THE UNIVERSITY OF ADELAIDE

“I can’t be green if I’m in the red”:

Combining precision agriculture and remote sensing technologies for sub field and regional decision making

Thesis presented for the degree of

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Chapter 5: Identifying the spatial and temporal variability of economic opportunity cost in Mediterranean grain growing regions

***Keywords**: spatial information, precision agriculture, spatial variability, temporal variability, economic opportunity cost, natural resource management, climate change.*

5.1 Abstract

A major impediment to the introduction of land use change in agricultural regions is the potential loss of income. Quantification of this loss is problematic because of the lack of economic information at an appropriate spatial scale, spatial resolution and temporal dimension, which is limiting the adoption of alternative land uses in agricultural regions. To overcome this problem, we propose a methodology which utilises high resolution yield data collected using precision agriculture technology, gross margin financial analysis and a temporal standardisation technique to highlight the spatial and temporal consistency of income generation. Scenario analysis based on the minimum, medium and maximum financial returns over the ten years of yield data were used to derive a proposed range of economic opportunity costs. These costs highlight the potential magnitude of economic trade-offs involved in the land use change decision making process under our selected gross margin assumptions.

Similar income to area ratios were found on three Western Australian grain growing farms, with 30% of farm income derived from 50% of each farm's area. However, the areas that generated the lowest percentage of income were temporally inconsistent due to field rotations. Temporal analysis of a farm with a cropping area of 2,924 hectares (ha) showed that 12-19% (343–543 ha) of production areas consistently produced the bottom 40-50% of farm income while 37-49% (1093-1430 ha) of the cropping area always produced over these thresholds. The economic opportunity costs ranged from \$172-\$404 per ha and \$195-\$444 per ha respectively for these percentages depending on the financial return scenario chosen. If land use alternatives can provide similar income returns then a mixed farming system is possible. This will provide growers with an adaptive capacity to adjust

to the constraints of climate change and react to the potential financial opportunities without negative financial repercussions.

5.2 Introduction

A major hurdle in the adoption of land use change is the identification of the economic opportunity cost associated with the change from traditional agricultural production to other more environmentally friendly alternatives (Sinden, 2004; Dorrough *et al.*, 2008). Adoption will likely occur in areas where profit from traditional cropping practices is comparative (Frost *et al.*, 2001; Lefroy *et al.*, 2005; Abadi *et al.*, 2006). This may occur in areas where the whole agricultural practice can be identified as marginal (Dorrough and Moxham, 2005; Maraseni and Dargusch, 2008), or where farms have diminishing financial returns to farm area (Groeneveld, 2005) caused by either unproductive soil types (John *et al.*, 2005; House *et al.*, 2008) or land where production has been affected by environmental degradation (O'Connell *et al.*, 2006).

Several studies have endeavoured to incorporate theoretical or modelled economic opportunity cost to understand economic and environmental trade-offs (Altman, 2001; Shogren *et al.*, 2003; Pacini *et al.*, 2004; Newburn *et al.*, 2005; Drechsler *et al.*, 2006; Fletcher and Hilbert, 2007; Iraizoz *et al.*, 2007). Others have relied on aggregated economic data collected at the global, regional, farm or if available at the field scale to inform public policy decisions (Norton-Griffiths and Southey, 1995; Lewandrowski *et al.*, 1999; Hajkowicz and Young, 2002; Sinden, 2004; Groot *et al.*, 2007; Dorrough *et al.*, 2008). The association of economic data to a spatial location and extent has extended the research field further with spatial targeting and comparison of production areas based on economic and environmental efficiency trade-offs as well as conflicting multiple objectives (Skop and Schou, 1999; Yang *et al.*, 2003; Münier *et al.*, 2004; Chomitz *et al.*, 2006; Groot *et al.*, 2007; Van der Horst, 2007; Barton *et al.*, 2008; House *et al.*, 2008; Wunscher *et al.*, 2008; Crossman and Bryan, 2009).

These studies provide valuable insight into the development of regional conservation strategies and the adoption of alternative land uses. However, they provide only limited value to management decisions which are made by the grower at the field scale and below. Data used in these studies is often collected at a scale and extent that is far greater than that of the average agricultural field. This is further compounded by the information's temporal currency where only a static annual snapshot of land use is used. This limits the ability of the studies to mimic the spatial and temporal dimension in areas where cereal rotations and break crops are apparent. One advancement in this area, is the use of remote sensing technology which can provide a finer spatial definition of land use to define economic opportunity costs (Lant *et al.*, 2005; Naidoo and Adamowicz, 2006; Naidoo *et al.*, 2006; Naidoo and Ricketts, 2006; Shrivastava and Gebelein, 2007).

Another limitation is that spatial variability of agricultural production is not considered. These studies spatially distribute a constant economic opportunity cost based on averages of production income, net rental income or land use land value derived from farm or regional agricultural surveys via the land use dataset. This potentially blurs the spatial variability of agricultural production within a region due to factors such as rainfall, soil type and agronomic management. Several studies have recognised this limitation and have applied variations in annual precipitation rates (Bryan *et al.*, 2008) and biomass production (Hajkowicz and Young, 2005) across spatially defined land units to further the spatial heterogeneity of production values.

To overcome these current data restrictions, agricultural production data needs to be collected at higher spatial resolution annually. Precision agriculture technology and in particular crop yield mapping provides one opportunity to collect high resolution estimates of spatially varying crop production. Yield mapping is the process in which the combine harvester is fitted with a global positioning system and a grain flow measuring device. As the combine harvests, the grain yield and current position are recorded. The accuracy of continuous yield monitoring has been reported to be range from 95% to 99.5% (Murphy *et al.*, 1995; Birrell *et al.*, 1996; Missotten *et al.*, 1996; Reitz and Kutzbach, 1996; Jasa, 2000; Arslan and Colvin, 2002a). The two-dimensional mapping of this data identifies the magnitude of spatial variability in grain yield within the field. The application of financial analysis can depict areas of differing profitability (Massey *et al.*, 2008) and hence provides a basis for the quantification of economic opportunity cost. Yield mapping can identify spatial variation of yield in one particular season. Several studies have shown mixed results in the stability of these zones over time, some have shown no apparent yield stability (Lamb *et al.*, 1997; Blackmore *et al.*, 2003; Joernsgaard and Halmoe, 2003;

Schepers *et al.*, 2004) while others demonstrated that temporal stabilkity of yield existed over time (Jaynes *et al.*, 2005; Cox and Gerard, 2007; Robertson *et al.*, 2008) .

The main aim of this paper is to apply precision agriculture technology to estimate and quantify the spatial and temporal consistency of economic opportunity cost at sub field resolution over the farm scale. As the majority of farm area in the study region is cropped to wheat, the analysis will investigate wheat yield data to identify three major objectives in the quantification of economic opportunity cost. The first objective is to identify the magnitude of spatial variability of wheat income present over three farms for different growing seasons. This will show degree of spatial income variability present. The second objective will attempt to identify whether the spatial consistency of income generation holds over different cropping seasons. This type of analysis will identify the location and extent of spatially and temporally consistent financial areas. The third objective of this study is to estimate the financial returns from traditional agriculture for these highlighted areas. This will determine the range and magnitude of economic opportunity cost which will be needed to be offset if land use substitution is to occur.

5.3 Methods

5.3.1 The study area

The study area encompasses three farms within the northern wheatbelt of Western Australia around the town of Buntine. Cropping areas ranged from 2,924 hectares (ha) for Farm 1, 2,000 ha for Farm 2 and 2,500 ha for Farm 3. The growing landscape is predominately broad sand plains with very little elevation and salty lands situated in the lower parts of the landscape. Cropping rotations are dominated by wheat (*Triticum aestivum*) with lupins (*Lupins consentini, Lupins albus*) and canola (*Brassica napus*) used as break crops. Pastures are also common for cattle and sheep grazing, as well as small randomly scattered stands of remnant native vegetation consisting of a mixture of evergreen shrubs and trees that are well adapted to the hot dry summers (Turner and Asseng, 2005). This region is characterised by a Mediterranean climate, with cool wet winters and hot dry summers. Over half of the annual rainfall (300–400 mm) occurs between May and September. As wheat is the dominant crop type for income generation, only wheat fields were examined in the anlaysis.

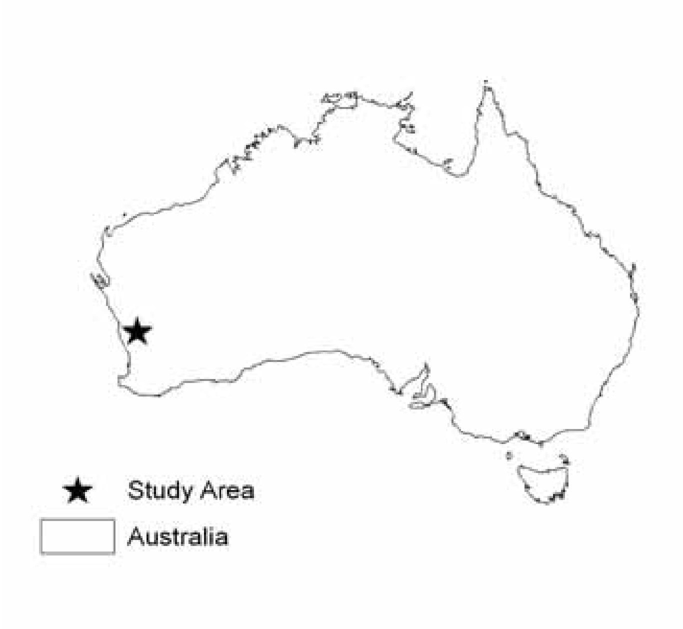

Figure 24 Location of the study area in the northern wheat belt of Western Australia

5.3.2 Yield monitored wheat grain yield

Wheat grain yield data from three different combine mounted yield monitors was collected from three farms. Different rates of adoption of yield mapping technology are evident across the Australian farming landscape (Jochinke *et al.*, 2007) and this is also apparent in this study area. Ten years of data were available for Farm 1 while Farms 2 and 3 had collected five and six years of yield mapping data respectively. Data collected in drought years (2000 and 2002) were removed. We passed 286 field datasets through specific error removal algorithms to eliminate errors associated with combine harvester dynamics, the interaction of measured parameters in the calculation of yield, the global positioning system and the combine harvester operator. This processing equated to 156 fields for Farm 1, 48 fields for Farm 2 and 82 fields for Farm 3. Undertaking the process of error removal produced yield distributions with a more normal distribution than observed in the raw datasets (Blackmore, 1998; 2003). We then used the VESPER kriging software (Minasny *et al.*, 2005) and a yield mapping creation protocol (Taylor *et al.*, 2007) to create an interpolated yield surface of pixels which were 25 by 25 metres for each field. Each yield surface provided wheat grain yield estimates for missing areas due to error removal and acted as a positional basis for spatial and temporal comparison.

5.3.3 Estimating field income based on cost-price scenarios

The definition of the correct measure of farm income to be used in research studies is inherently problematic (Bateman *et al.*, 1999). Several studies have used gross margin analysis as a standard measure of annual profitability (Yang *et al.*, 2003; Pacini *et al.*, 2004; Sinden, 2004; Bryan *et al.*, 2008; Hunt, 2008; Wale, 2008), profit at full equity (Hajkowicz and Young, 2005), cash flow or partial budgeting (Dorrough *et al.*, 2008; House *et al.*, 2008) or estimated profits (economic rent) from land use (Yang *et al.*, 2003; Münier *et al.*, 2004; Holzkamper and Seppelt, 2007). In this study, we selected a spatial gross margin analysis which gave financial value in terms of a per hectare (/ha) return.

Across each year and farm, interpolated wheat yield values were sorted into ascending order and the per pixel gross margin (*GMpx*) was calculated as the grain price (*GP*) multiplied by the mapped estimate of yield (*YLD*) minus the variable production cost (*VC*), adjusted by the pixel area (*Apx*) (Equation 1).

$$GMpx = (G * YLD - VC) * Apx \qquad \text{(Equation 1)}$$

Values that produced negative gross margins were extracted and deemed 'loss making areas'. For positive gross margins, the individual values of gross margin and contributing area were summed and their associated percentages calculated to determine their cumulative contributions. This analysis was applied across the three farms and enables the ranking of each area by income importance.

Although specific yearly estimates can be used to calculate the yearly gross margins, the price received and the variable costs of production such as the prices of fuel, seed and fertiliser are determined by the international market. For grain growers, fluctuations in the yearly price provide a great deal of uncertainty in relation to land use change decisions. Here, small changes in crop area can have significant impacts on farm profit when crop prices are good (Martin, 2005; House, 2008). A best case scenario for the grower was established to allow for a justified land use comparisons based on good financial returns. A grain price of $330 per tonne was selected. This price represented a recent high in 2008 (AWB, 2008) and exceeded the historical average of $219 per tonne with a standard deviation of $29.17 for the time period between 1995 and 2006 (Anderton and Kingwell, 2008). Variable cost records for each farm were not available, so published estimates of $170 per hectare (/ha) without fertilisation costs (Farquharson *et al.*, 2008) and $116 /ha for fertiliser (Department of Agriculture and Food, 2007) for medium to high cropping intensity enterprises within the region were used. These total variable cost estimates were similar to those for southern Australia (Rural Solutions, 2008) and Australia (ABARE, 2008). Fixed costs (such as machinery and interest on loans) were not included on the assumption that the majority these costs will be incurred regardless of the intensity of agricultural enterprises undertaken both now and in the future. The use of the gross margin equation provided a conservative first pass estimate of the potential income generation cost, given that each grower within a specific locality will have a similar production (variable) costs but substantially different business (fixed) costs .

Based on the selected grain price and the total variable cost, the break even yield was 0.84 tonnes per hectare (t/ha). This represented good financial returns for the grower when compared to the recent historical break even yield ranges of 0.81-1.28 t/ha in 2003 (Department of Agriculture, 2002) and 1.24-1.94 t/ha in 2005 (Department of Agriculture and Food, 2005).

5.3.4 Identifying the spatial and temporal variability of production income

Applying a gross margin analysis to the yield mapping data enables the quantification of spatially variable income and the identification of marginal areas of income generation. For land use change decisions based on economic rationale these areas must also have the same income consistency regardless of seasonal conditions. One method to combine spatial and temporal variability is to normalise annual variability so that yields from different years and sometimes different crops can be compared (Sadler *et al.*, 2005). The calculation of the z-score is one standardisation technique which for a specific item indicates how far and in what direction that item deviates within a distribution. Within agricultural research, the z-score has been used to compare grain yield variability (Eghball and Power, 1995; Lamb *et al.*, 1997) and temporal drought assessment (Wu *et al.*, 2001; Morid *et al.*, 2006; Sirdas and Sahin, 2008).

Z score analysis was confined to Farm 1 as it had the greatest temporal range of yield mapping data available. For each annual gross margin surface, each pixel was standardised by the yearly average gross margin and the associated standard deviation. Appling this formula ranked how far above or below each pixel's income performance is from the annual average gross margin.

Each pixel's income contribution can change temporally and seven income contribution scenarios were constructed based on whether each pixel fell below a specific p-value representing the bottom 5-50% of income creation. Due to field rotations and fluctuations in field harvest area, pixels which had a single occurrence over the temporal dataset were excluded. For each income scenario, a probability surface of temporal income consistency was created based on the number of pixel occurrences below a income scenario divided by the number of occurrence years (such as 1 in 6 years ~16%) and temporal consistency thresholds were then applied. These values identified degree of temporal variability and the amount of area associated with the income scenarios. These included areas that were characterised as where land use change should not be considered (0% classified at "Zero"), 16-40% ("Low") areas of management or pest induced variation, 50% ("Medium") areas that may consistently fluctuate and are either seasonally or rotationally dependant, 60-83% ("High") medium to high temporal consistency and 100% ("Consistent") which indicated areas that always fall below the income scenarios. The spatial distribution of each scenario was then mapped to identify if areas of similar economic value were clustered or randomly distributed.

By applying this temporal standardisation, low income areas that are not temporally stable due to management or pest induced variability can be differentiated from those low income areas that are temporally consistent. If the spatial distributions of these temporally stable low income areas show a clustered pattern then land use change opportunities can be targeted. Alternatively, if a randomly distributed pattern is evident, a field based approach will be a more appropriate method for land use decision making.

5.3.5 Estimating the range and magnitude of economic opportunity cost based on financial returns scenario

To understand the loss of income due to reassignment of area that are currently cropped, the likely range and magnitude of economic opportunity costs was calculated. Three scenarios based on the minimum, median and maximum of financial returns were generated for each pixel across all years. Each financial returns scenario was ranked in ascending order of magnitude and plotted against the corresponding percentage of farm area. This gave the magnitude of gross margin and contributing area for each scenario. The spatial distribution of these values was then mapped to show where the range of values occurred.

