incomes, farmers routinely adopt mitigation strategies involving various adjustments in enterprise mix, and production technologies and techniques (Kelkar *et al.,* 2008). Diversification of farm enterprise mixes through the rotation of several different crops and livestock (hereafter simply *diversification*), has been considered as one strategy for mitigating climate-induced variability in net returns from rainfed agriculture (Amita, 2006; Correal *et al.,* 2006; Azam-Ali, 2007).

Most of the benefit of diversification comes from hedging against market input and commodity price fluctuations (Bhende and Venkataram, 1994; Ramaswami *et al.,* 2003; World Bank, 2004). Notwithstanding variance in market input costs and commodity prices (Ramaswami *et al.,* 2003), climate-induced yield variability is a significant source of farm business risk. The proposition that diversification may also be beneficial for hedging against climatic variability is considered in this study.

The benefits of diversification are premised on the utilization of imperfectly correlated net returns from multiple agricultural enterprises. When the impacts of climatic variability differ between multiple agricultural enterprises, losses from investments in some activities are offset by gains, or moderated by less severe losses, in other activities thereby reducing the impact on overall net returns (Ramaswami *et al.,* 2003; Fraser *et al.,* 2005). As such, the nature and strength of correlated yields across alternative agricultural activities need to be fully understood and quantified when assessing the potential benefits of agricultural diversification. There is a general consensus from the finance literature that not considering the nature and strength of correlated yields may under- or over-estimate the benefit of diversification (Markowitz 1952a&b, 1994; Chan *et al.,* 1998, 1999; Bangun *et al.,* 2006).

Few studies have considered long term sources of uncertainty and risk such as climate, and assessments of enterprise mix diversification as a strategy for mitigating climate risks to ensure long term viability of farm businesses are sparse. Lien et al. (2009) speculate that this is because relevant historical data necessary for long term analyses are usually sparse and that most studies have had to rely on a few observations of economic returns. However, in the context of increasingly frequent droughts in many of the world's agricultural regions (Howden *et al.,* 2007; IPCC, 2007; Furunya and Kobayashi, 2009; Lotze-Campen and Schellnhuber, 2009), the impact of diversification on avoiding high cost of crop failure in the long term bears significant relevance.

In this study, a method for assessing the potential for enterprise mix diversification to mitigate climate-induced variability in long-term economic net returns from rainfed agriculture is presented. Using a case study in the 11.8 million hectare Lower Murray region in southern Australia, probability density functions were fitted to modelled long term crop and livestock yield data. Monte Carlo simulation was used to quantify the variability in yields and, via a profit function, net returns. The benefits and costs of enterprise mix diversification including the trade-off between the reduced variability in returns and reduced expected net returns were quantified, and the implications of diversification as an adaptation strategy for farmers to cope with increasing climatic variability are discussed.

2. Methods

2.1. Study area

The Lower Murray region (Figure 1) in southern Australia covers a total area of 11,871,363 ha. Mean annual rainfall ranges from 200 mm/yr in the drier northern areas of the South Australia Murray Darling Basin (SAMDB) to 1,400 mm/yr in the southern Wimmera. Rainfed agriculture is the dominant land use covering over 50% of the region and is an important component of the regional economy (Bryan *et al.,* 2007). The average farm size used for rainfed agriculture in the study area is around 1,000ha. Farming systems vary greatly across the region depending on climate and soil types. The cropping of cereals (wheat, barley), pulses (lupins, beans, peas), and sheep grazing are typical farm enterprises. Cropping and grazing rotations vary over the region from continuous cropping in the Wimmera and southern Mallee regions, crop/pasture rotations in the Mallee and southern SAMDB regions, and continuous grazing in the central and northern SAMDB (Bryan *et al.,* 2011). Most farmers engage in some form of annual crop/livestock rotation for a number of reasons including protection of crops from diseases, management of weeds, diversification, and response to economic opportunities.

2.2. Modelled farming systems

Yields and economic outcomes for three non-diversified farming systems and two diversified farming systems in the study area were modelled and compared. The three non-diversified farming systems were defined as continuous single-crop farming systems of wheat, lupins, and sheep grazing on modified pastures (hereafter, *sheep*). The two diversified systems were analysed to compare relative impacts of varying extents of diversification in the study area given that whilst some farmers practice continuous single-crop farming systems, most farmers in the case study already diversify for other reasons including disease management, and as part of routine crop rotation practice. The diversified farming systems were defined as a mixed enterprise comprising continuous cropping (and grazing) of wheat, lupins, and sheep in varying proportions of available farmland in any one year production horizon. In one diversified system, *Diversified*, equal proportions of available farmland were allocated to each activity with each activity taking up to a third of the farmland. In the other diversified system. *Diversified2*, half of the total available farmland was allocated to wheat, the predominant activity, and the remaining farmland was allocated equally to sheep and lupins. Among farmers that practice diversification in the case study area, there is typically one predominant enterprise of specialisation taking up at least half of the total available (Bryan *et al.,* 2007). Effects of land management on yields were controlled for thereby ensuring that variability in yields can be largely attributed to variability in climate.

2.3. Crop yield modelling

Agricultural Production Simulator (APSIM, Keating *et al.,* 2003) results were used to predict annual yields for wheat, lupins, and sheep for 138 unique soil/climate zones over 116 years. The soils/climate zones were identified by overlaying a layer defining 15 soil types (Bryan *et al.,* 2007) and a layer defining 16 climate zones. The 15 soil types were classified using field-derived soil survey data. Climate zones were defined by overlaying climate variables including mean annual rainfall, mean annual temperature, and annual moisture index layers. Soil/climate zones were assumed to have homogeneous production potential for the purposes of this study. Historical daily climate records were acquired for the 116-year period from 1889 to 2005 from the SILO data base (Bryan *et al.,* 2011). Typical land management regimes (sowing windows, fertiliser application rates) were defined for the study area based on expert opinion. For full details and other applications of this modelling readers are referred to Bryan et al. (2007, 2009, 2010, 2011) and Wang et al. (2009a&b). Of the 138 zones modelled across the entire region, APSIM zone 96 (figure 1), located in the south eastern parts of South Australia, was selected to illustrate results from quantification of the potential benefits of diversification.

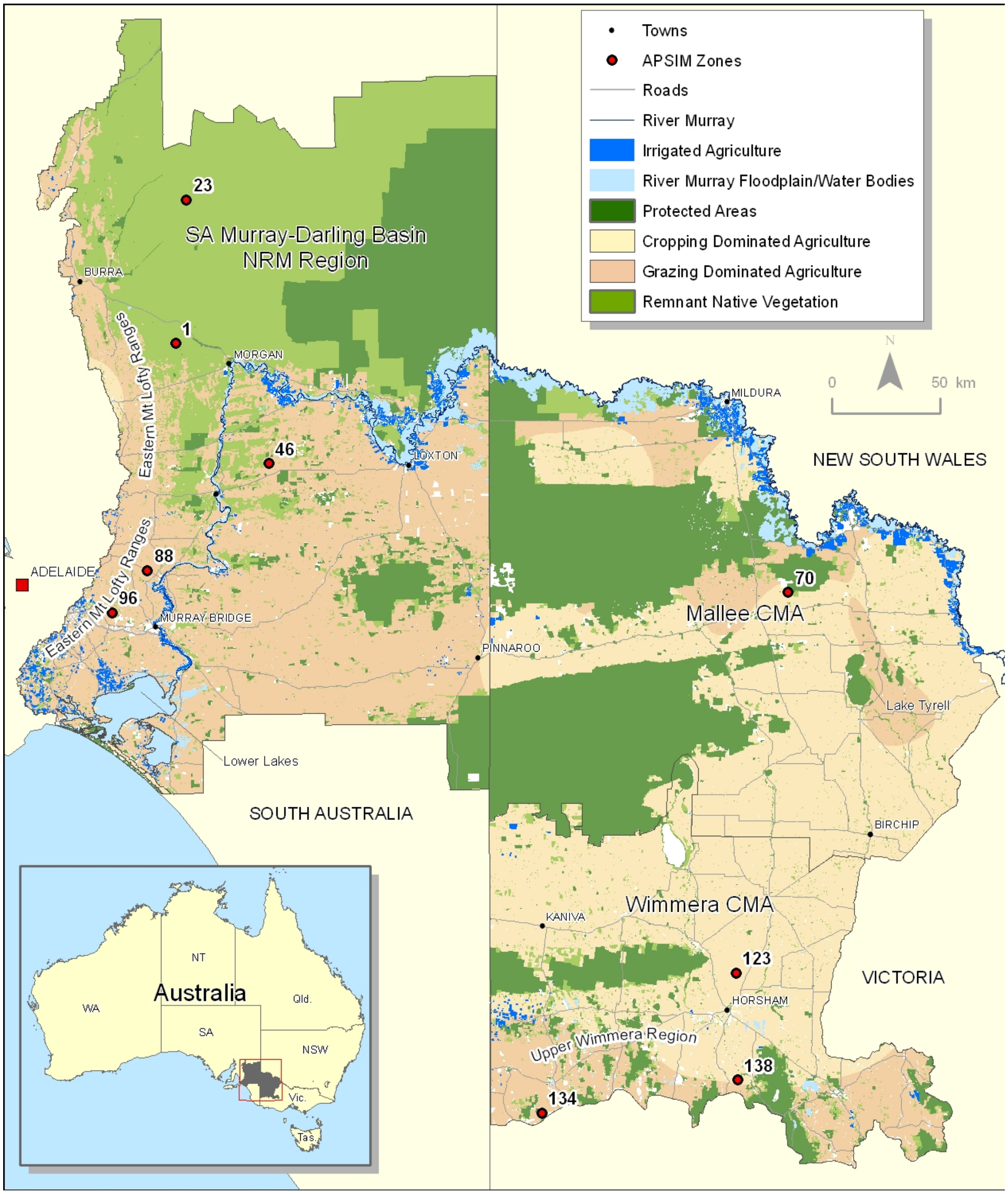


Figure 1. Location and land use in the Lower Murray study area (Kandulu *et al.,* 2012).

2.4. Quantifying climate-induced yield variability

To assess benefits from diversification, annual net returns were treated as stochastic. This is premised on the assumption that climate, the key variable driving yield variability which is the focus of this study, is generally assumed to be stochastic (Iglesias and Quiroga, 2007; Furunya and Kobayashi, 2009). Probability theory provides a suitable framework for the quantification of climate-driven uncertainty and variability in net returns over a given time horizon (Hardaker *et al.,* 2004; Lien *et al.,* 2009).