Each gross margin scenario was overlain across the temporal consistency dataset and gross margins were aggregated by the temporal consistency thresholds. We can hypothesise that for the reassignment of traditional cropping areas to alternative land uses, two opportunity cost scenarios could be expected. The first, the economic opportunity costs created from cropping areas that have similar temporal income consistently. The second situation, involves a temporal trade-off where areas of higher temporal variation in income creation are grouped with temporally consistent regions (DeFries *et al.*, 2007). We will attempt to quantify both situations.

5.4 Results

5.4.1 Income to area relationships over three farms

In the land use decision making process, areas that produce a financial loss independent of seasonal conditions would be the first to be targeted. Given the cost price structure used in the analysis, the income generated over each farm suggests that these areas are minimal (Table 7). Estimated loss areas where less than 5% for each farm over different growing seasons.

Table 7 Percentage of loss making areas by year

Year	1996	1997	1998	1999	2001	2003	2004	2005
Farm 1	1.7	0.2	4.6	4.0	0.4	0.1	1.2	0.1
Farm 2	*	*	1.9	1.8	< 0.1	0.3	*	*
Farm 3	*	*	*	4.1	0.1	0.1	0.3	*

* Not yield monitored

Due to the yearly variations in rainfall and the selection of fields cropped, the amount of income derived from wheat cropping and the area committed to deriving it will vary from year to year. The use of yield mapping technology can quantify this variation establishing yearly income to area relationships. These relationships can be expressed as a cumulative association between the percentage of yearly wheat income and the percentage of area cropped to wheat used to derive it.

As differing years of yield mapping are available on each farm, the derived income distributions can be grouped and their extents quantified into farm income envelopes (Figure 25). For each farm all income distributions fall within these envelopes.

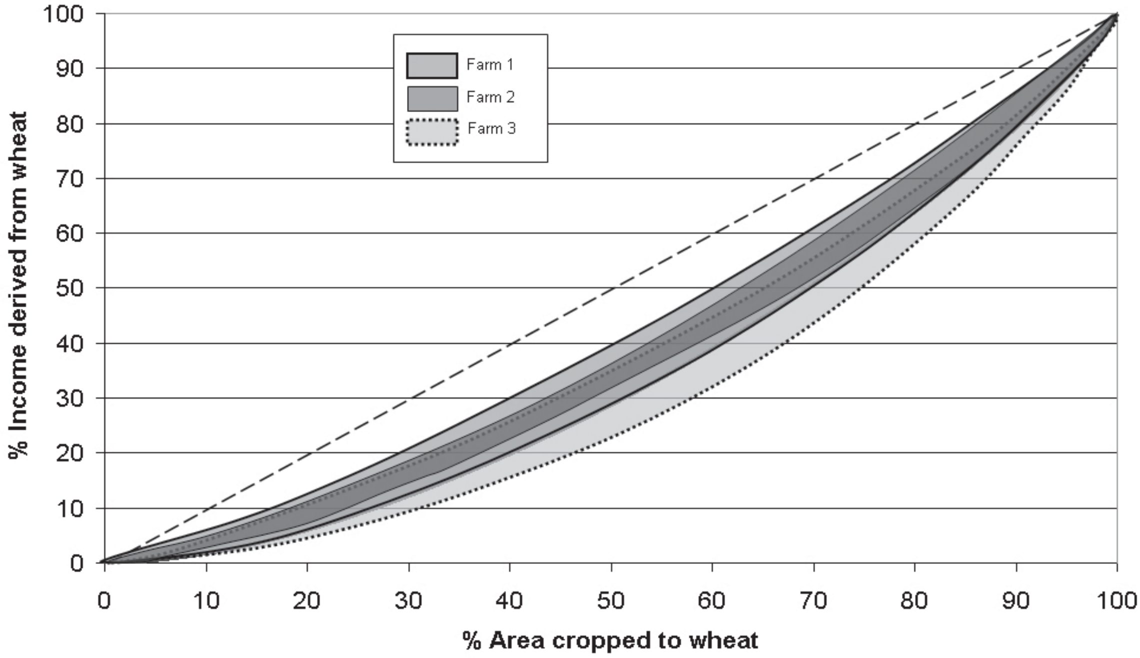

Figure 25 Income envelopes that encompass the extents of yearly income and area distributions for three farms in Western Australia

The derivation of the economic opportunity cost without high resolution information is limited to the application of average yields present in the cropping region or if available the average field yields. The use of this information confines the estimation of opportunity costs to slight deviations away from the 1:1 line (Figure 25). This line characterises the production function where no spatial variability of yield is present, namely, where 20% of the land generates 20% of farm income and that 20% of income will be lost given the 20% reallocation of agricultural land.

The use of spatially explicit yield estimates suggests that this is not the case (Figure 25). For the best case cost-price scenario, around 50% of farm area generated around 30% of income on all farms. Small distances between each envelope boundary demonstrate that income to area relationships hold across different growing seasons and the overlapping of these envelopes illustrate highlight similar relationships across all three farms.

5.4.2 The spatial distributions of gross margin returns for Farm 1

Gross margins per hectare estimates for Farm 1 provide an indication of the of the expected yearly opportunity costs. In these calculations, the amount of in-season rainfall and the rotations of wheat fields highlight two types of gross margin distributions (Figure 26). The first type (Distribution 1) shows a rapid increase in gross margin in the first 5-10% of area. In these years, 15-30% of the production area produces a value of around \$300/ha. The second distribution (Distribution 2) suggests a flatter function where the returns are quite low. Values range under \$300/ha for 50% of the cropping area, \$65-\$180/ha for the first 10-20% of land cropped to wheat.

Where fields were included in both distributions, the contributing area of these fields made up the lower part of the gross margin values in Distribution 1 and the higher part of the gross margin values in the Distribution 2. These results indicate that although the area to income relationships hold across seasons (Figure 25), the different areas actual contribution to income can vary substantially when looked at temporally. Although not shown here, the relationships present in Figure 26 are similar for the other two farms.

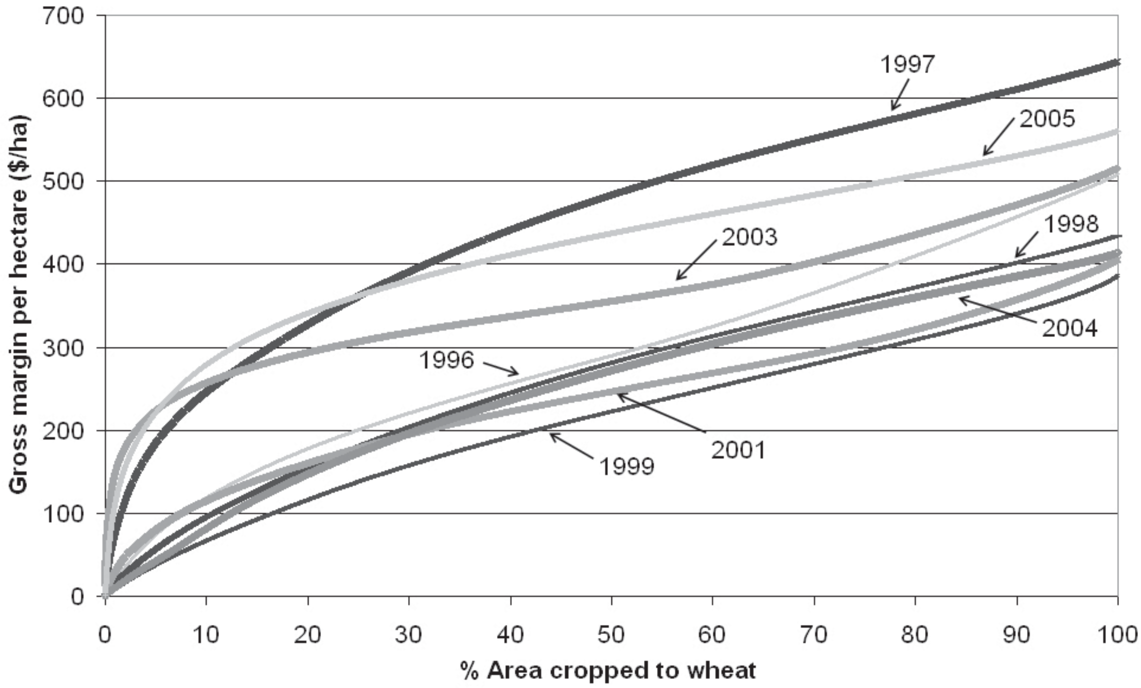

Figure 26 Gross margin per hectare by percentage area cropped to wheat for eight years

5.4.3 Spatial and temporal consistency of gross margin returns

The rotation of fields has shown that the contributing area to yearly income may differ substantially. For any robust land use change decision making to take place, an understanding of the degree of temporal consistency based on each areas contribution to the overall yearly income must be identified (Table 8). Areas that consistently produced in the lowest income scenario (5%) were marginal, occurring at the field boundary (Figure 27) while 87% of cropped area produced above this criterion. Reduction area in the “Zero” classification occur at the 20% scenario to around 57% (1,650 ha) and decrease to 29% (855 ha) and 21% (614 ha) when the income scenario is raised to 40% and 50% respectively. Aggregation of this classification with the “Low” category indicates that around 37-49% (1093-1430 ha) of area has a high probability of producing income above the 40-50% of income threshold.

Areas that consistently produced below these income scenarios were not substantial with 12-19% (343-543 ha) of cropping area, the addition of areas that have a high temporal probability ("High") double this estimate to 32-43% (936-1257 ha) for both scenarios respectively.

Table 8 Percentage farm area by temporal consistency classification within each percentage income scenario

Percentage Income (%)	Zero (0%)	Low (16% - 40%)	Medium (50%)	High (60% - 83%)	Consistent (100%)
5	87.4	8.8	3.1	0.3	0.4
10	80.6	13.3	4.8	0.8	0.6
15	76.3	15.8	5.8	1.3	0.9
20	56.5	22.5	12.0	6.2	2.9
30	40.5	22.8	17.0	13.1	6.6
40	29.3	19.6	19.3	19.5	12.3
50	21.0	16.4	20.1	23.2	19.3

We have shown the magnitude of temporal consistency for each income scenario. For change in land use to occur these areas must be spatially clustered so that they can be easily managed. Figure 27 shows the increased clustering of areas as we move through income scenarios. Using the grey colour spectrum we see a movement of areas from lighter grey to black indicating a movement from lower probability to higher probability of areas falling below the income thresholds. It is not until we reach the bottom 50% income threshold that entire fields could be earmarked for total land use reassignment. Alternatively, we have also highlighted clustered high income performing areas.

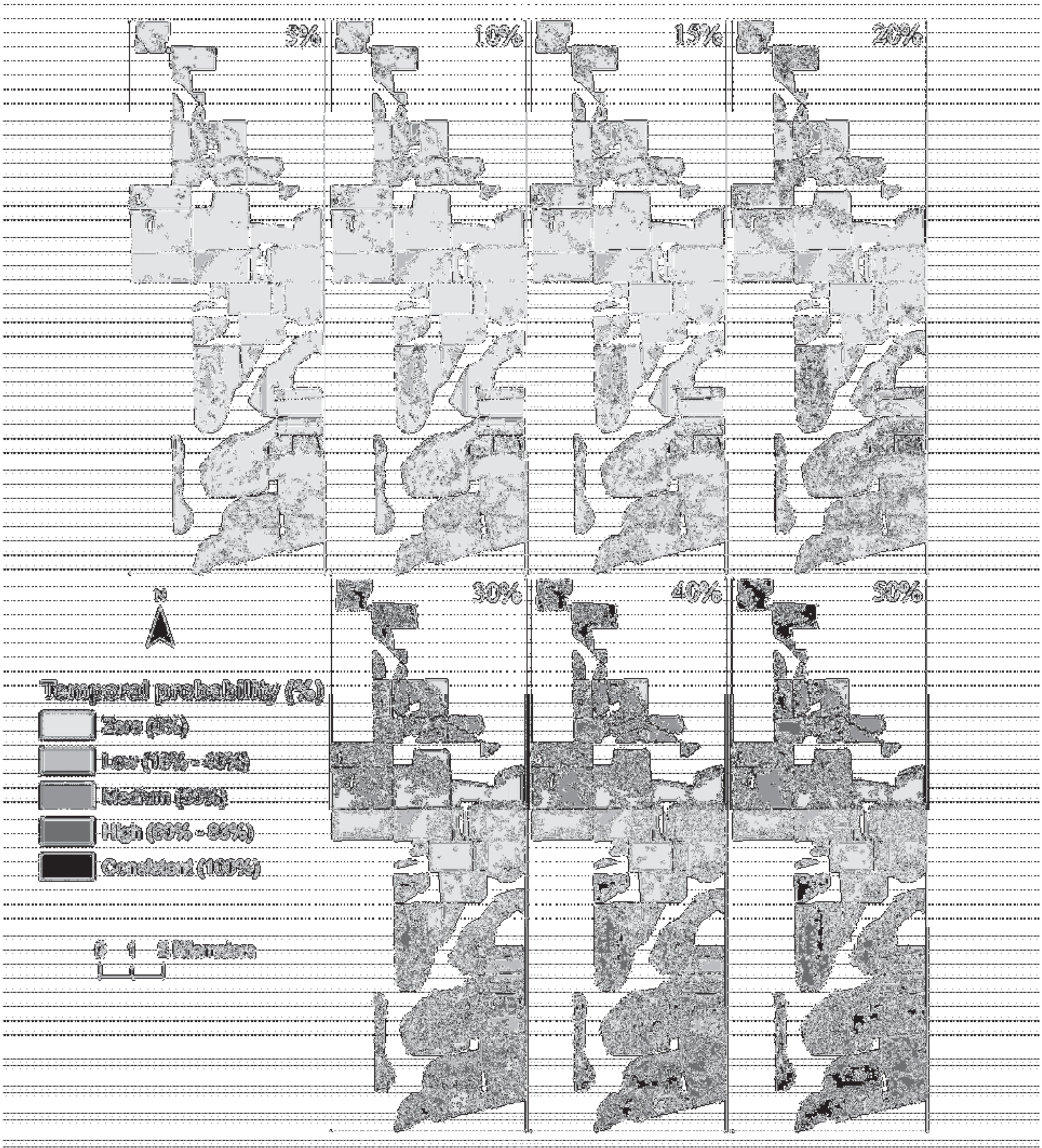

Figure 27 Clustering of production areas with increasing income scenarios (5-50%)

5.4.4 Estimating the magnitude of economic opportunity cost based on three financial returns scenarios

Mapping the temporal consistency of production areas highlights the locations that consistently produce the bottom percentages of income. Calculating the associated per hectare gross margin over all years provides a means to identify not only the range of financial reward that needs to be generated from an alternative land use but the associated amount of area (Figure 28). The median and maximum financial returns curves ($/ha) show a large rise in the first 10% of area followed by a flattening of the curve to a steady until the last 10% of production area. This initial rise was flatter for the minimum financial returns curve.

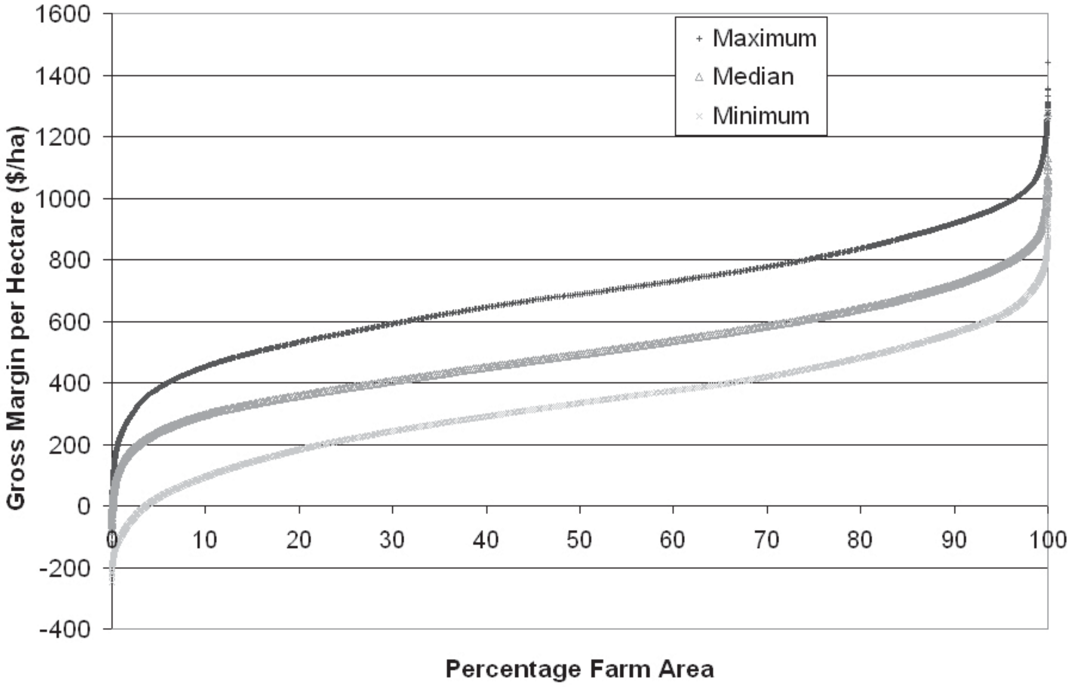

Figure 28 Cumulative gross margins per hectare and the corresponding percentage farm area for the three financial returns scenarios

For the assumed cost price structure, the majority of cropped areas are profitable to varying degrees with the exception of 4% of the farm area when the minimum scenario is chosen. For 30% of the farm area, gross margin per hectare values range from over $200-$600 /ha. These ranges rise within increased farm area, with 50% of farm area ranging from $375-$700 /ha.