Frequency histograms were generated for yields $Q1_i$, for each of the three enterprises *i*, where *i* is an element of *I*{wheat, lupins, sheep}. Yield data for pasture grazing sheep was created by averaging the yield data surfaces (DSE/ha) of Bryan and Marvanek (2004) by Statistical Local Area. The Turn-off Rate (*TRN*) is the number of sheep sold as a proportion of total herd for sheep. *TRN* was set to one for wheat and lupins (see Table 1). Next probability density functions were fitted to the frequency histograms to characterize climate-induced variability in yield outputs using the @RISK software.

Three tests were used to determine the best fit including Chi-square, Anderson-Darling, and Kolmogorov-Smirnoff tests (Iglesias and Quiroga, 2007), and all three tests identified the lognormal distribution as having the best fit. The essential property of the lognormal distribution which made it more suitable for quantifying the uncertainty of yield over other distributions is that it has a minimum of zero and thus there are no non-negative observations. In addition, it has relatively more intuitive interpretation compared to other distributions.

These distributions were used in Monte Carlo simulation of net economic returns.

2.5. Quantifying variability in economic returns

To fully account for the effect of climate variability on economic net returns from rainfed agriculture in the study area, variability in long term average net revenue per hectare was quantified (Kurukulasuriya, 2007; Deressa and Hassan, 2009; Bryan *et al.,* 2009) while controlling for all other economic factors including costs of production and commodity prices after Benhin (2008). Economic net returns were defined as revenues from sale of commodities produced less the fixed and variable cost incurred in the production of agricultural commodities. A profit function was used to calculate net economic returns per hectare for wheat, lupins and pasture grazing sheep such that:

$$NR_i = (P1_i \times Q1_i \times TRN_i) + (P2_i \times Q2_i \times Q1_i) - ((QC_i \times Q1_i) + (AC_i + FDC_i + FOC_i + FLC_i)) \quad \text{Equation 1}$$

Net returns to the diversified farm enterprise system, NR_d. were calculated as:

$$NR_d = \frac{\left(\sum NR_i\right)}{3} \in i \ \{\text{wheat, lupins, sheep}\} \quad \text{Equation 2}$$

Table 1 outlines notation descriptions and values used in Equation 2 (Bryan *et al.,* 2009). The profit function does not include capital gains nonetheless it has been found to provide a reasonable estimate of economic returns to agriculture (Bryan *et al.,* 2011).

The benefits of diversification in relation to climatic variability rely on imperfect correlation between yields of crops and grazing systems (Correal *et al.,* 2006; Iglesias and Quiroga, 2007). Hence, it is important to quantify yield correlations and include these in simulation of net returns. Pair-wise Pearson correlation coefficients were calculated for yields $\rho_{i,i}$ between wheat and lupins, wheat and sheep, and lupins and sheep from the modelled yield data (Table 2).

To quantify climate-induced variability in net returns for the diversified farm enterprise system, NR_d, 10, 000 Monte Carlo simulations were generated (Hardaker and Lien, 2010) of net returns using Equation 2 with random samples for the yield parameter $Q1_i$ drawn from the modelled probability density functions for yields, and considering yield correlations $\rho_{i,i}$. Frequency histograms were then developed for the average of net returns under the three non-diversified enterprises and under the diversified enterprise.

Table 1 Notation descriptions and values for NR_l calculations (See Equation 2)

Notation	Definition	value		
		Wheat	Lupins	Sheep
P1	Price of Primary Commodity Farmed ($/tonne or $/DSE)	257	211	22
Q1	Quantity of the primary product (t/ha, DSE/ha)			
TRN	Turn-off Rate (number of sheep sold as portion of total herd, = 1 for cropping)	1	1	0.31
P2	Price of Secondary Commodities ($/kg of wool, only applies to sheep)	0	0	4.0
Q2	Quantity of Secondary Commodity (kg of wool/ha)	0	0	2.73
QC	Quantity Costs ($/tonne or $/DSE)	0	0	4.0
AC	Area Costs ($/ha)	149	96	3
FDC	Fixed Depreciation Costs ($/ha)	19	13	2
FOC	Fixed Operating Costs ($/ha)	48	31	4
FLC	Fixed Labour Costs ($/ha)	35	23	3

Table 2 Pair-wise linear correlation coefficients between wheat and lupins, wheat and sheep, and lupins and sheep from simulated yield time series data.

	Lupin	Wheat	Sheep
Lupin	1		
Wheat	0.79	1	
Sheep	0.46	0.54	1

2.6. Quantifying potential benefits from diversification

To assess the benefits of diversification, farmers in the study area can be considered as investors faced with the challenge of choosing among five alternative farm enterprises with uncertain net returns. In the absence of farmer risk profiles in the study area, investment decisions from the point of view of s risk-neutral farmers were considered and characteristics of the probability distribution functions of net returns under alternative farm enterprises were analysed and compared.

Four indicators were considered including expected values, standard deviations, the likelihood of realising net returns higher than the maximum under diversification, and the likelihood of realising net returns lower than the minimum under diversification. This technique, technically termed *stochastic dominance*, was preferred because it involves consideration of the whole distribution of returns with no restrictions.

3. Results

Results from one APSIM zone out of the 138 APSIM zones modelled for purposes of illustration are presented. This area lies in the moderate to high rainfall region with annual rainfall ranging between 500 and 800mm. Using results from APSIM yield modelling, this area was identified in the 50th percentile of the average of potential yields for the three enterprises considered - lupins, wheat and pasture grazing across the region.

3.1. Climate-induced yield variability

Figures 2, 3, and 4 show the outcome of the probability distribution fitting procedure used where the probability density functions were fitted to frequency histograms generated from 117 years of simulated yield data for wheat, lupins and pasture respectively.

Figure 2. Probability density functions fitted to simulated yield time series data for wheat (tonnes/ha)

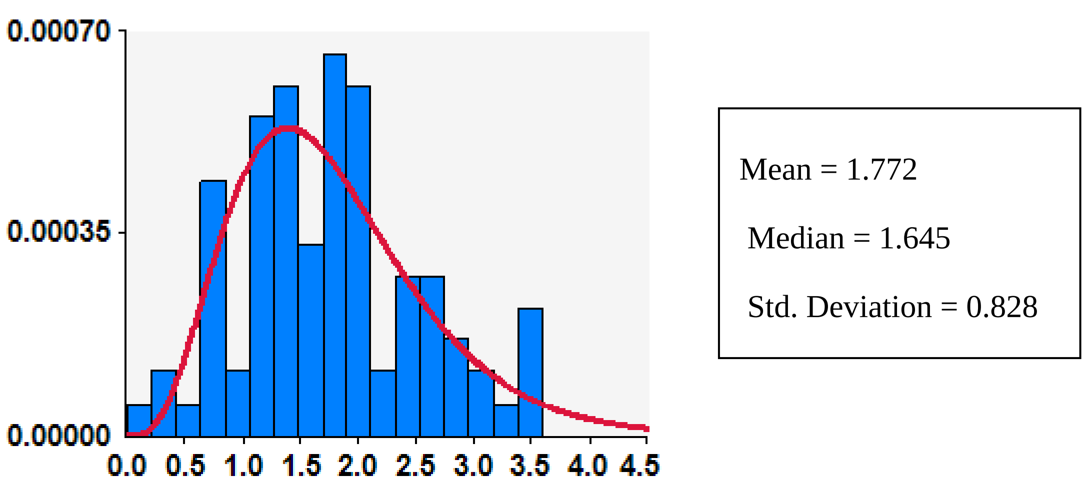


Figure 3. Probability density functions fitted to simulated yield time series data for lupins (tonnes/ha)

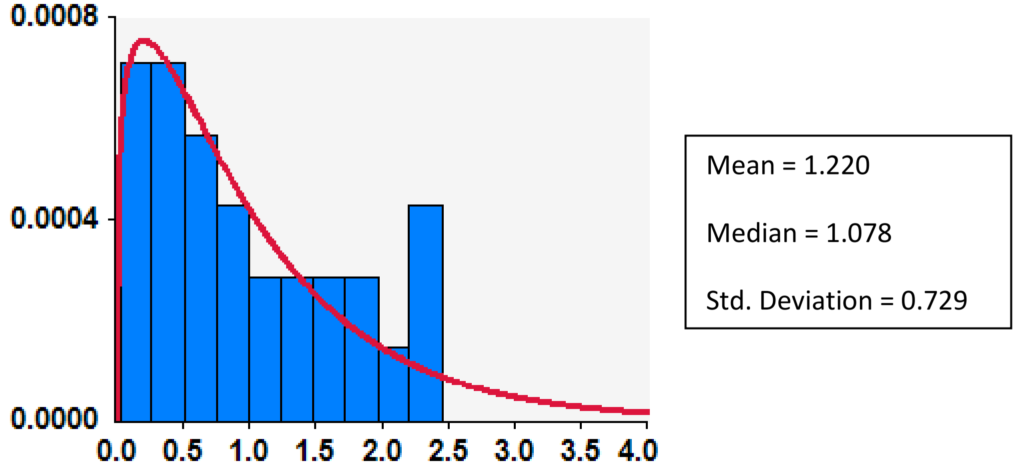
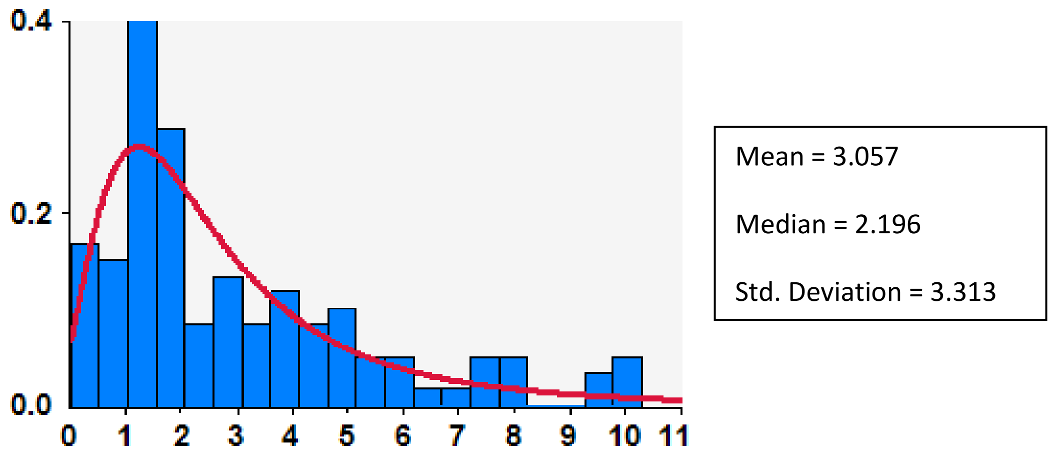


Figure 4. Probability density functions fitted to simulated yield time series data for pasture grazing sheep (DSE/ha)



Three probability density functions of various forms were fitted and Chi square statistics from goodness of fit tests (Equation 1) ranged from 2.2 to 20.4. In all cases, observed frequencies (counts) were not significantly different from the frequencies that would be expected using the fitted probability density functions, and estimates from the probability density function were consistent with observed data from frequency distributions 90% of the time.