Mapping of the three scenarios show the location of the gross margins generated and the ability to spatially target production areas with similar economic opportunity cost (Figure 29). For the minimum scenario, several areas are apparent where either management or yield mapping data errors have occurred (straight lined area). A high degree of spatial clustering is apparent for both areas where gross margin was below $200 /ha and above $600/ha. For the median scenario, values in the range of $200-$400 /ha were dominate, clustering around lower gross margin values. Income variability for the maximum scenario showed similar clustered locations albeit with greater gross margin per hectare values.

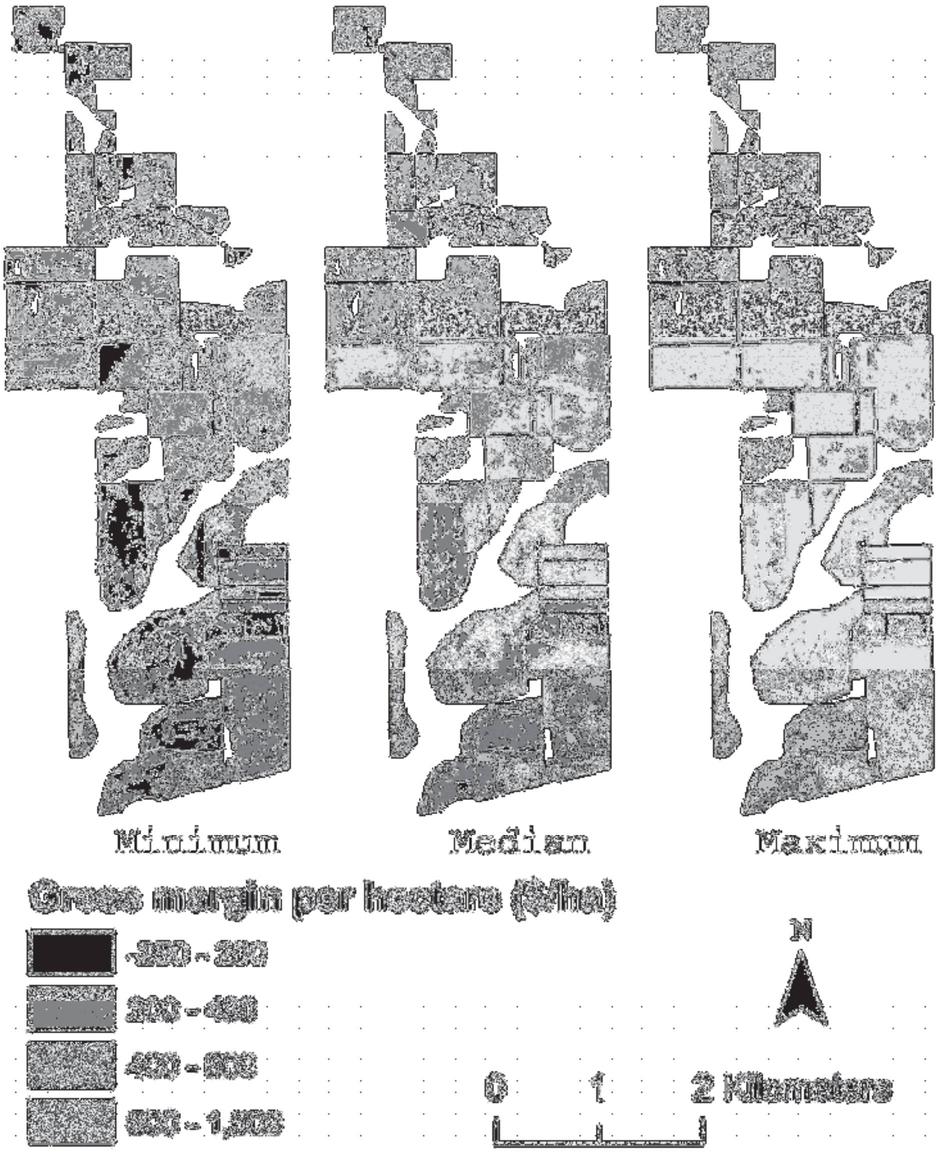

Figure 29 Spatial distribution of gross margin per hectare values ($/ha) for the three financial returns scenarios

5.4.5 Average economic opportunity cost by areas of spatial and temporal income consistency

In the previous steps we have established the spatial and temporal consistency of income creation and a range of gross margins per hectare values for the farm area. From the collation of both the area and the estimated gross margin per hectare values associated with a scenario, the amount of production area and average economic opportunity costs was calculated (Figure 30A). As highlighted previously, the magnitude of production area was small for the income scenarios below 40-50%. At these thresholds, areas that were classified as “Consistent”, ranged from 12-19% with economic opportunity costs varying from \$172-\$404 /ha and \$195-\$444 /ha respectively.

Results from Figure 27 illustrated that the spatial and temporal clustering of areas with similar production capabilities was evident. By relaxing the temporal criteria to include areas of greater temporal variability, 5 seasons in 6 (83%) and 4 seasons in 5 (80%) we can extend the amount of area available (Figure 30B). For the 40-50% income thresholds, production area increased to 15% and 22% while the average economic opportunity costs varied from \$164-\$434 /ha and \$186-\$471 /ha. Further extension to incorporate the 75% (3 in 4 seasons) temporal probability category (Figure 30C) demonstrated an area increase to 22% and 33% with average economic opportunity costs ranging from \$188-\$507 /ha and \$213-\$538 /ha.

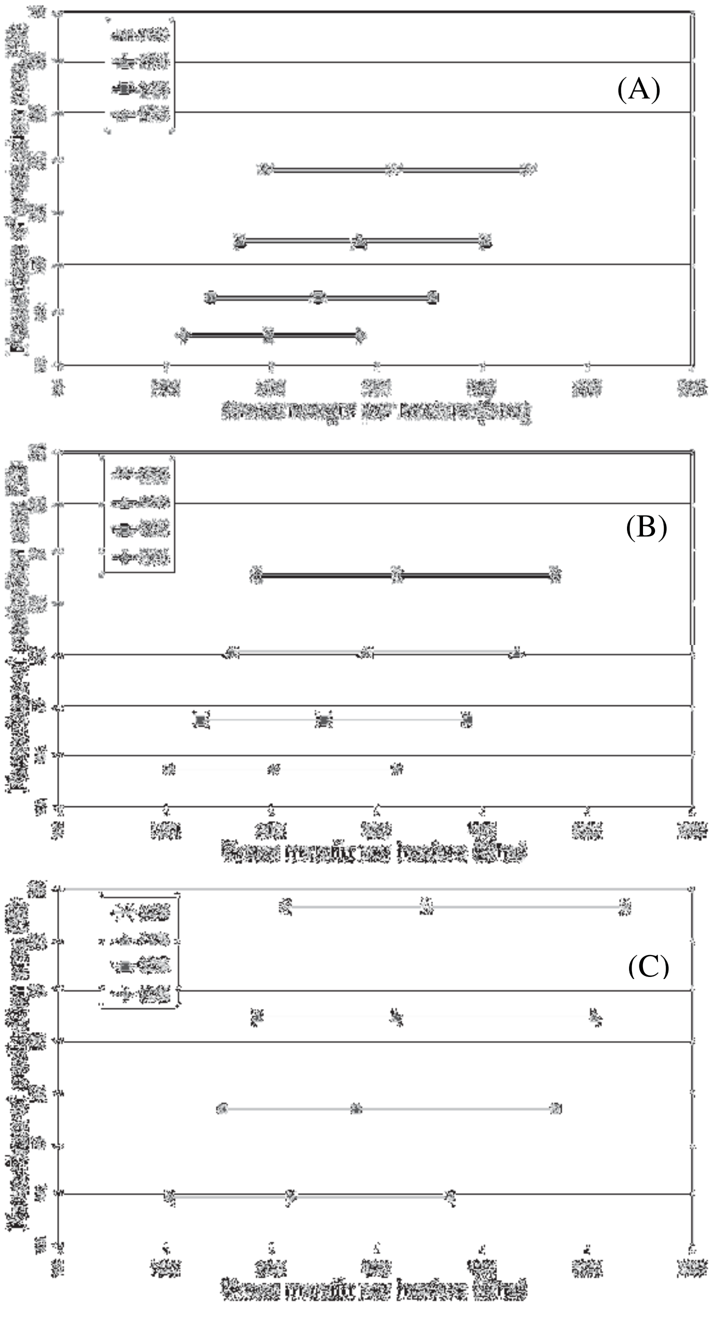

Figure 30 Magnitude of production area and ranges of economic opportunity costs for the "Consistent" (A), 80-100% (B) and 75-100% (C) temporal probability classifications of producing below the bottom 20-50% of income

5.5 Discussion

In Australia, relatively little compensation is paid to growers for land uses that provide public environmental benefits. In this situation, adoption will be based purely on an economic decision, that is, are the alternative land uses more profitable than current traditional agricultural enterprises. Current economic information on the profitability of grain growing enterprises can provide an overall idea of the financial repercussions of land use change. But their coarse collection and temporal resolution mask the inherent spatial variability of profitability over the agricultural landscape. In this study, we have proposed a methodology using yield mapping, a precision agriculture technology, to quantify farm profitability at a higher spatial and temporal resolution. We have shown that a 1:1 relationship does not exist between income and area and that spatial variability of income generation exists both spatially and temporally. The extent of spatial variability in wheat income based on our "best case scenario" cost price structure demonstrated that on three farms over a variety of different climatic seasons, only a small amount of area (< 5%) made a financial loss. For positive income to area relationships, around 30% of farm income for each farm was generated by around 50% of the farm area. These results demonstrate the theoretical argument of diminishing financial returns to farm area proposed by (Groeneveld, 2005) and occur across all three farms regardless of seasonal characteristics.

As production areas change annually due to field and crop rotations, the temporal standardisation technique showed that areas that produced the bottom 30% of income was small (< 7%). Extension to the bottom 40% and 50% of income showed an increase to 12-19% of the farm area. Relaxing the temporal probabilities to 3 out of 4 seasons saw the amount of area increase to 22% and 33% respectively. Even with this temporal adjustment, the magnitude of area that was under the 30% income scenario was seen as marginal (<15%). These results indicate that a smaller amount of area is available than that highlighted with a purely spatial approach and profit for alternative land uses must be greater than that generated from the bottom 40-50% of income generated by traditional agricultural production.

We also highlighted areas of wheat production that have a high temporal probability of generating income above the 40-50% income classification. These are areas where the financial returns of alternative land uses may find it hard to compete. These areas represent 37-49% (1093-1430 ha) of the wheat production area and signify the staple area of income generation from traditional agriculture.

The existence of spatial and temporal clustering suggests that the farm area can be delineated into areas of income importance based on wheat production based financial returns. Previous studies have highlighted that data availability may pose significant problems for drawing conclusion on the temporal stability of yield (Lamb *et al.*, 1997; Joernsgaard and Halmoe, 2003; Florin *et al.*, 2009). Jaynes and Colvin, 1997 highlight that long term monitoring may need to be greater than six years. Due to the early adoption of yield mapping by the growers used in this study, eight years of data was utilised although certain fields or field areas had only 2 years. These areas must be looked at more thoroughly in future analysis. Also, this analysis only investigated the spatial and temporal of one crop type, wheat and removed seasons that were drought affected. Spatial and temporal analysis of yield maps and their limited availability has meant the majority of studies have used different crops and hence attempt to understand spatial yield stability over time with different climate, management, soil and crop growth interactions. While some of these interactions will still occur they will not be as pronounced if different crop types are included. This type of temporal analysis has been proposed by Joernsgaard and Halmoe, 2003 who highlighted the potentially high intra-field yield variation over different crops for a variety of years. Recent long term crop yield simulation modelling of the wheat crop type and yield map analysis in the study area (Lawes *et al.*, 2009; 2009b) have shown similar consistent spatial and temporal stability. Particularly in seasons as the ones used in this study where wheat average yields were between 1-3.5 tonnes per hectare.

The use of yield mapping technology to create maps of temporal income performance means that more informed income comparisons can be made between current and alternative income streams for specific areas across a farm. Areas with high returns from traditional agriculture can remain untouched with the adoption of alternative land uses in areas where financial returns are greater or at least as comparable. This will provide income diversity to the farming enterprise and will increase the adaptive capacity of the farm to deal with factors such as climate change and international commodity price volatility. Further information is needed on the suitability and availability of the alternative land use opportunity especially their likely response in to areas that have been highlighted as producing low financial returns from annual cropping. Investigation into some of the hidden costs of adaptation such as the transaction costs of moving from traditional agriculture to the alternative land use (Mburu *et al.*, 2003; Groeneveld, 2005) must also be included in the analysis.

The mapping of these results highlight that areas of similar income generation and temporal consistency are not randomly distributed but clustered across the farm. This spatial and temporal clustering demonstrates that sizeable areas of low profitability are available for land use reassignment. Depending on which income scenario are chosen, a strategy incorporating a 'small loss big gain' scenario (DeFries *et al.*, 2007) may have to be chosen. Here, profitable and unprofitable areas may be grouped together so as to achieve an environmental or ecological outcome as well as an easily manageable area for the grower. The utilisation of spatial optimisation routines (Crossman and Bryan, 2006; Crossman *et al.*, 2007; Crossman and Bryan, 2009) to determine the appropriate land use trade-offs should be explored further.

Annual income from production areas change seasonally and therefore the magnitude of economic opportunity costs will also vary. The eight year time series of yield mapping data and its spatial stability over time gave us the ability to create the gross margin per hectare values across a farm, based on the expected range between minimum, medium and maximum financial returns. Choice on the type and magnitude of land use reassignment is therefore dependant on the growers' willingness to forego future income for future environmental benefits. These ranges of magnitude of opportunity costs can be identified by certain typologies of landholders and farm types based on particular grower behaviour (Fielding *et al.*, 2005; Mayberry *et al.*, 2005; Emtage *et al.*, 2007; Seabrook *et al.*, 2008; Wilson, 2008). The minimum financial return scenario may well represent a grower with high environmental altruism while the maximum value indicated a grower purely interested in profit maximisation.

As an introductory analysis, we concentrated on the profitability of the dominate crop in the region, wheat. Future work should extend this analysis to other break crops. We also provide a simple financial analysis to offer a first pass estimation of the economic opportunity cost. The choice of cost-price structures used in this study suggest that the estimated economic opportunity costs are overestimated but this choice provides a conservative approach given that land use change decisions are clouded by decision uncertainty generated by the fluctuations in international commodity markets. If the financial returns from alternative land uses cannot compare to these estimates presented in this study, further spatial temporal analysis should be conducted with other cost-price structures. This will determine at what cost price structures do the financial returns from land use alternatives become comparable and how sensitive they are to commodity market changes. Further analysis of these high resolution datasets in a whole farm modelling framework will provide an understanding as to the divergence from the farms' baseline net profit and the return to capital change that will follow with the adoption of alternative land uses (Bathgate and Pannell, 2002; John *et al.*, 2005; Rivington *et al.*, 2007; Gibson *et al.*, 2008).