Figures 2, 3, and 4 show that overall, expected yields for lupins are lower than those for wheat, and yields are lowest and most variable for pasture grazing sheep. Yields of 1.77 for wheat; 1.22 for lupins; and 3.06

DSE ha^{-1} for sheep would be expected on average in the illustrative area. Figures 2, 3, and 4 also shows that variability, measured using standard deviation, was estimated at 0.82 tonnes ha^{-1}, or 46% of mean for wheat; 0.73 tonnes ha^{-1}, or 60% of mean for lupins; and 3.31 DSE ha^{-1}, or 108% of mean for sheep.

3.2. Correlations

Overall pair-wise linear correlation coefficient between net returns and price was estimated at 0.483, and between net returns and yields 0.3579. This shows that in addition to yields, variation in commodity prices is an important determinant of variation in net returns.

Table 2 outlines pair-wise Pearson correlation coefficients calculated for yields $\rho_{i,i}$ between wheat and lupins, wheat and sheep, and lupins and sheep from the modelled yield data for the illustrative APSIM zone. Overall, yields are strongly positively correlated for all land used with highest positive correlations between 0.46 and 0.79. The correlation matrix in table 2 shows that yields are not perfectly correlated (i.e. are less than 1) in all the cases. It can be deduced, therefore, that there is scope for beneficial diversification in the region.

Overall pair-wise linear correlation coefficient between yields and the net difference between rainfall and evapotranspiration varied across the three enterprises showing different responses to climate variables. Specifically, wheat had the highest correlation coefficient estimated at 0.4059, and then lupin at 0.2787, and sheep had the smallest correlation coefficient estimated at 0.1322. This may be in part why wheat, lupin and sheep yields are not perfectly correlated because they respond non-linearly to climate variables thereby enabling the essential condition for beneficial diversification. The difference in responses to climate variables can further be explained by different sowing and harvest schedules across the three enterprises. Sheep has the smallest correlation to climate variables and this may be in part because pastures utilise out of season rainfalls.

3.3. Variability in economic net returns

Figure 5 shows that the relative orders of magnitude for the four indicators are highly varied across the farm enterprise systems reported.

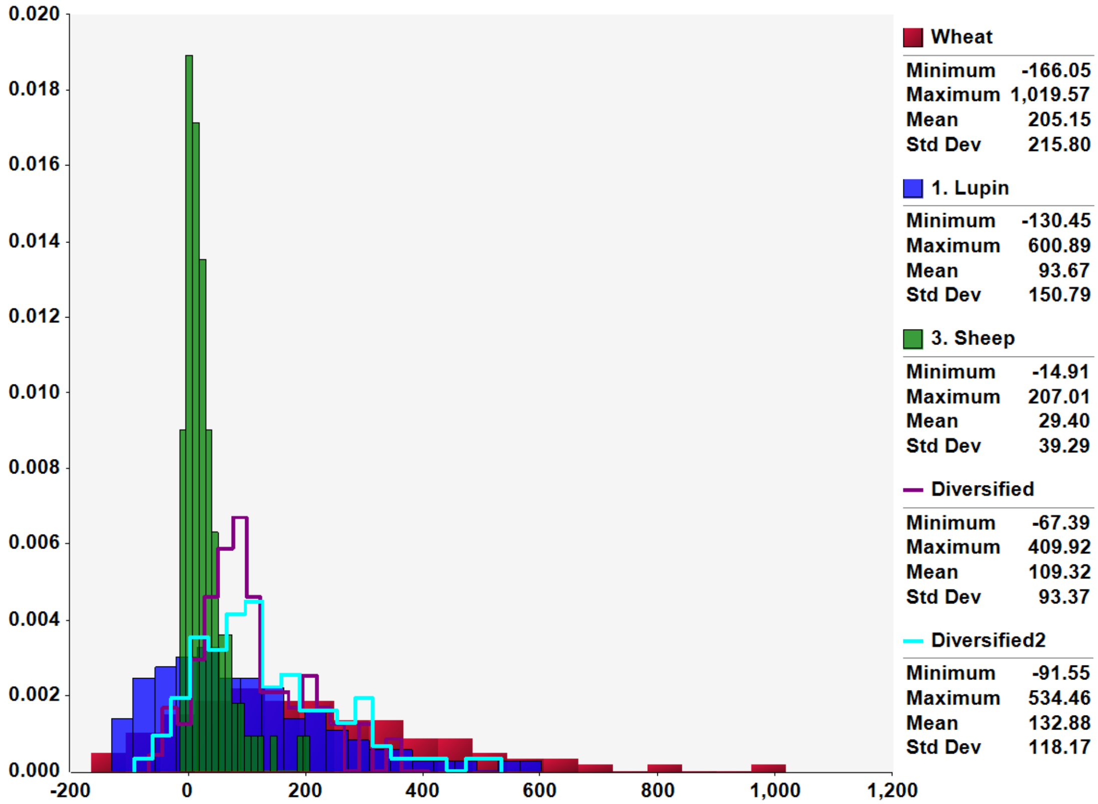
Overall, sheep has lowest expected net returns of all enterprises at A$30 ha^{-1}, followed by lupins at $94 ha^{-1}, and wheat has highest mean net returns at A$205 ha^{-1}. The expected net return from the diversified enterprise with equal proportions is A$109 ha^{-1}. All the three non-diversified enterprises have higher values for standard deviation, as a proportion of mean, than the diversified enterprise. Lupin has the highest value at 163% of mean; followed by sheep at 146% of mean; then wheat at 104% of mean. The diversified enterprise has the lowest standard deviation at 95% of mean.