Our proposed methodology is based on the assumption that a grower has adopted and has been using yield mapping technology for a number of years. Where this information is not available due to the lack of adoption (Jochinke *et al.*, 2007), surrogate high resolution wheat yield information can be created. This relies on the temporal availability of historical yield data collected by early adopters in the region and remotely sensed biomass estimates. Good relationships between final wheat grain yield and remotely sensed biomass have already been established over different satellite sensors (Rudorff and Batista, 1991; Quarmby *et al.*, 1993; Smith *et al.*, 1995; Hamar *et al.*, 1996; Labus *et al.*, 2002; Ferencz *et al.*, 2004; Reeves *et al.*, 2005; Liu *et al.*, 2006; Patel *et al.*, 2006) and at the field scale for site specific agricultural management (Thenkabail, 2003; Dobermann and Ping, 2004; Enclona *et al.*, 2004). The development of these relationships with mid resolution imagery (up to 30 metres) over a large optical extent (up to 185 kilometres) provides an ability to create a historical record of high resolution broad extent wheat yield information. The creation of this information and the application of the methodology outlined in this paper can provide high resolution economic information to inform alternative land use.

Over the last decade conservation studies have identified the benefits of using spatial targeting for conservation and environmental planning (Newburn *et al.*, 2005), this opportunity has been very rarely pursued by economic studies (Vermaat *et al.*, 2005). With the development of the economic data in this study the gap between the resolutions of environmental and economic datasets has now been narrowed.

5.6 Conclusion

The magnitude of economic opportunity costs associated with the reassignment of production areas to alternative land uses plays a major part in the land use decision making process. For adoption to occur alternative land uses must be as profitable, if not more profitable, than current financial returns from traditional agriculture. This paper develops a methodology that uses high resolution wheat yield mapping data provided by precision agricultural technology to highlight the spatial and temporal interactions of income generation on Australian wheat farms. We found through simple gross margin analysis conducted on three yield mapped farms that yearly financial returns have similar income to area ratios, with around 30% of yearly farm income generated by 50% of the farm area. However, these spatial relationships did not hold temporally due to the yearly rotations of crops within fields. Undertaking temporal analysis showed that 12-19% of production areas consistently produced the bottom 40% to 50% of farm income. The economic opportunity costs whose range depend on the financial returns scenario chosen was between $172-$404 /ha and $195-$444 /ha respectively. These estimates increased slightly when the temporal probability of areas that produced below these income thresholds were relaxed.

The quantification of area and the range of economic opportunity cost show the financial returns needed by alternative land uses for land use reassignment to occur. Around 37-49% of the wheat production area always produced above the 40-50% income thresholds. These estimates suggest that a mixed farming system with wheat cropping in the most profitable areas and adoption of alternative land uses in areas with comparable or lower financial returns may be possible. This will provide income diversity to the farming enterprise and will increase the adaptive capacity of the farm to deal with factors such as climate change and international commodity price volatility.

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Chapter 6: A high resolution broad scale spatial indicator of grain growing profitability for natural resource planning

***Keywords**: spatial information, precision agriculture, remote sensing, natural resource management, climate change.*

6.1 Abstract

The balancing of sustainable agricultural production with environmental, social, cultural and community objectives has become an increasing priority worldwide. Political focus has been on the prevention of environmental degradation and improving biodiversity values under the uncertainty of the impacts of climate change on rural livelihoods. In Australia, dry land salinisation is a major cause of environmental degradation in grain growing regions: at a farm scale the adoptions of key environmental strategies, such as revegetation, need to be considered.

This study proposes that the identification and quantification of the spatial variability of wheat grain yield within the cropping landscape may help guide this revegetation. We used precision agriculture technology to collect data at the sub field scale in conjunction with satellite imagery at the regional scale to create a high resolution regional indicator of wheat yield. This indicator is used to identify the economic value of land at sub-field scale which then allows identification of areas of marginal cropping value. This information provides an indication of how much land can be devoted to revegetation and quantifies the economic trade-off needed for this substitution to take place.

Results of this study demonstrate that 90% of the income generated within the area of interest was produced by 55-74% of the wheat growing area depending on the choice of cost-price scenarios. Between 27-44% of the study area made a financial loss or marginal monetary return indicating that trade-offs providing increased environmental benefits may be possible with minimal income loss from a substantial magnitude of cropping area. Although further analysis at larger regions with longer time series is necessary, results presented here show that overall economic returns may be improved by the reassignment of land use in selected cropping areas.

The study also suggests that feasibility analyses of land use change at farm and regional scales should be conducted with a spatial resolution that is fine enough to reflect the spatial variability observed from yield mapping. While this information will not be available on every farm, this study shows that it may be possible to predict yield variability from remotely sensed imagery, thus providing a means to circumvent this problem and to produce high resolution indicators at a regional extent.

6.2 Introduction

Consideration of environmental, social, cultural and community objectives within agricultural production landscapes has become an increasing priority, worldwide (Vos and Meekes, 1999; Foley *et al.*, 2005; Wiggering *et al.*, 2006; Otte *et al.*, 2007). Performance indicators of agro-ecosystems are needed at farm and landscape scales in order to identify a mix of land-use options for a sustainable agricultural production.

A main driver for alternative land uses comes from the potentially adverse effects of climate change on agricultural production and the potential of woody perennial systems for carbon sequestration (Dean *et al.*, 2004; Harper *et al.*, 2007). In the United States of America, predictions of the impact of climate change on wheat yield range from a 31% increase to a 76% decline in wheat yield (Lobell and Asner, 2003; Antle *et al.*, 2004; Thomson *et al.*, 2005; Isik and Devados, 2006). Similar results are apparent in the wheat growing regions of Europe (Olesen and Bindi, 2002; Ewert *et al.*, 2005; Porter and Semenov, 2005; Rounsevell *et al.*, 2005) and Australia (Howden and Jones, 2001; Luo *et al.*, 2003; Van Ittersum *et al.*, 2003; Luo *et al.*, 2005a; Luo *et al.*, 2005b; Ludwig and Asseng, 2006; Anwar *et al.*, 2007). These studies suggest that in dry land wheat production regions, marginal areas will be most affected by climate change (Thomson *et al.*, 2005), or have the poorest resource endowments (IPCC, 2001; Antle *et al.*, 2004; IPCC, 2007).

Regional impact assessments of climate change identified agricultural land with a Mediterranean climate as the most vulnerable to reductions in yield (Harrison and Butterfield, 1999; Olesen and Bindi, 2002; Ewert *et al.*, 2005), land abandonment (Ewert *et al.*, 2005; Berry *et al.*, 2006) and lack of capacity to adapt to potential impacts of future change (Metzger and Schröter, 2006). These studies have specific relevance to the grain regions of Australia which are typified by a Mediterranean climate. Regional analyses to understand of the impacts of CO_2 and climate change on wheat grown under Australian conditions also suggest that large regional differences will occur. Higher rainfall regions will become more suitable for cropping (Howden and Jones, 2001; Ludwig and Asseng, 2006) and wheat yields in the drier regions will be greatly reduced (Luo *et al.*, 2005a; Luo *et al.*, 2005b; Ludwig and Asseng, 2006; Anwar *et al.*, 2007) with significant economic repercussions.

Next to climate change, prevention of environmental degradation and enhancing biodiversity benefits are major issues worldwide. In Australia, salinity has been a major cause of environmental degradation and loss of biodiversity expressed through the extinction of plant species and invertebrates in low lying parts of the agricultural landscapes (George *et al.*, 1997; George *et al.*, 1999; Beresford *et al.*, 2001). Clearing of native woodland or perennial grassland for cropping has led to an increase in the proportion of rainfall unused by vegetation and has resulted in larger rates of infiltration and recharge to groundwater aquifers. This increased recharge has caused saline aquifers to rise, causing secondary salinisation and reducing water quality (George *et al.*, 1997; Clarke *et al.*, 1999, Clarke *et al.*, 2002; Hatton *et al.*, 2003). Large impacts on agricultural areas have been predicted for the western region of Australia, where an estimated 8.8 million hectares will be lost due to salinity by 2050 (National Land and Water Resources Audit, 2001). The most promising option for mitigation is the re-introduction of deep rooted perennial plants (trees and shrubs) to large proportions of the landscape (Clarke *et al.*, 2002; Barrett-Lennard *et al.*, 2005; Lefroy *et al.*, 2005; Ridley and Pannell, 2005). Hydrological studies to assess the area required for salinity reductions suggest that mass plantings must be between 30 to 80% of the rural landscape (Stirzaker *et al.*, 1999, Clarke *et al.*, 1999; George *et al.*, 1999; Pracilio *et al.*, 2003; Hodgson *et al.*, 2004).

Clearly, the major drawback to the adoption of a such a strategy is the negative economic implications on the farm business (Cary and Wilkinson, 1997; Pannell, 2001; Pannell and Ewing, 2006), since the short term on-farm salinity prevention benefits would be of secondary importance to the grower (Bathgate and Pannell, 2002). Several studies have shown the potential economic benefits of a revegetation strategy which may offset the potential loss in income (Flugge and Abadi, 2006; Whittock *et al.*, 2006; Harper *et al.*, 2007; Bryan *et al.*, 2008). However, the attractiveness of adoption will be based on their profitability with respect to the overall financial position of the farm business (Pannell, 2001; Bathgate and Pannell, 2002; John *et al.*, 2005; O'Connell *et al.*, 2006) as well as the magnitude of the opportunity cost associated with the replacement of traditional cropping practices (Cary and Wilkinson, 1997; Curtis and Lockwood, 2000).

The implementation of revegetation strategies needs to be considered on two scales. At a farm scale, change will likely occur first on those areas where profit from traditional cropping practices is comparable (Frost *et al.*, 2001; Lefroy *et al.*, 2005). At the regional scale, where revegetation policies are formulated, it is necessary to anticipate the limiting factors that will affect each farms capacity to change. To understand this problem of scale, several studies have integrated socio-economic data either through nationally collected census or farm surveys to better understand the broader scale economic, social and land use implications (Greiner, 1998; Curtis *et al.*, 2003; Kington and Pannell, 2003; Hall *et al.*, 2004). Others have taken a targeted approach to optimise limited resources by identifying areas for revegetation that provide only marginal financial returns, have high biodiversity value or impact on valuable human infrastructure (Heaney *et al.*, 2000; Bryan *et al.*, 2008; Crossman and Bryan, 2009).

A significant problem with previous research is that conclusions are constrained by the scale at which their data is collected. These studies use aggregated financial estimates, either an average for a geographic area or average estimates from farm accounts. Incorporating such averages will mask the inherent spatial variability of crop productivity within the farm and region, blurring specific areas that would be benefit from change both economically and environmentally. Data is therefore needed at a higher resolution from which land use decisions can be made.

Precision agriculture technology, particular yield mapping technology, produces yield estimates at a high, sub field resolution that reflect the annual spatial variability of grain yield. Yield mapping is the process in which the grain harvester is fitted with a global positioning system and grain flow measuring device to collect yield estimates and their corresponding geographic position at a 1-2 second interval. Mapping of this data identifies areas that exhibit yield variability and linking this data with crop input expenditures (i.e.

fuel, fertiliser) enables the production of detailed maps of profitability (Massey *et al.*, 2008). Currently, the economic benefits of deriving this spatial information to the farm business lie in the specific placement of inputs to match crop potential (Robertson *et al.*, 2008).

Although some growers have been collecting crop yield data for over a decade in Australia, adoption of the technology has been is patchy (Jochinke *et al.*, 2007) and therefore is unavailable at broader scales. One way to circumvent this problem is to use vegetation indices derived from remotely sensed imagery to act as plant biomass or vigour indicators to quantify large areas with differing biophysical condition (Walker *et al.*, 2006; Ludwig *et al.*, 2007). Several studies have shown good relationships between these indices and actual crop yield, with the explanation of 50% to 91% of yield variation (Quarmby *et al.*, 1993; Labus *et al.*, 2002; Wendrotha *et al.*, 2003; Dobermann and Ping, 2004; Enclona *et al.*, 2004; Weissteiner and Kühbauch, 2005; Liu *et al.*, 2006).

Climate change and environmental degradation in agricultural landscapes require indicators of yield and economic performance of current cropping systems. Research on the propensity of land holders to adopt structural change has traditionally used data at the regional level, neglecting spatially variable crop yield. However, it may be possible for land holders to identify portions of their land where change can be economically beneficial. Previous analyses are too coarse to assess this potential. This paper evaluates the possibility of creating spatial indicators of wheat yield at a high spatial resolution and broad extent. Spatial yield indicators are derived using a combination of precision agriculture and remote sensing technology in order to reflect the realistic spatial pattern of wheat yield at a regional extent. The creation of this indicator and its integration with production cost price structures provide useful additional information to quantify the regional extent of land that might be used differently without substantial loss of farm income.

6.3 Study area

The study area is a 25 by 25 kilometre area within the northern wheatbelt of Western Australia. The growing landscape is predominately broad sand plains with very little elevation and salty hollows situated in the lower parts of the landscape. Cropping rotations are dominated by wheat (*Triticum aestivum*), lupins (*Lupins consentini, Lupins albus*), canola (*Brassica napus*), and to a lesser extent barley (*Hordeum vulgare*) and oats (*Avena byzantina*). Pastures are also common for cattle and sheep grazing, as well as small randomly scattered stands of remnant native vegetation consisting of a mixture of evergreen shrubs and trees that are well adapted to the hot dry summers (Turner and Asseng, 2005). Flowering and grain filling of crops occurs in spring (September) with harvest in late spring and early summer (November-December).

This region is characterised by a Mediterranean climate, with cool wet winters and hot dry summers. Over half of the annual rainfall (300 – 400 mm) occurs between May and September with high water evaporation rates during the summer months. In this grain growing environment, water is the major limitation to plant productivity (Turner and Asseng, 2005).

The study area incorporates two neighbouring farms each greater than 2,000 hectares in size that collected yield data for the 1999 growing season. For the year under review, annual precipitation was 585mm with in-season rainfall of 364 mm. Analysis of historical rainfall records for the study area showed that this year was within the top 10 % of the last hundred years of measured rainfall.

6.4 Methods

The premise of this paper is to correlate remotely sensed imagery collected at the regional level with yield mapping data obtained at the sub field scale. This results in information of spatial variability of wheat yield at a regional extent. Analysis of this information will highlight areas that might be suitable for a different land use with both economic and environmental benefits. An analysis without this crucial information would be too coarse and hence blur or smooth over such areas. To create this spatial indicator of economic performance at a regional scale, we propose a four-step methodology. Data at the farm (crop type of fields and the yield pattern within the fields) is extrapolated to the regional extent by using remote sensing and then used to estimate the economic indicators (Figure 31).

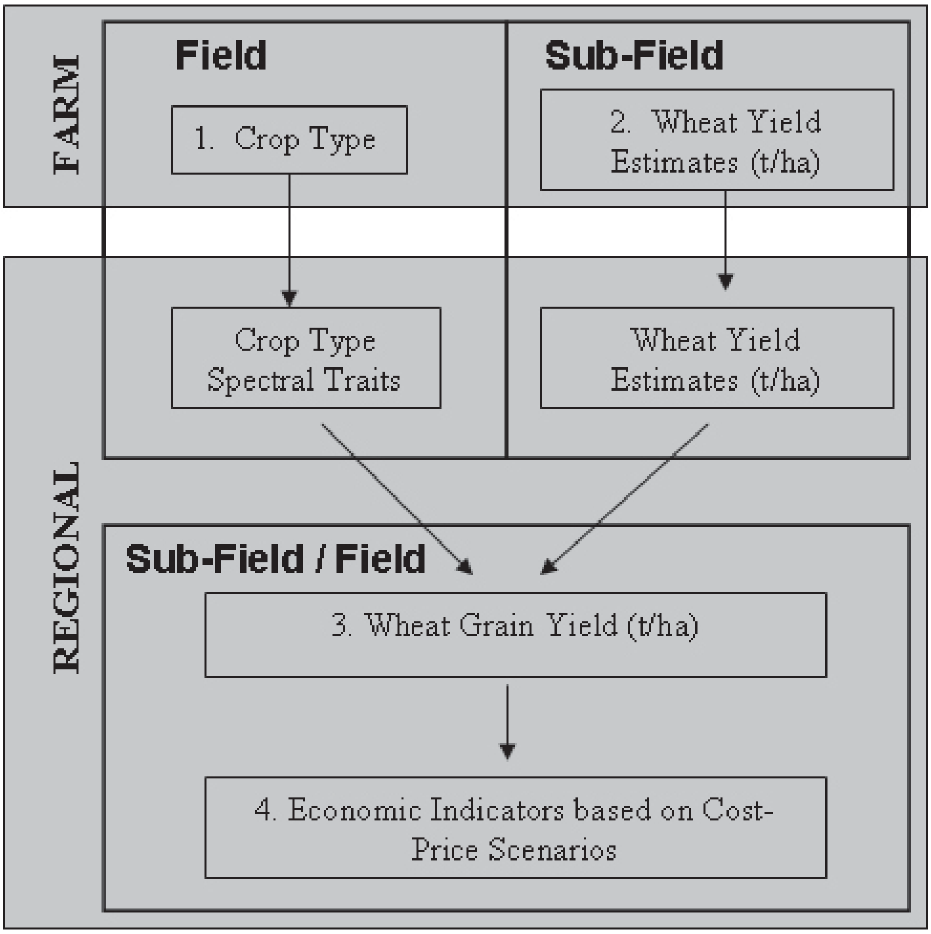

Figure 31 Process to develop the high resolution broad scale spatial indicator of grain growing profitability

6.4.1 Step 1: Regional crop type classification

Crop types on two neighbouring farms were used for a supervised classification of the remotely sensed imagery. Three categories of crop types predominate in the region: 'Wheat', 'Lupin', 'Canola'. In addition a class 'Other' was used to represent pastures or fallow land. Seven cloud free Landsat 7 Enhanced Thematic plus (ETM+) images were acquired from early August to mid November for the 1999 growing season. The spectral signatures for each of the four crop types in each image were identified. A 25 metre buffer was placed inside each field boundary in order to remove the spectral mixing of vegetation types close to the boundary. Maximum likelihood supervised classification with an equal probability threshold was then undertaken.

The overall crop type discrimination accuracies for each image were assessed using the field crop type information from the neighbouring farm. A total of 400 points were randomly selected from each of the crop types validation sets and associated with their predicted classification from each of the seven images. Contingency table (producer's and user's accuracy) and KAPPA statistic were calculated to verify the discrimination accuracy of the supervised classification. As crop types within fields are homogenous, a majority filter was applied to each field. The image with the highest accuracy was then used in the next step of the extrapolation process.

6.4.2 Step 2: Modelling wheat yield from satellite imagery

Wheat yield data was collected from two neighbouring farms for the 1999 growing season. Data was acquired using two different combine mounted yield monitors. Each field dataset was run through several cleaning algorithms to remove erroneous yield values associated with harvester dynamics, including, speed changes, overlaps and turns (Lyle and Ostendorf, In review). A wheat yield surface at 25m pixel resolution was then interpolated using the VESPER kriging software (Minasny *et al.*, 2005) following the yield map creation protocol highlighted in Taylor *et al.*, 2007.

This processing provided wheat grain yield estimates for missing areas due to error removal and acted as a locational basis for spatial comparison with the satellite data. Yield data from one farm was assigned as the training set while the yield data from the neighbouring farm data was used for validation.

A Normalised Difference Vegetation Index (NDVI) was calculated for five Landsat 7 ETM images collected between August and October. Index values were extracted for each field classified as a "Wheat" crop type from Step 1. NDVI values from these classified wheat fields were related to the corresponding kriged wheat yield estimates. This association created five regression relationships over the five corresponding images. Predicted yield estimates from NDVI values and the associated kriged yield mapped data on the neighbouring farm was then used to validate the strongest yield-NDVI regression relationship.

6.4.3 Step 3: Estimating grain yield at a high spatial resolution

To estimate wheat yield, the strongest regression relatinship developed in Step 2 was applied to the all NDVI pixels that were classified as wheat in the satellite image (Figure 32). It was assumed that planting occurred within a similar time frame across the 25 by 25 kilometre image. This produced wheat yield estimates at a 25 metre resolution across the study area. The image was tabulated to aggregate the number of pixels (Count) that corresponded to a specific yield value (*Yv*) and adjusted by the pixel resolution size to derive the number of hectares (*Hy*) (Figure 32). The number of hectares for all *Hy* values were then summed (Σ *Hy*) for all yield values (Yv_1 to Yv_n).

6.4.4 Step 4: Estimating gross margin based on different cost price scenarios

In order to be useful for decision making, potential areas for revegetation must be identified based on financial considerations involving the spatial variability of yield. Decisions to remove land from traditional cropping are easy to make if areas can be identified that continually produce a financial loss but these are often small (Lawes and Dodd, 2009a). A much harder decision is removing areas with positive income generation. One way to identify where these areas may exist is determining the economic significance at each location compared to both farm and regional income returns. As farm boundaries were not available for this study, a regional scale analysis, based on the study area boundary, was undertaken. Within the study area, areas with comparatively low to medium financial reward can then be targeted because the average income generated off these areas will be more likely to compare with the present income opportunities associated with the re-introduction of a revegetation substitute.

Step 3 provides information on wheat yield variability across the study area. This information provides the basis for a gross margin analysis which is usually done within the agricultural sector as a first step in gauging enterprise profitability (Department of Agriculture and Food, 2005). Traditionally, gross margin (GM) is calculated as the difference between the price received for grain (per tonne) multiplied by the average yield of a field (tonnes per hectare (t/ha)) minus the variable input costs, such as such as fertiliser and fuel, on a per hectare basis. Here, GM from wheat cropping (*GMy*) was calculated on a per hectare basis for each predicted yield estimate (Yv_1 to Yv_n) (Figure 2). Yield was then ranked from lowest to highest and area (Hectares) as well as gross margin ($/ha) was computed for all yield classes. In addition, accumulative area proportions expressed as a percentage of total area (*%Hy*) and accumulative gross margin expressed as a percentage of the total gross margin (*%GMy*) for the region was derived.

Although specific 1999 estimates could have been used to calculate the actual gross margin, we analysed four possible cost price scenarios. It was assumed that agronomic management was similar across the study region. This meant that the magnitude of input costs was held constant at $200 per hectare. Grain price was varied from $150 to $300 per tonne. These price changes reflected the following four per hectare scenarios that will be used in the analysis. These were i) the price received was less than the variable cost (the -$50 scenario), ii) the price received was equal to the variable cost (the $0 scenario) and iii) the price received was greater than the variable cost (the $50 scenario and the $100 scenario). These scenarios mimic the range of potential financial returns that may be available to a grower taking into account annual fluctuations in international commodity market prices. By quantifying the range of these returns, the possible financial repercussions of a revegetation strategy within the study area can be assessed.

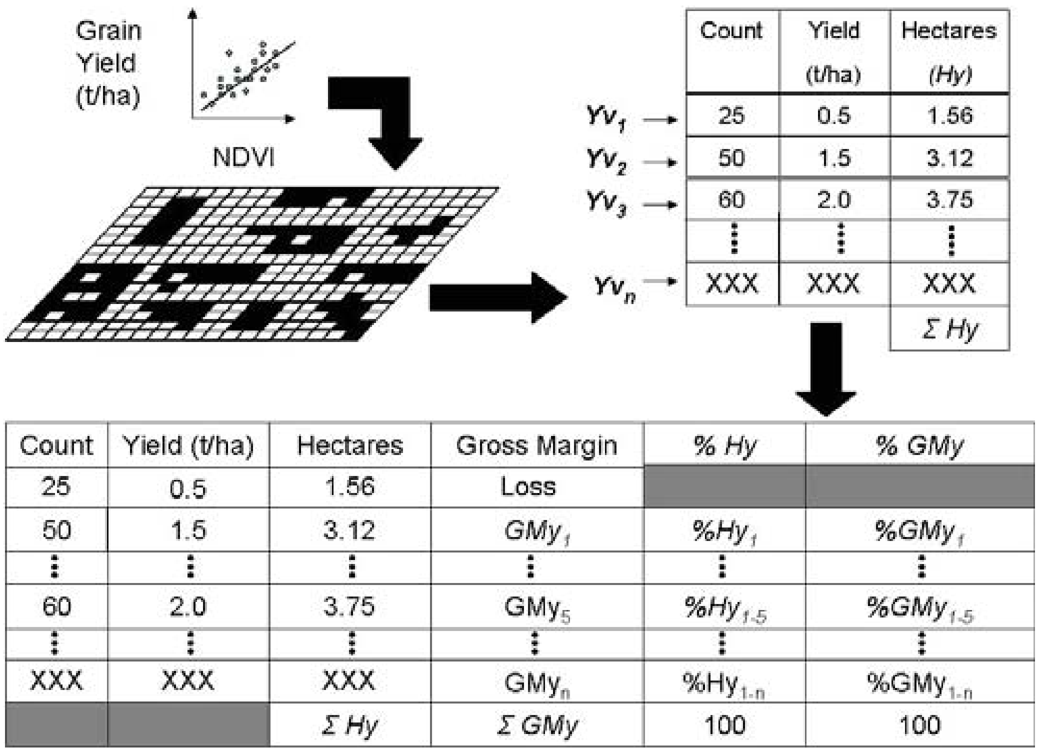

Figure 32 Flow chart of the methods used to estimate income to area relationships. Extrapolating the yield NDVI regression model over an NDVI image predicts the spatial pattern of wheat yield. Yield is sorted from lowest to highest. Gross margin (GM) is estimated based on yield and production costs. Loss values are removed. The corresponding area and GM of each yield class is then expressed as an accumulative percentage of the total area (%Hy) and the total study area GM (%GMy)

For each of the four scenarios, areas that produced a financial loss were separated from those that created positive returns. These values were summed separately and aggregated to identify the total loss, total positive financial returns, total overall income and the income per hectare produced from wheat cropping. Accumulative percentage values of both area and wheat income for each scenario were then graphed to highlight the income to area relationships. Average wheat income (GM) values for each change in percentage area were also derived.

6.5 Results

6.5.1 Crop type discrimination accuracy

Results of the overall classification accuracies (producer's and user's) and Kappa statistic (times by 100) for each image date are shown in Figure 33. Both analyses show similar accuracies and trends across the images dates within the growing season. The per-pixel classification accuracy from early season was low, rising through September to a maximum of 77% in the late September image (29/09/1999). Of significance is the sudden drop of classification accuracy in early October, caused by a reduction in classification accuracy of the ‘Lupin’, ‘Canola’ and ‘Other’ crop type. Figure 33 shows a rise in overall accuracy of the early November image, probably due to an increase in classification accuracy of the ‘Canola’ crop type which had been harvested when the classification was carried out. The late September (29/09/1999) image provided the best results for crop type discrimination. Producer’s and user’s classification accuracies were 86% and 84% for the ‘Wheat’ crop type, 84% and 90% for the ‘Lupin’ crop type, 79% and 75% for the ‘Canola’ crop type and 84% and 74% for the ‘Other’ crop type. For the ‘Lupin’ crop types, analysis showed that a reasonable producer’s and user’s accuracy was estimated from early August (> 60%) to the crop’s maximum in late September. However, validation of the ‘Lupin’ crop type in early October saw producer’s accuracy halve. For the classification of ‘Wheat’ crop type over the images dates, producer’s and user’s accuracies in early August were around 50% and 70%, rising to greater than 75% for images acquired in early and late September. The application of a majority filter based on within field crop type distributions resulted in September classifications accuracy increasing from 63% to 77% while the late September image also increased from 77% to 90%.

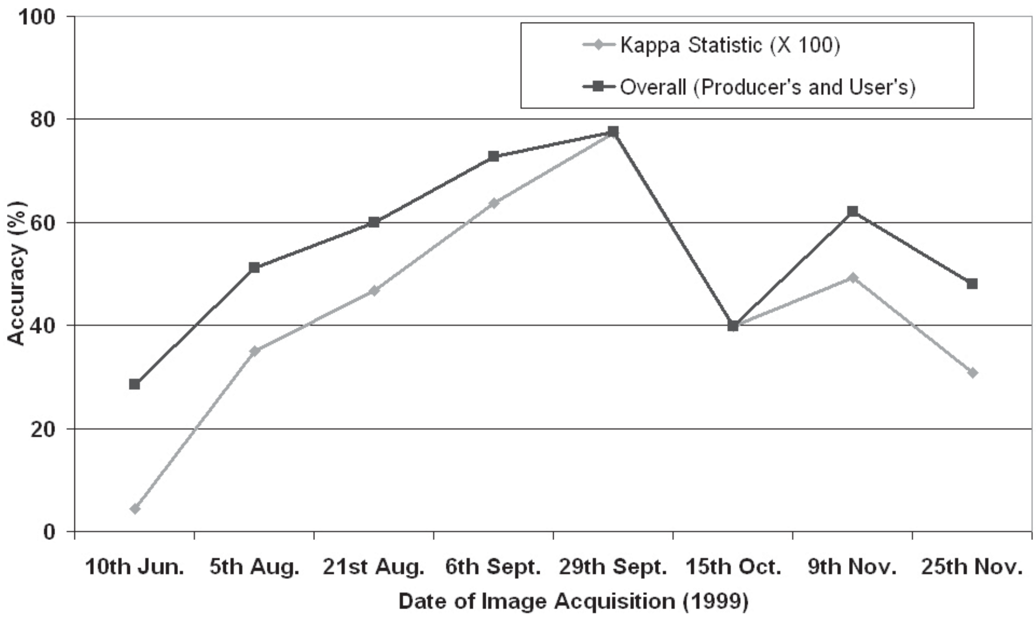

Figure 33 Per-pixel accuracy for crop type discrimination for the 1999 growing season

The late September image was seen as the best possible crop type estimate for the 1999 season with 46,538 hectares devoted to rotational cropping (908 fields) in the 25 by 25 kilometre study region. For 1999, a total of 78% (36,236 ha) of the total cropping hectares was classified to 'Wheat' (21,667 ha), 'Lupin' (8,388 ha) and 'Canola' (6,180 ha) crop types while a total of 10,302 ha were classified to the 'Other' specified crop type. The 'Wheat' crop type made up 47 % of the total cropping area with the 'Lupin' and 'Canola' crop types 18 % and 13 % respectively. These percentages were similar to the crop diversification on the two farms used in the study area and estimates for the Western Australian region (ABARE, 2000; Planfarm, 2000).

6.5.2 Relationship between sub field wheat grain yield estimates to NDVI estimates over the study area

A total of 21,667 hectares were classified as accurately matching the 'Wheat' crop type from the late September image. The wheat fields' spatial location was used to extract the corresponding NDVI values for five images. The training set comprised of 15 yield mapped wheat fields which was regressed against the corresponding locational NDVI values. Table 9 shows the strength of the relationships between the interpolated yield surface and NDVI values. The strongest relationship in the 1999 growing season was in early September (06/09/1999).

Table 9 Regression relationships between kriged wheat yield and NDVI values by imagery acquisition date

Acquisition Date	R squared
5th August 1999	0.37
21st August 1999	0.45
6th September 1999	0.48
29th September 1999	0.41
15th October 1999	0.33

The relationships between interpolated yield estimates and NDVI values for the 15 fields (data not shown) varied with good to poor associations. Forty seven percent of the fields showed their strongest relationship between wheat yield and NDVI in the early September image (06/09/1999). Each field had a differing influence on the yield-NDVI relationship at this acquisition time period. The highest relationship was 0.7 while the lowest was 0.21, however, it was noted that this field had a very low yield–NDVI relationship across the whole growing season. An assumption was made that the regression models should be forced through zero, indicating that zero yield was associated with zero NDVI value. This should be expected given that the wheat canopy should be fully developed at the imagery acquisition date. We fitted several types of regression models and found that the polynomial regression model associated with the yield-NDVI datasets for the image acquired in early September had the best relationship (Figure 34). This model illustrates that a simple wheat yield prediction model can be developed and highlights the apparent association of yield mapping data and remotely sensed biomass across a large number of fields.