In figure 5, whilst diversification can reduce the standard deviation of net returns by up to A$122ha^{-1} and increase the worst probable net loss by A$99ha^{-1}, diversification can reduce the expected net returns by up to A$96ha^{-1} and reduce the maximum probable net gains by up to A$602ha^{-1}. Further, under non-diversified enterprises, the likelihood of realising net losses higher than the maximum probable net loss under the diversified enterprise was estimated at up to 6%. Conversely, under the non-diversified enterprise, the likelihood of realising net gains higher than the maximum probable net gains under diversified enterprises was estimated at up to 16%.

Figure 5 also shows net returns under the two alternative diversified enterprise farm systems. Consider shifting from *Diversified2*, currently the most diversified farm system in the case study area involving predominantly wheat (half of the total available farmland), and the remaining farmland equally allocated to lupins and sheep, to *Diversified* (involving equal proportions of available farmland allocated to whet, lupins and sheep).

The impact of this shift to a more diversified enterprise would be a reduction in the standard deviation of net returns by up to A$25ha^{-1} and an increase in the worst probable net loss by A$24ha^{-1}, however, this would reduce the expected net returns by up to A$24ha^{-1} and reduce the maximum probable net gains by up to A$125ha^{-1}. Further, under *Diversified2*, the likelihood of realising net losses higher than the maximum probable net loss under *Diversified* can be estimated at 1%. Conversely, and the likelihood of realising net gains higher than the maximum probable net gains under *Diversified* can be estimated at 3%.

Figure 5. Potential net economic returns under alternative non-diversified and diversified enterprise farm systems.



3.4. Impact of diversification

To assess potential benefits from diversification, the decision to switch from a highest expected return non-diversified farm enterprise system to the diversified farm enterprise system was considered. In Figure 5, the highest expected return non-diversified farm enterprise system is wheat.

Figure 5 shows that there is potential for beneficial diversification and there may be a case for considering a decision to switch from wheat to the diversified farm enterprise system. Whilst wheat is estimated to have the highest expected net returns at A\$204 ha^{-1}, wheat also has the most variable net returns with standard deviation values estimated at 104% of mean. In this location, the decision to switch to the diversified farm enterprise system is estimated to result in lower net returns than wheat at A\$109 ha^{-1} however, the variability in net returns, standard deviation, would also be lower at 94%. In switching to a diversified farm enterprise system, expected returns would be reduced 46%, but the orders of magnitude of standard deviations of net returns would be reduced even more, by 52%. The diversified enterprise benefits from a combination of risk-reducing characteristics of sheep, and high expected return characteristics of wheat. Together these characteristics moderate losses in years with unfavourable climate to compensate for high-return and high-variability properties of wheat and reduce the likelihood of extremely low net returns.

4. Discussion

Using a case study in the Lower Murray region in southern Australia, the potential for beneficial diversification as a strategy for mitigating the impacts of climate-driven variability in net returns from investments in rainfed agriculture was assesed. Enterprise mix diversification can be beneficial the trade off between the benefit of reduced variability and the cost of reduced expected net returns was quantified. To compare the impacts of climate variability with and without diversification, the variability, expected net returns, and probability and severity of below-average net returns across the alternative diversified and non-diversified agricultural investment options were quantified taking explicit account of correlations between yields.

Results of this study are consistent with findings from previously cited studies that state that there is potential for beneficial diversification from investments in multiple agricultural activities that respond differently to variability in climate. Table 2 shows that yields are imperfectly correlated as different activities respond differently to variability in climate in the study location. Results of this study are also consistent with the expectation that the benefit of reduced variability from diversification comes at a cost of reduced expected net returns when alternative non-diversified activities offer higher expected net returns.

However, there are some limitations to this study. The analysis of only two alternative diversified enterprises does not represent the complete portfolio of all possible diversified enterprises and may be suboptimal as it may represent an over (under) investment in some activities depending on individual's risk-return preferences.

The presence of diversification can be explained by many factors, not just as a response to climate risk and historically, the main reason farmers diversify is to hedge against short term variability in input and commodity price (Kingwell, 1994; Pannell *et al.,* 2000; Cooper *et al.,* 2008; Lien *et al.,* 2009).This study holds variations in prices constant and assesses the potential impact of diversification to mitigate climate-induced variability on yields and long-term economic net returns . Future studies may build on this study and explore relative importance of all key sources of farm income risk to assess potential for beneficial diversification considering multiple sources of farm business risk.