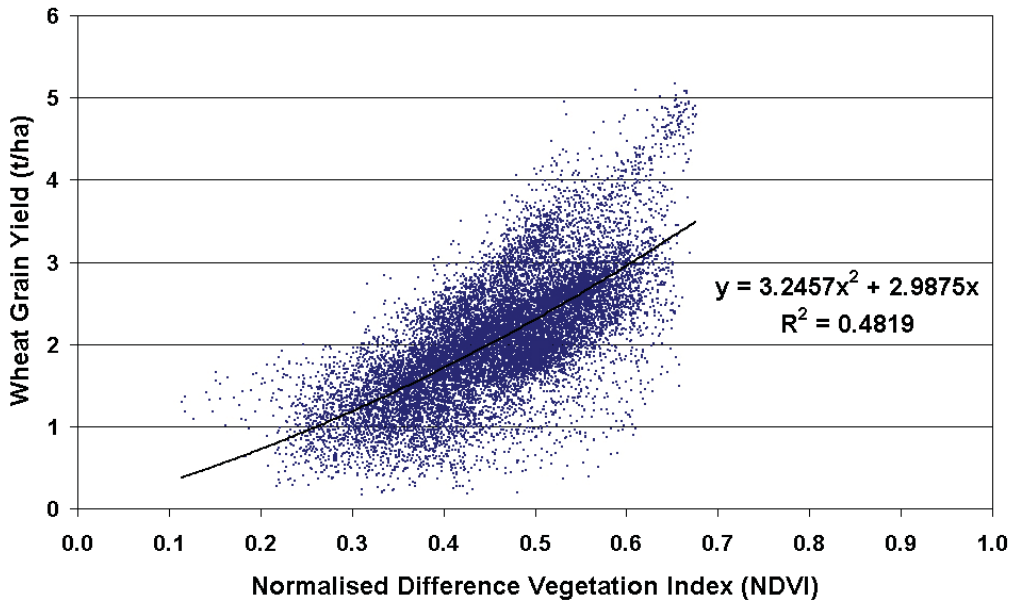

Figure 34 Regression relationship between wheat yield estimates (t/ha) and NDVI values for the 06/09/99 Landsat 7 ETM+ image

6.5.3 Model validation and sensitivity analysis

Yield mapping data collected on the neighbouring farm was used as an independent test of the yield prediction capability. The predicted model was applied to the NDVI values of nine wheat fields (663 hectares) and compared to the yield mapped estimates. On average, the model underestimated the interpolated yields by 0.39 t/ha. The root mean squared error (RMSE) was calculated at 0.72 t/ha, which was 31% of the mean yield derived from the validation set. Figure 35 shows the predicted yield estimates from the regression model versus the corresponding observed yield for the validation set. The 1:1 line illustrates perfect agreement between both variables and highlights the deviations in the estimation in predicted from observed values. On average, the model overestimated yield at 1.5 t/ha or less by 0.39 t/ha and underestimated yield at above 2.5 t/ha by 0.92 t/ha. Another way to validate the regression model is to identify the difference in income derived from the validation dataset at a given difference between wheat price and the variable cost, in this case the \$100 scenario. In monetary terms, the income returns for the nine yield mapped fields was estimated at \$154,886 while the modelled income returns predicted a value of \$128,373, an under prediction \$26,512 or 17%.

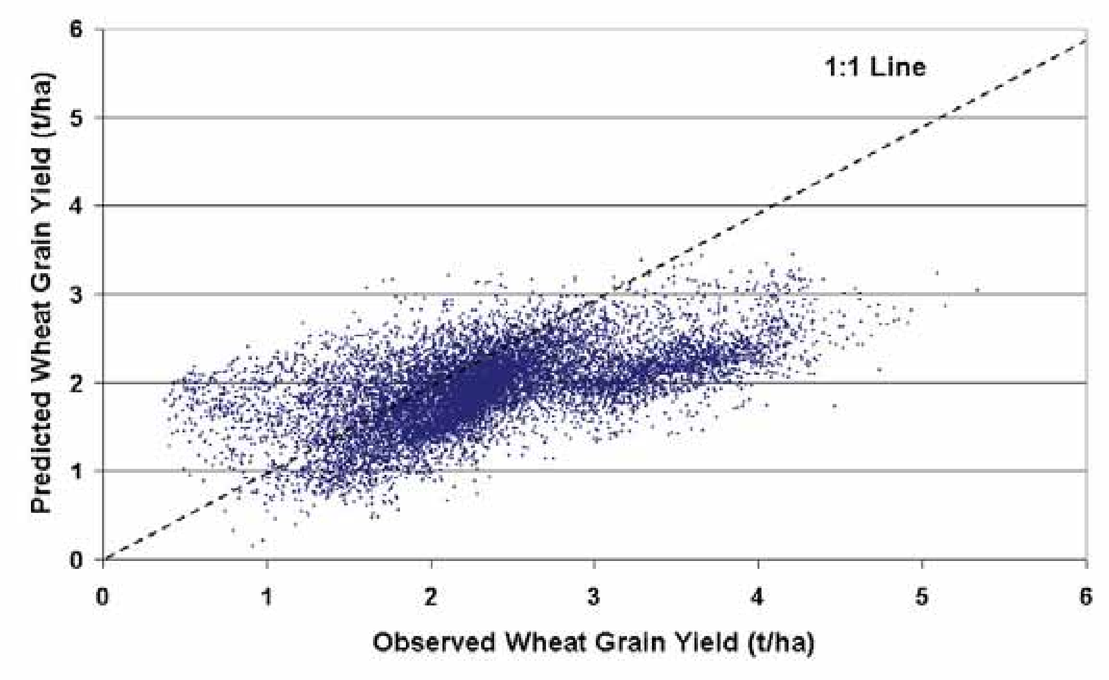

Figure 35 Predicted wheat grain yield (t/ha) versus observed grain yield (t/ha)

6.5.4 Sensitivity analysis of the regional estimates

The regression model was applied to the wheat fields (as classified from the discriminated September 1999 image) to estimate yield from NDVI. This produced wheat yield estimates at a 25 metre resolution across the 25 by 25 kilometre study area. Yield varied spatially within the region from 0 to 3.84 t/ha (Figure 36) with an average of 1.9 t/ha.

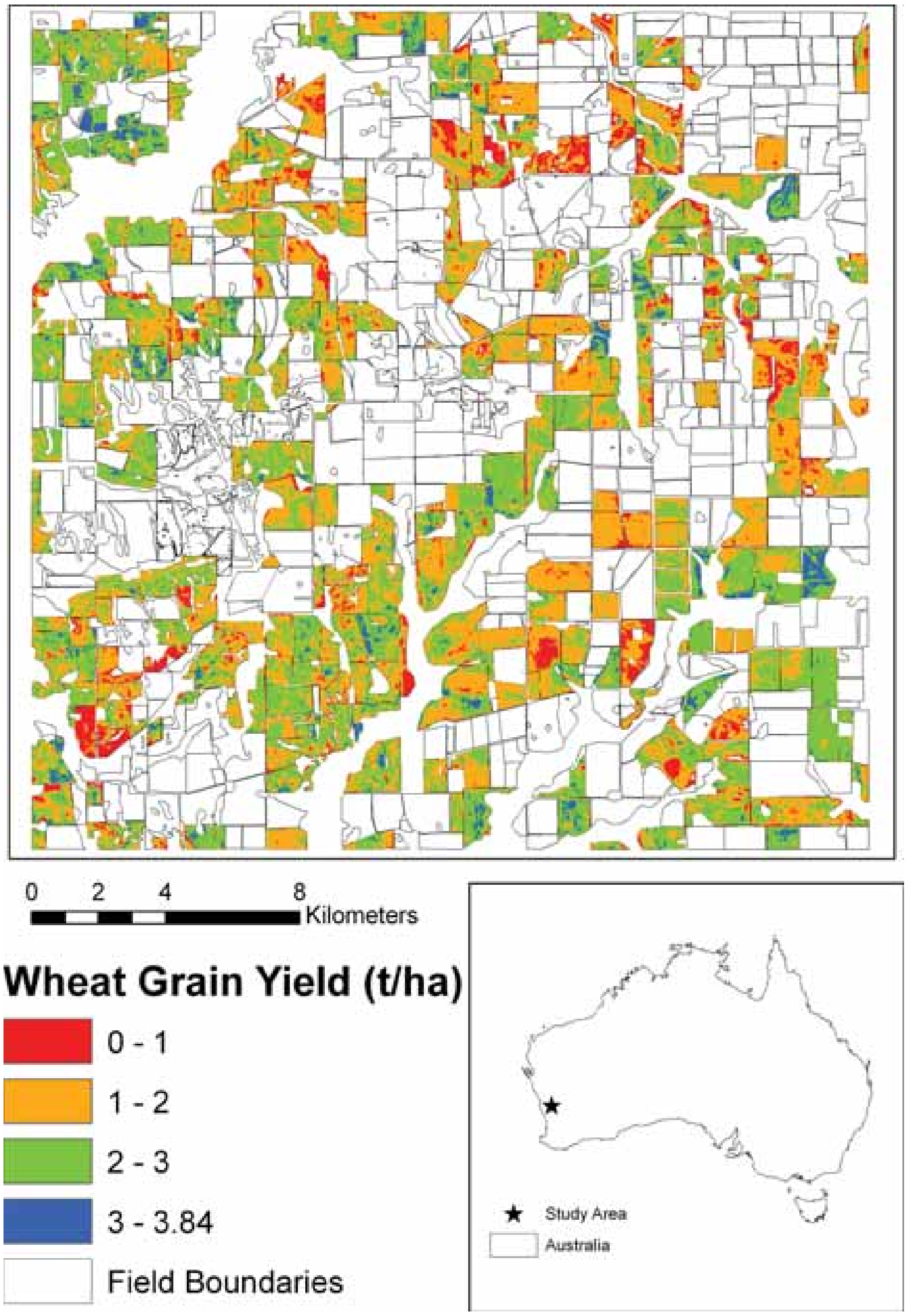

Figure 36 Predicted wheat grain yield and field boundaries for the study area

The four cost price structures (-\$50, \$0, \$50 and \$100) explained in Section 6.4.4 were used in conjunction with the 1999 wheat crop estimates across the study area to understand the effect on regional income with changes in commodity prices. Loss making areas are evident throughout all scenarios, with losses from AUD\$34,000 to AUD\$212,000 (Table 10). The two scenarios (-\$50 and \$100) show that variations around the zero scenario can cause the total wheat gross margin for the study area to range from AUD$2 million to AUD$8 million.

Table 10 Loss, positive income, total income and income per hectare for each cost price scenario ($AUD)

Cost Price Structure ($)	Loss ($'000s)	Positive Income ($'000s)	Total Income ($'000s)	Income per Hectare ($/ha)
-$50	-212	2,091	1,879	87
$0	-93	4,042	3,950	182
$50	-52	6,073	6,020	278
$100	-34	8,126	8,091	373

Visualisation of the percentage income derived from wheat (GM) as a function of accumulated area (as computed in step 4) demonstrates that the income derived from grain growing areas was not equally distributed, as illustrated by the divergence of these distributions from the 1:1 line (Figure 37). The origins of the four lines within the graph show the magnitude of loss based on the four scenarios. This equated to 3-20% (543-4,250 hectares) of the study region cropped to wheat in the 1999 season depending on the cost price structure scenario chosen. An estimated 24-26% (5,246-5,621 hectares) of the area cropped to wheat generated the bottom 10% of total income. A totalling of these areas that produced a financial loss and were contributing to the bottom 10% of income resulted in area estimates of between 27-44% (5,789-9,511 hectares). Areas which produced the top 50%-100% of the total income ranged from 23-32% (4,893-6,947 ha). The most profitable areas (the top 80% of income) were small in comparison with magnitudes ranging from 7-11% (1,668-2,353 hectares) of the 1999 wheat area for the range of cost price scenarios investigated.

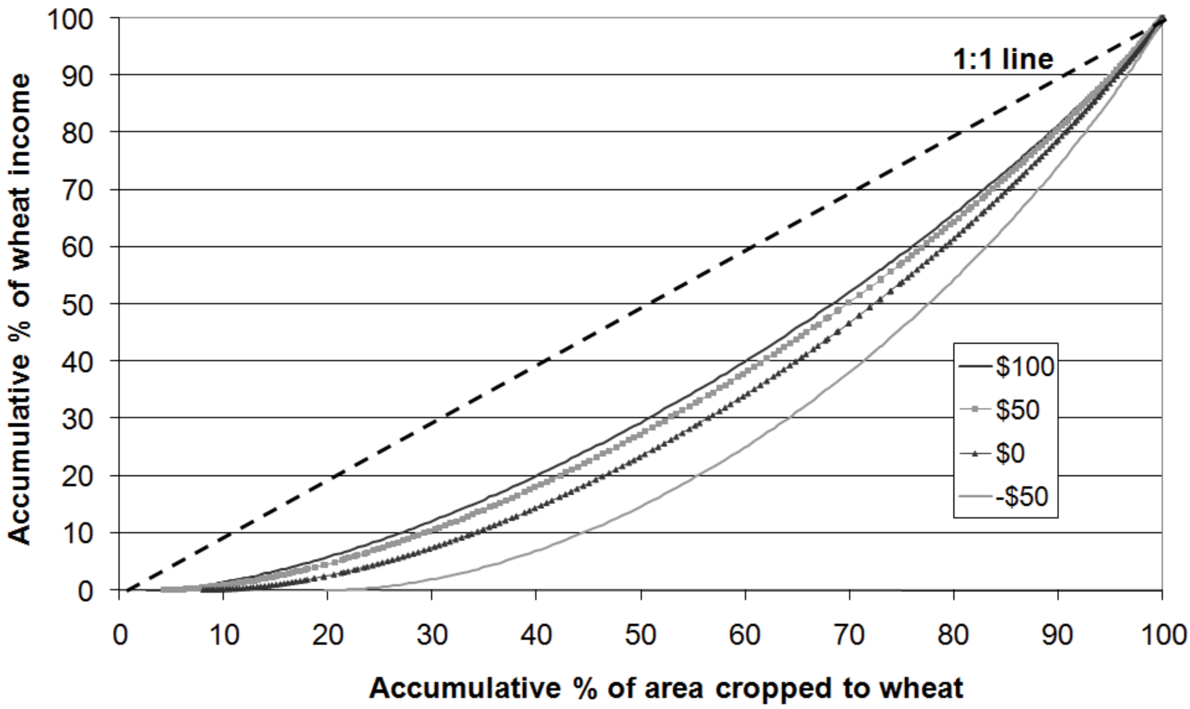

Figure 37 Accumulative relationship between the percent of wheat income derived from the percentage of area cropped to wheat

The existence of spatial variation in income returns (Figure 37) and the inclusion of a variety of selected cost price structures suggest that the derived average gross margin per hectare will vary from scenario to scenario (Figure 38). Depending on the scenario selected, the gross margin per hectare increases from a loss of $200 /ha (the variable cost per hectare) where no yield was recorded to estimates between $376/ha and $952/ha. The -50 scenario demonstrates that losses will be made in 20% of the area while changing the scenario indicates a variety of positive income returns. For the 100, 50 and 0 scenarios, between 20-55% of the land allocated to wheat cropping produces less than $200/ha. For the -50 scenario, 87% of the area cropped to wheat never produces above this value. Alternatively for the 0, 50 and 100 scenarios, 45-80% of 1999 wheat crop area produces over this value.

Figure 37 highlighted that for positive gross margins; around 10% of total income was derived from around 25% of the area. The gross margin per hectare values for these areas ranged from $72-$270/ha depending on which scenario was chosen.

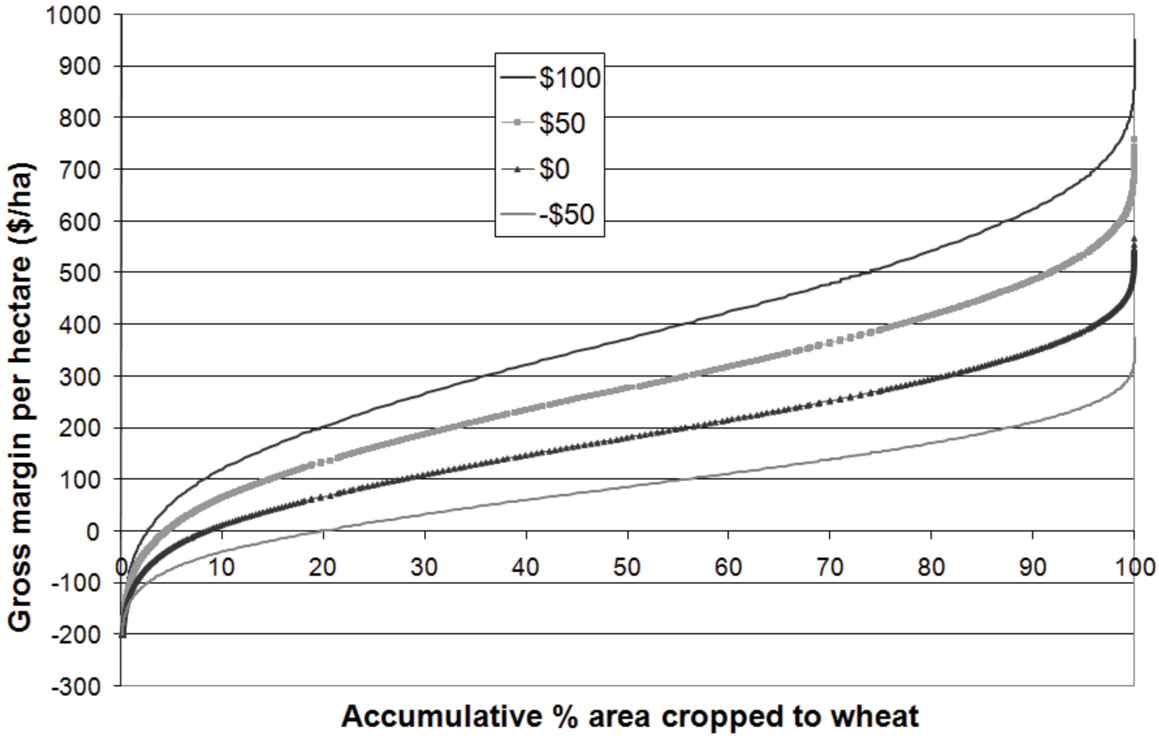

Figure 38 Gross margin per hectare for the accumulated percentage area cropped to wheat

6.6 Discussion

The advent of precision agriculture technology has meant that previously unquantified grain yield spatial variation within grain growing fields can be now quantified relatively easily and accurately. The extrapolation of these estimates to a regional scale through satellite imagery has provided a spatial indicator of crop yield variability and financial returns from undertaking a traditional wheat cropping enterprise. Being able to have such highly detailed spatial information is beneficial to both the grower and the regional natural resource manager because the implication of on ground decisions can be accurately quantified. For the grower, land use decisions are made at the sub-field, field and farm level without full consideration for regional outcomes. For the regional manager, policy decisions are made at the regional scale with limited comprehension of the likely effects at the farm level or below. The outputs from the present study bridge both decision making levels providing a potentially higher accuracy in estimating the economic outcomes of potential regional land-use change strategies.

To construct this high resolution yield estimates several steps were developed and independently validated.

The first step dealt with the identification and assessment of the spatial distribution of crop types within the study area. As canopy characteristics differ amongst crops, a classification of crop type is a necessary prerequisite for a spatial regression between yield and NDVI. The highest accuracies were obtained in early and late September, around 12 to 14 weeks before harvest. The results have shown that high classification accuracies can be achieved at a range of dates, giving a wide enough time window for the multiple acquisitions of satellite imagery.

Secondly, the results from the creation of yield-NDVI regression models showed reasonable relationships over the August to October image dates. This result was similar to the conclusions by a previous study undertaken in Australia (Smith *et al.*, 1995). These results demonstrate that a two month window may exist for generating fairly robust wheat-NDVI regression models. However, over different years the correct timing of these windows will be dependent on the actual date of sowing in the region. Further research is needed to determine if this window holds for other years besides 1999.

The study showed that NDVI values in the image acquired in early September (06/09/1999) had the strongest relationship with wheat yield explaining nearly 50% of the yield variation. This provides a very reasonable relationship given the models development over 15 fields with variations in crop phenology, field planting dates, timing of herbicide applications and the influence of different soil types on plant growth. The strength of relationship between yield and NDVI for both the aggregated and field based models was similar to other studies which have used yield mapping and remotely sensed imagery to highlight crop yield and NDVI relationships (Thenkabail, 2003; Dobermann and Ping, 2004; Enclona *et al.*, 2004)

While not occurring in this study, yield-NDVI relationships will be affected by temporal events such as weed or pest infestation or frost damage which may occur after imagery acquisition. It was also assumed in this study that the climatic variability was minimal due to the flatness of the Western Australian grain growing region and the size of the image extent selected. This might not be the case for regions at the broader spatial scale where terrain induced climate variability such as rainfall and temperature gradients may affect the strength of the yield-NDVI relationship.

Finally, the validation of the model using a neighbouring farm's yield mapping data suggested that the model on average, overestimated wheat grain yield by 0.39 t/ha at 1.5 t/ha or less and underestimate yield by 0.92 t/ha at above 2.5 t/ha. In terms of identifying areas with low profit potential, the overestimation provides an effective tolerance from which conservative predictions of wheat yield can be made. Another way to validate the regression model is to identify the difference in income derived from the validation dataset. In monetary terms, the gross margin for the nine yield mapped fields was estimated at $154,886 while the modelled gross margin predicted a value of $128,373, an under prediction $26,512 or 17%. This underpins our confidence that the wheat yield-NDVI relationship based on a small subset of fields on one farm provides a good performance indicator in proximity of farms for which yield mapping is unavailable.

As a proof of concept, this study has collected and analysed data for only one season. The 1999 growing season was of particular significance because it provided enough cloud free days to acquire and test the relationships between wheat yield and NDVI over the growing season. Additional analysis is needed to incorporate yield mapping and remotely sensed imagery from other growing seasons along the rainfall gradient. This type of temporal analysis will define the pattern of wheat yield across other cropped areas of the study region due to the temporal variation of crop rotations on farms. This type of dataset will provide the capability to analyse the temporal consistency of financial returns for a region and will be able to separate areas that are consistently low producing from those that fluctuate temporally. As well as providing more robust analysis of the methods and relationships developed in this study, the construction and analysis of a dataset that reflects a range of wheat growing seasons will further reduce the uncertainty involved in land use change decision making.

Further attempts should also be made to quantify the relationship between remotely sensed vegetation indices and other dominant crop types such as lupin and canola which in this study was estimated to be grown on 31% of study area. As these crops provide another source of financial return their corresponding spatial and temporal contributions to income should be included for a comprehensive land use change analysis.

The major limitation to determining both the spatial distribution of crop type and the yield-NDVI relationship is acquiring cloud free imagery during the indentified time period. While the probability of this occurring can be minimised by using both the Landsat TM and ETM+ sensors, current problems with the ETM+ sensor (Markham *et al.*, 2004) make this sensor a less appealing option to be used in this type of analysis.

Undertaking scenario analysis using the spatial economic indicator provides a means to understand and quantify the potential range of income returns and financial tradeoffs associated with price fluctuations in the international commodity market.

The separation of negative and positive financial returns allows for the identification of areas that contribute differently to the determination of income. Areas that produce negative returns can be seen to be where growers may easily adopt alternative land uses. The study shows that these are relatively small in magnitude, ranging from 3-20% of the study area cropped to wheat for the 1999 season depending on the cost price scenario chosen. The occurrence of these small areas may indicate why growers have not adopted alternative land uses previously or have only adopted relatively small scale approaches. Inclusion of areas which were loss making and those that produced the bottom 10% of income accounted for 27% (5,789 ha) to 44% (9,511 ha) of the study area cropped to wheat in 1999. Calculation of the average gross margin per hectare value for the areas that produced the bottom 10% of income illustrated income earnings ranging from $72-$270/ha depending on which scenario was chosen. Several Australian studies have evaluated the potential profitability of industries and production options associated with the introduction of woody perennials as a revegetation strategy (Bell, 1999; Flugge and Abadi, 2006; Bennell *et al.*, 2007; Harper *et al.*, 2007; Hobbs *et al.*, 2007; Bryan *et al.*, 2008). Recent carbon sequestration studies by Hobbs, 2009 and Polglase *et al.*, 2008 suggest that income returns could be in the order of $200 per hectare per year. However, this value depends on the price paid for carbon, the likely carbon sequestration rates across the region and the start-up and management costs involved. Given these caveats, comparisons between income from revegetation for carbon sequestration and those returns from traditional cropping estimated in this study suggest that for the 100 to 0 cost price scenario, around 20% to 55% of the study area cropped to wheat could be reassigned with little to no economic loss. These area values are in the lower range of catchment based revegetation targets, (30-80% of the landscape) required for salinity reduction benefits (Clarke *et al.*, 1999; George *et al.*, 1999; Pracilio *et al.*, 2003 Hodgson *et al.*, 2004).

This study has taken a purely economic view of determining whether a revegetation strategy could be feasible with the Australian grain industry. No attempt has been made to optimise the spatial arrangement and configuration of the selected areas based on multiple objectives (Crossman and Bryan, 2006; de Groot, 2006) or ecological flows (Bailey *et al.*, 2006). At the regional scale, applying ecological arrangement rules may reduce the feasibility of such a strategy considering high value land may need to be incorporated with low value land in order to create a greater ecological outcome. One major constraint in identifying these arrangements will be the large dynamics of the planting machinery. This will hinder the revegetation of areas within fields if the selected areas are too fragmented.

The issue of scale and resolution in developing ecological indicators has recently received substantial attention (Uuemaa *et al.*, 2005; Walker *et al.*, 2006; Cushman *et al.*, 2008; Walz, 2008; Zurlini and Girardin, 2008). This study has shown that it is possible to create high resolution yield data at a broad spatial scale. In particular if it is necessary to address economic performance, availability of detailed pattern can provide a greater understanding of the economic and environmental tradeoffs involved. Examination of these trade-offs within a broader decision making framework (Lenz and Peters, 2006; Wiggering *et al.*, 2006; De Aranzabal *et al.*, 2008) can help assess the opportunities and limitations involved in the agricultural sector.

6.7 Conclusion

This paper has presented a framework for developing a spatial indicator that quantifies the economic returns from traditional agricultural production in the Australian grains industry. The high resolution and broad extent of this information allows for a thorough evaluation of the financial returns needed to substitute traditional agricultural practices with revegetation strategies.

We have found that the crop types that dominate the region can be accurately discriminated with remotely sensed imagery, specifically with the Landsat 7 ETM+ sensor. This initial investigation has highlighted that these accuracies hold relatively stable over the month of September illustrating the existence of a time window for image acquisition in future studies.

The use of precision agriculture technology, in particular yield mapping, has been specifically designed for quantifying within field yield variation. Extending this information spatially, through its correlation with a satellite derived vegetation index, has allowed for an expansion of these estimates to a broader scale, while still maintaining a high spatial resolution of yield prediction. Validation of the regression model showed that predicted wheat yield values were overestimated in the less than 1.5 t/ha range thus providing a conservative estimate of yield in areas that can be identified for possible revegetation activities.

Application of the spatial indicator across the study region and the application of four financial scenarios highlighted the sensitivities involved in considering where land use changes can be made, with the expected wheat grain price and variable cost being the major determinate.

Using the pattern of spatial yield variability at a large regional extent is possible and will increase realism in broad-scale economic analysis. Adaptation of this method to other areas is possible given that there are a few early adopters of yield mapping technology in the area and cloud free imagery is available at crop anthesis for the region.

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Chapter 7: Estimating wheat yield from Landsat TM and ETM+ imagery and precision agriculture technology

***Keywords**: Precision agriculture, yield mapping, wheat yield estimation, Landsat, model validation, model reliability.*

7.1 Abstract

Models relating wheat yield estimates and remotely sensed biomass surrogates have been trialled extensively for the forward prediction of yield in agricultural areas. The long term archiving of remotely sensed imagery and yield mapping data sensed by precision agriculture technology has meant that historical relationships can be used to predict yield over large areas for multiple seasons. For decision making to be made from this data, an understanding of the magnitude of prediction errors is needed. In this study, we examine the transferability of the predictive wheat yield relationships developed on one farm and its potential error when used to extrapolate yield on another. We further attempt to understand how the accuracy and reliability of these relationships and their yield predictions alter temporally with changes in the amounts of annual and in season rainfall.

We acquired Landsat imagery and wheat yield measured by combine-mounted yield monitors for three Western Australian farms. Empirical relationships were developed between Normalised Difference Vegetation Index (NDVI) and wheat yield for different image acquisition dates measured in low, medium and high rainfall years. Yield prediction models developed on one farm were validated against independent yield data from two other farms. Overall model prediction accuracy was assessed by three statistical efficiency criteria, while visualisation of the distribution of prediction error versus observed yield was used to analyse errors in relation to where they occurred along the yield spectrum.

Over all seasons, the most accurate in-season wheat yield prediction was achieved with imagery acquired in mid September. Of the six seasons reviewed, four showed very reasonable prediction accuracies, with the low and high rainfall years providing very good predictions. Medium rainfall years showed the greatest variation in prediction accuracy

with marginal to poor predictions resulting from narrow ranges of wheat yield and NDVI values.

These results demonstrate that over years with differing rainfalls, robust wheat yield prediction models can be created from Landsat sensed NDVI and wheat yield measurements sensed by combine-mounted yield monitors. The validated models can then be applied to satellite imagery to derive spatially varying estimates of yield over a range of historical growing seasons. The future inclusion of financial estimates of agricultural production enables the creation of spatially and temporally varying economic performance that is both broad in extent and high in resolution. The physical dimensions of this information are complementary to the scales of data needed to inform both growers and policy makers on agronomic, business and environmental decisions.

7.2 Introduction

Remote sensing has been used widely in dryland agricultural areas to provide early prediction of wheat crop performance for government and farming decision makers. As extensive agricultural lands are dedicated to wheat, prediction of pre-harvest yield can be used to inform governmental planning and policy by providing early warning for food security, famine and drought forecasting (Hutchinson, 1991; Quarmby *et al.*, 1993; Liu and Kogan, 1996; Prasad *et al.*, 2007). For growers, early yield prediction through remote sensing has been used in the validation of biophysical crop models (Moulin *et al.*, 1998; Basso *et al.*, 2001), as a substitute for yield maps to analyse yield consistency (Pinter *et al.*, 2003) and as surrogates for soil fertility to estimate fertiliser recommendations (Raun *et al.*, 2001; Flowers *et al.*, 2003; Reyniers and Vrindts, 2006b). Timely yield prediction also reduces crop yield uncertainty for both growers and insurance companies (Vicente-Serrano *et al.*, 2006; Wall *et al.*, 2008) as well as notifying grain collection companies of logistical issues (Wall *et al.*, 2008), pricing policies, and marketing and trading decisions (Lobell *et al.*, 2003; Liu *et al.*, 2006).

The reliability of relationships developed between wheat yield and satellite-derived spectral measurements is governed by the selection of the yield prediction model, choice of satellite sensor and the resolution of the yield data collected. Previous approaches to wheat yield prediction have ranged from empirical regression relationships (Benedetti and

Rossini, 1993; Sharma *et al.*, 1993; Sridhar *et al.*, 1994; Hamar *et al.*, 1996; Vicente-Serrano *et al.*, 2006; Wall *et al.*, 2008) to more advanced models which included agronomic and metrological relationships (Rudorff and Batista, 1991; Manjunath *et al.*, 2002; Prasad *et al.*, 2007) and the measurement of Photosynthetically Active Radiation (PAR) and Absorbed Photosynthetically Active Radiation (APAR) parameters (Bastiaanssen and Ali, 2003; Lobell *et al.*, 2003; Patel *et al.*, 2006; Duchemin *et al.*, 2008). Previous predictions of wheat grain yield from remotely sensed imagery have used coarse data from low resolution sensors because of its low cost, availability, extensive spatial coverage and frequent acquisition dates. The majority of regional wheat yield prediction studies have used sensors with broad synoptic views such as AVHRR (Benedetti and Rossini, 1993; Gupta *et al.*, 1993; Quarmby *et al.*, 1993; Doraiswamy and Cook, 1995; Labus *et al.*, 2002; Bastiaanssen and Ali, 2003; Boken and Shaykewich, 2005; Kastens *et al.*, 2005; Vicente-Serrano *et al.*, 2006; Prasad *et al.*, 2007; Salazar *et al.*, 2007; Wall *et al.*, 2008), IRS (Sharma *et al.*, 1993; Dubey *et al.*, 1994; Sridhar *et al.*, 1994; Dadhwal and Sridhar, 1997; Singh *et al.*, 2002; Patel *et al.*, 2006) and MODIS (Reeves *et al.*, 2005; Ren *et al.*, 2008). This choice of imagery is advantageous when modelling broad scale crop progression, crop canopy emergence, maturation and senescence but sacrifices higher spatial resolution for greater temporal frequency and broader area investigation.

Validations of predictions from these yield models with yield data measured at the district, farm or field level have shown reasonable accuracies. However, the minimisation of landscape heterogeneity caused by the coarse resolution at which both the satellite imagery and yield data are collected can over-inflate these results (Benedetti and Rossini, 1993; Doraiswamy and Cook, 1995; Reeves *et al.*, 2005). Furthermore, coarse resolution imagery has limited applicability to the farm scale and below because the data does not adequately characterise crop productivity at this scale (Garrigues *et al.*, 2006; González-Sanpedro *et al.*, 2008) and can include other crop types and remnant native vegetation (Labus *et al.*, 2002; Doraiswamy *et al.*, 2004).

Several authors have used the substantial historical archive of the Landsat sensor to predict wheat yield. Data collected at the farm, field or geo-referenced hand-sampled scale have shown very reasonable correlations with Landsat-derived spectral vegetation indices (Rudorff and Batista, 1991; Singh *et al.*, 1992; Hamar *et al.*, 1996; Lobell and Asner, 2003;

Ferencz *et al.*, 2004; Liu *et al.*, 2006). However, a major problem with this type of study design is that extensive field programmes to collect yield data at the regional scale labour intensive and expensive (Groten, 1993).