Further, this study used historical time series data and therefore assumes that historical climate patterns will continue into future. The impact of climate change on net returns from yields and the effectiveness of diversification in mitigating variability in long term net returns from agriculture will vary depending on assumptions about future climate change. Future climate variability and uncertainty in climate and yields is assumed to be partly based on historical data however, there is need to use other information and judgments to improve the relevance of the results. As an extension to this study, several climate scenarios may be considered in assessment of potential for beneficial diversification. Subjective probabilities capturing effects of climate change on future climate variability can be used to incorporate the effects of climate change in the assessment (Hardaker and Lien, 2010).

Further strategies for adapting to future climate change might involve including other enterprises with less correlated yields in the diversification of farm enterprise systems. Specifically, there are new opportunities to diversify farm enterprise through provision of ecosystem services to benefit from emerging eco-markets (for example through management of remnant native vegetation, agro forestry for carbon and biodiversity markets) increase the potential for beneficial diversification as a strategy for mitigating climate-induced income risk. Alternative means of diversifying income source may involve obtaining off-farm employment, or investing in shares. Another ways to reduce yield risk is geographic diversification of a farm business. An assessment of the extent to which whole-farm yield variability can be reduced by holding land in different places could be another logical extension of this study.

Farmers' risk preferences in the case study area are poorly understood. The extent to which farmers are prepared to accept lower returns in exchange for less risk depends on their risk preferences. A useful extension to this study would be to quantify risk preferences and incorporate them in the risk analysis. Methods such as stochastic dominance with respect to a function (SERF) can then be used to evaluate the tradeoff between expected reduction in returns and reduced risk and whether farmers are 'better off" under diversification.

5. Conclusion

Diversified farming systems offer farmers a potential strategy for hedging against climatic risk in economic returns. In the context of increasing climate variability and frequency of droughts in many of the world's agricultural regions (Howden *et al.,* 2007; IPCC, 2007; Furunya and Kobayashi, 2009; Lotze-Campen and Schellnhuber, 2009), and emerging markets for ecosystem services, diversification may grow in significance and relevance as a strategy for avoiding high cost of crop failure and managing long term farm income risk.

6. Reference List

Amita, S. (2006) Changing interface between agriculture and livestocks: A study of livelihood options under dry land systems in Gujarat. Working Paper - Gujarat Institute of Development Research, Ahmedabad, 25 pp.

Azam-Ali, S. (2007) Agricultural diversification: The potential for underutilised crops in Africa's changing climates. Rivista Di Biologia-Biology Forum 100, 27-37.

Bangun, P., Nasution, A.H., Mawengkang, H. (2006) Evaluating Covariance and Selecting the Risk Model for Asset Allocation. IMT-GT Regional Conference on Mathematics, Statistics and Applications, Universiti Sains Malaysia, Penang, June.

Benhin, J.K.A. (2008) South African crop farming and climate change: An economic assessment of impacts. Global Environmental Change-Human and Policy Dimensions 18, 666-678.

Bhende, M.J., Venkataram, J.V. (1994) Impact of diversification on household income and risk - a whole-farm modeling approach. Agricultural Systems 44, 301-312.

Bryan, B.A., Crossman, N.D., King, D., McNeill, J., Wang, E., Barrett, G., Ferris, M.M., Morrison, J.B, Pettit, C., Freudenberger, D., O'Leary, G., Fawcett, J., and Meyer, W. (2007) Lower Murray Landscape Futures Dryland Component: Volume 3 – Preliminary Analysis and Modelling. CSIRO Water for a Healthy Country, 378.
http://www.landscapefutures.com.au/reports/LMLF_Volume3_Dryland_Report_Data_Modelling.pdf

Bryan, B.A., Hajkowicz, S., Marvanek, S., Young, M.D. (2009) Mapping economic returns to agriculture for informing environmental policy in the Murray-Darling basin, Australia. Environmental Modeling & Assessment 14, 375-390.

Bryan, B.A., King, D., Wang, E. (2010) Biofuels agriculture: landscape-scale trade-offs between fuel, economics, carbon, energy, food, and fiber. Global Change Biology – Bioenergy 2, 330-345.

Bryan, B.A., King, D., Ward, J. (2011) Modelling and mapping agricultural opportunity costs to guide landscape planning for natural resource management. Ecological Indicators 11, 199-208.

Bryan, B.A., Marvanek, S. (2004). Quantifying and Valuing Land Use Change for Integrated Catchment Management Evaluation in the Murray Darling Basin, 1996/97 to 2000/01. Stage 2 Report to the MDBC, CSIRO Land and Water Client Report.

Chan, L.K.C., Karceski, J., Lakonishok, J. (1998) The risk and return from factors. Journal of Financial and Quantitative Analysis 33, 159-188.

Chan, L.K.C., Karceski, J., Lakonishok, J. (1999) On portfolio optimization: Forecasting covariances and choosing the risk model. Review of Financial Studies 12, 937-974.

Cooper, P.J.M., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B., Twomlow, S. (2008) Coping better with current climatic variability in the rainfed farming systems of Sub-Saharan Africa: An essential first step in adapting to future climate change? Agriculture Ecosystems & Environment 126, 24-35.

Correal, E., Robledo, A., Rios, S., Rivera, D. (2006) Mediterranean dryland mixed sheep-cereal systems. Sociedad Espanola para el Estudio de los Pastos (SEEP), pp. 14-26.

Deressa, T.T., Hassan, R.M. (2009) Economic impact of climate change on crop production in Ethiopia: Evidence from cross-section measures. Journal of African Economies 18, 529-554.

Fraser, E.D.G., Mabee, W., Figge, F. (2005) A framework for assessing the vulnerability of food systems to future shocks. Futures 37, 465-479.

Furuya, J., Kobayashi, S. (2009) Impact of global warming on agricultural product markets: Stochastic world food model analysis. Sustainability Science 4, 71-79.

Hardaker, J.B., Huirne, R.B.M., Anderson, J.R., Lien, G. (2004) Coping with risk in agriculture. Coping with Risk in Agriculture, xii + 332 pp.

Hardaker, J.B., Lien, G. (2010) Probabilities for decision analysis in agriculture and rural resource economics: The need for a paradigm change. Agricultural Systems 103, 345-350.

Howden, S.M., Soussana, J.F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H. (2007) Adapting agriculture to climate change. Proceedings of the National Academy of Sciences of the United States of America 104, 19691-19696.

Iglesias, A., Quiroga, S. (2007) Measuring the risk of climate variability to cereal production at five sites in Spain. Climate Research 34, 47-57.

IPCC (2007) Climate Change 2007: Synthesis. Summary for policy makers. Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

John, M., Pannell, D., Kingwell, R. (2005) Climate change and the economics of farm management in the face of land degradation: Dryland salinity in Western Australia. Canadian Journal of Agricultural Economics-Revue Canadienne D Agroeconomie 53, 443-459.

Kandulu, J.M., Bryan, B.A., King, D., Connor, J.D. (2012) Mitigating economic risk from climate variability in rain-fed agriculture through enterprise mix diversification. Ecol. Econ. 79, 105-112.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J. (2003) An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy 18, 267-288.

Kelkar, U., Narula, K.K., Sharma, V.P., Chandna, U. (2008) Vulnerability and adaptation to climate variability and water stress in Uttarakhand state, India. Global Environmental Change-Human and Policy Dimensions 18, 564-574.

Kingwell, R.S. (1994) Risk attitude and dryland farm-management. Agricultural Systems 45, 191-202.

Kurukulasuriya, P., Ajwad, M.I. (2007) Application of the Ricardian technique to estimate the impact of climate change on smallholder farming in Sri Lanka. Climatic Change 81, 39-59.

Lien, G., Hardaker, J.B., van Asseldonk, M., Richardson, J.W. (2009) Risk programming and sparse data: How to get more reliable results. Agricultural Systems 101, 42-48.

Lotze-Campen, H., Schellnhuber, H.J. (2009) Climate impacts and adaptation options in agriculture: What we know and what we don't know. Journal Fur Verbraucherschutz Und Lebensmittelsicherheit-Journal of Consumer Protection and Food Safety 4, 145-150.

Markowitz, H.M. (1952a) Portfolio Selection. Journal of Finance, 7, 77-91.

Markowitz, H.M. (1952b) Portfolio Selection: Efficient diversification of investments. Yale University Press, New Haven, CT.

Markowitz, H.M. (1994) The general mean-variance portfolio selection problem. Philosophical Transactions of the Royal Society of London Series a-Mathematical Physical and Engineering Sciences 347, 543-549.

Marton, L., Pilar, P.M., Grewal, M.S. (2007) Long-term studies of crop yields with changing rainfall and fertilization. Agrartechnische Forschung-Agricultural Engineering Research 13, 37-47.

Naylor, R.L., Battisti, D.S., Vimont, D.J., Falcon, W.P., Burke, M.B. (2007) Assessing risks of climate variability and climate change for Indonesian rice agriculture. Proceedings of the National Academy of Sciences of the United States of America 104, 7752-7757.

Pannell, D.J., Malcolm, B., Kingwell, R.S. (2000) Are we risking too much? Perspectives on risk in farm modelling. Agricultural Economics 23, 69-78.

Ramaswami, B., Ravi, S., Chopra, S.D. (2003) Risk Management in Agriculture. Discussion Papers in Economics 03-08. Indian Statistical Institute, Delhi Planning Unit.

Suppiah, R., Preston, B., Whetton, P.H., McInnes, K.L., Jones, R.N., Macadam, I., Bathols, J., Kirono, D. (2006) Climate change under enhanced greenhouse conditions in South Australia: An updated report on: Assessment of climate change, impacts and risk management strategies relevant to South Australia. CSIRO regional climate change report for SA Government.

Wang, E., Cresswell, H., Bryan, B., Glover, M., King, D. (2009a) Modelling farming systems performance at catchment and regional scales to support natural resource management. Njas-Wageningen Journal of Life Sciences 57, 101-108.

Wang, E.L., McIntosh, P., Jiang, Q., Xu, J. (2009b) Quantifying the value of historical climate knowledge and climate forecasts using agricultural systems modelling. Climatic Change 96, 45-61.

World Bank (2004) Agricultural Diversification for the Poor, Guidelines for Practitioners. March 2004 http://siteresources.worldbank.org/INTARD/825826-1111044795683/20460111/Diversification_Web.pdf (Accessed 22.10.10)