One way to circumvent this logistical problem is to take advantage of precision agriculture technology where combine mounted yield sensors collect yield measurements throughout fields every 1 to 3 seconds. The demonstrated accuracy of such yield values tested by scientific and commercial agricultural sectors ranges from 95% to 99.5% (Murphy *et al.*, 1995; Birrell *et al.*, 1996; Missotten *et al.*, 1996; Reitz and Kutzbach, 1996; Jasa, 2000; Arslan and Colvin, 2002a) with accurate yield estimates achievable at resolutions of 20-25 metres (Lark *et al.*, 1997). To take advantage of this high resolution yield data the corresponding instantaneous field of view of satellite imagery should be of a similar resolution. Studies using yield mapping data have reported high calibration correlations between combine-collected wheat yield estimates and vegetation indices derived from Landsat and IKONOS (Thenkabail, 2003; Dobermann and Ping, 2004; Enclona *et al.*, 2004; Reyniers and Vrindts, 2006b). Although these models explain a high proportion of the spatial variability in crop yield, rarely they have been extended and validated in independent fields. This is because the validation is retrospective, providing only insight into past performance and doing little to satisfy the need for timely pre-harvest yield information (Reeves *et al.*, 2005).

We propose, however, that two significant benefits can be achieved by creating and validating such retrospective relationships based on historical yield mapping data and the spatial resolution and coverage of the Landsat imagery archive.

Firstly, such an approach could assist growers who have not yet adopted or those who have recently adopted precision agriculture technology (Bullock and Bullock, 2000; Robertson *et al.*, 2008) to more readily access the benefits of precision farming, or to assess the profitability of fields (Massey *et al.*, 2008). The mapping of past yield performance at the resolution (30 metres) and broad extent (potentially 185 km by 185 km) of Landsat gives these growers the opportunity to access past sub-field yield performance information from neighbouring early adopters of the yield mapping technology. This opportunity will enable growers to leap-frog the time consuming process of archiving yield maps each year before any future management decisions can be made.

Secondly, the creation of a time series of yield performance at the resolution and extent of the Landsat sensor may assist in future environmental policy decisions. By quantifying the degree of yield variability over time and the incorporation of financial estimates of agricultural production, a spatial economic comparison between the returns from traditional cropping and those from an alternative environmentally friendly land use can be made. This comparison identifies the financial implications of changing from one land use to another, known as the economic opportunity cost. The resolution at which this calculation is made is at a scale where growers make decisions. While the extent at which the calculation is made is at the scale where policy makers make decisions. Previous research into quantifying agricultural economic performance and the associated economic opportunity costs have produced estimates at similar resolutions and extents (Yang *et al.*, 2003; Münier *et al.*, 2004; Lant *et al.*, 2005; Naidoo and Adamowicz, 2006; Naidoo *et al.*, 2006; Naidoo and Ricketts, 2006; Barton *et al.*, 2008; House *et al.*, 2008). However, these analyses have relied on the use of regional or farm based yield statistics making little use of spatial information to quantify spatially varying crop yield and therefore spatially varying economic opportunity cost.

In order to access these two potential benefits, we examine the transferability of the predictive wheat yield relationships developed on one farm and its potential error when used to extrapolate yield on another. This aim focuses on deriving empirical relationships developed from high resolution wheat yield mapping data and Landsat imagery collected across three farms. These datasets provide the basis for prediction model development and validation. We further attempt to understand how the accuracy and reliability of these relationships alter temporally with changes in the amounts of annual and in season rainfall. To highlight the sensitivities associated with annual wheat yield prediction, statistical comparisons between the three farms are made.

7.3 Study area

The study area covers 25 by 25 kilometres within the northern wheat belt of Western Australia (Figure 39). This area incorporates four neighbouring farms that collected yield data for the 1996 to 2004 growing seasons. The region is characterised by a Mediterranean climate, with cool wet winters and hot dry summers. Over half the annual rainfall (300-400 mm), occurs between May and September, with high evaporation rates in summer. Mean and standard deviation of average monthly rainfall over 104 years show the considerable variation in rainfall for the study region, especially within the growing season (May and September) (Figure 38).

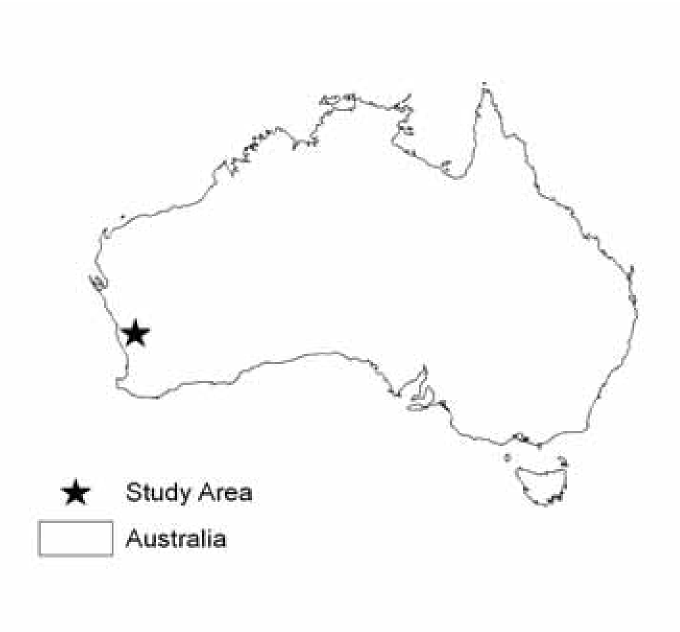

Figure 39 Location of the study area in the northern wheat belt of Western Australia

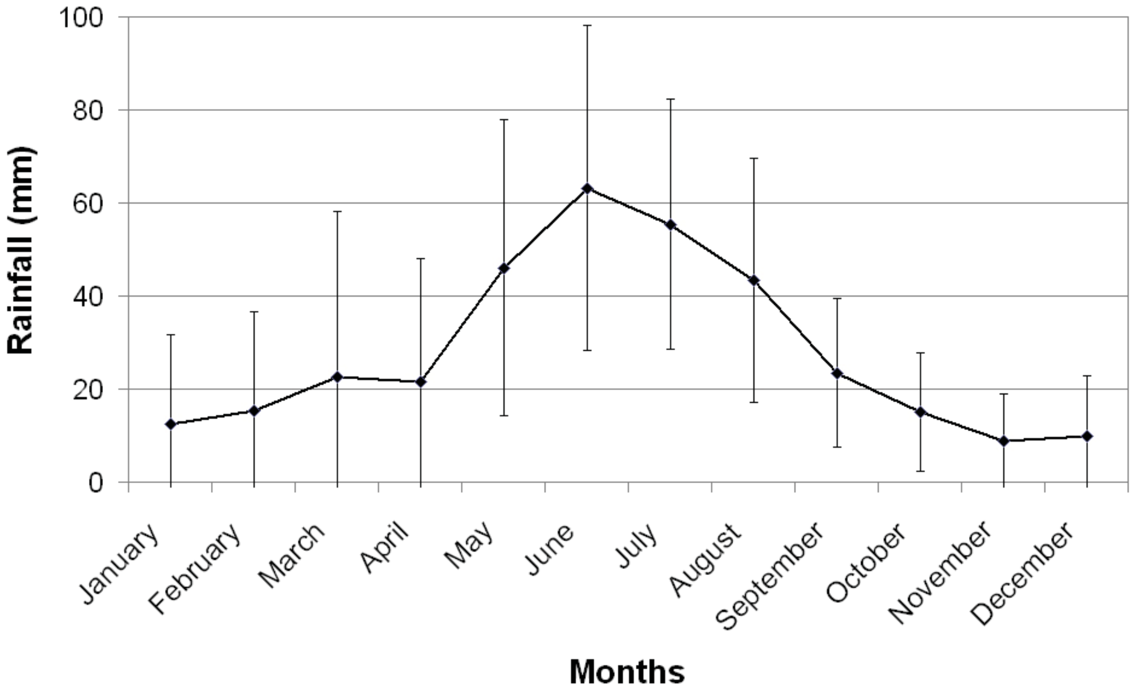

Figure 40 Study area average and standard deviation (Y-error bars) of monthly rainfall for 1900 to 2004 (Source: Australian Bureau of Meteorology).

In this grain growing environment, water is the major limitation to plant productivity (Turner and Asseng, 2005). The agricultural landscape is predominately broad sand plains with very little relief and salty discharges situated in the lower parts of the landscape. Farms in the region are large with over 2,000 hectares of cropping area. The broad-acre cropping rotations are dominated by wheat with lupins, canola and to a lesser extent barley and oats as break crops. Pastures for cattle and sheep grazing are also common, as well as small scattered stands of remnant native vegetation consisting of a mixture of evergreen shrubs and trees that are well adapted to the hot dry summers (Turner and Asseng, 2005). Flowering and grain filling of crops occurs in spring (September) with harvest in late spring and early summer (November-December).

7.4 Methods

We developed empirical relationships between wheat yield measured on three farms with precision agriculture yield mapping capability and the Normalised Difference Vegetation Index (NDVI) derived from Landsat 5 TM and 7 ETM+ imagery. The strength of these relationships was tested at different times within the growing season and over differing rainfall conditions. Validation of the predictive power of the models was tested against independent yield mapped data. To undertake these objectives several steps were taken.

7.4.1 Characterising years by rainfall distributions

In order to test the robustness of yield prediction models developed over differing rainfall conditions we used data from a range of years and seasonal conditions (Table 11). Years where yield mapping data and Landsat imagery were available were classified according to total growing season rainfall into low (> 200 and < 230 mm), medium (> 230 and <330 mm) and high (> 330 mm). These years were further differentiated based on the amount of rainfall recorded within the months of April-May, June-July and August-September. Within the dry-land farming environment, end of season wheat yield is determined by the plants ability to get water within specific phases of development (Sadras and Rodriguez, 2007). These phases fall into these bi-monthly classifications.

Classifications were made where rainfall was less than 70mm, between 70mm and 100mm and greater than 100mm (Table 11). For low rainfall years, two seasons (2001, 2004) were selected with measured rainfall predominantly less than 70 mm across the bi-monthly spectrum. Three medium rainfall scenarios were also characterised. 1996 represented a year where the majority of rainfall fell in the last 4 months; in 1998 the majority fell in the first 4 months and in 2003 rainfall predominately fell in the last 2 months. 1999 was classified as a year of high rainfall with high falls across the first 4 months. In the selection of these low, medium and high rainfall scenarios we test the robustness of the simple regression models developed over differing rainfall conditions.

Table 11 Identification of low, medium and high rainfall scenarios and their corresponding growing season rainfall

Rainfall Scenario	April – May (mm)	June – July (mm)	August – September (mm)	Growing Season Rainfall (mm)	Year
Low 1	< 70	< 70	< 70	218	2001
Low 2	< 70	70 - 100	< 70	223	2004
Medium 1	< 70	> 100	70 - 100	316	1996
Medium 2	70 - 100	> 100	< 70	284	1998
Medium 3	< 70	70 - 100	> 100	271	2003
High	> 100	> 100	< 70	482	1999

7.4.2 Wheat phenology and image acquisition date

In agricultural areas the phenological cycle of seeding, growth, maturity and harvesting of managed agricultural vegetation is repeated on an annual basis (Alexandridis et al., 2008). Several authors (Carlson and Ripley, 1997; Basso et al., 2001) suggest that vegetation indices such as NDVI taken at critical times during the growing season can help characterise the spatial variability in crop performance. Lobell et al., 2003 suggests that accurate wheat yield predictions are possible using only one image, provided the image is acquired towards the middle of the growing season when most wheat crop canopies are fully developed. This can justify the use of higher resolution satellite imagery which is costly, less frequently acquired and has small spatial coverage The selection of the correct image acquisition date therefore depends on firstly, the relationship of NDVI to particular wheat development stages, and secondly the relationship between NDVI taken at this time to the final wheat grain yield. Laboratory-based spectral studies targeting crop development have found that NDVI is very sensitive at leaf area index (LAI) between 0 and 2 (Aparicio *et al.*, 2000). Spectral analysis after this stage (during the ripening process) showed an asymptotic association between NDVI, LAI and wheat grain yield (Aase and Siddoway, 1981; Aparicio *et al.*, 2002; Royo *et al.*, 2003; Liu *et al.*, 2006). This indicates that the use of NDVI for biomass and yield prediction is limited to crop stages where LAI values are < 3 (Aparicio *et al.*, 2000). These findings have also been supported by satellite based studies which indicated good associations between NDVI and wheat grain yield at 50 to 110 days after plant emergence (Rudorff and Batista, 1991; Benedetti and Rossini, 1993; Gupta *et al.*, 1993; Quarmby *et al.*, 1993; Doraiswamy and Cook, 1995; Smith *et al.*, 1995; Ferencz *et al.*, 2004; Beeri and Peled, 2006). This is a critical phenological phase for predicting the final wheat yield, since these stages correspond to the formation and organisation of the canopy structure after the occurrence of the flag leaf (Raun *et al.*, 2001; Moges *et al.*, 2004; Beeri and Peled, 2006), at the end of stem elongation and beginning of the heading (Aparicio *et al.*, 2002; Boken and Shaykewich, 2005) and grain formation stage (Boissard and Pointel, 1993). Further investigation into the measurement of spectral reflectance of wheat growth stages from a tractor mounted radiometer (Scotford and Miller, 2004) showed similar asymptotic relationships of NDVI and LAI values during this time period. Other studies (Liu *et al.*, 2006; Vicente-Serrano *et al.*, 2006) and those undertaken in Australia (Dawbin *et al.*, 1980; Smith *et al.*, 1995 Lyle and Ostendorf, In review) suggest that for cereal crops, biomass or LAI measures at the flowering or anthesis stage (September to November) are closely related to final grain yield.

For this study, cloud free Landsat 5 TM and 7 ETM+ data were acquired (path-row 113/81 and 112/81) between August and October (Table 12). Images were processed to USGS Level 1G and further orthocorrection to the Geocentric Datum of Australia 1994 and systematic radiometric corrections were made by the vendor, Geoscience Australia. Pixel size was resampled to 25m. As no direct comparison was made between the images, they were cloud free and the time between the acquisitions was short (usually 16 days) no further radiometric calibration was made. The Normalised Difference Vegetation Index (NDVI; band4-band3/band4+band3) was then calculated for all images.

Table 12 Catalogue of Landsat images acquired for the low, medium and high rainfall scenarios, sensor in brackets

Rainfall Scenarios	August (Sensor)	September (Sensor)	October (Sensor)
Low	26 Aug 2001 (7)	11 Sept 2001(7)	13 Oct 2001(7)
		11, 27 Sept 2004(5)	
Medium	26 Aug 1998(5)	11 Sept 1998 (5)	
		16 Sept 2003(5)	2 Oct 2003(5)
		21 Sept 1996 (5)	
High	21 Aug 1999 (7)	6, 29 Sept 1999 (7)	15 Oct 1999(7)

7.4.3 Wheat grain yield mapping

Wheat grain yield mapping data was obtained from four different yield monitoring systems over four farms for each of the growing seasons identified in Table 12. Previous research has concentrated on identifying spatial variability of yield within a single or a limited number of fields. In this study, by contrast, we have aggregated wheat yield data by farm and year meaning that amount of data collected per year was around 10 to 16 fields, each over 70 hectares in size. The total area cropped to wheat per year was over 1,500 ha per farm.

The extent of data available for analysis was limited by when the yield monitoring technology was adopted by each grower (Table 13). Four farms were used in the analysis. Data was available for only one farm for the earliest year of the investigation (1996). For the last year of analysis, yield mapping data from Farm 2 was unavailable. However, the yield monitor used in Farm 1 was trialled on another neighbouring farm and this was used as a replacement dataset to Farm 2. This farm had yield monitored wheat area totalling around 600 hectares.

Table 13 Availability of yield mapping data by farm

Farm	Year yield mapped
Farm 1 (F1)	1996, 1998, 1999, 2001, 2003, 2004
Farm 2 (F2)	1998, 1999, 2001, 2003
Farm 3 (F3)	1999, 2001, 2003, 2004
Farm 4 (Substitute for F2)	2004

Each field dataset was cleaned with several algorithms to remove erroneous yield values associated with harvester dynamics and operator error (Lyle and Ostendorf, In review). Wheat yield was then interpolated to a 25 by 25 metre grid using the VESPER kriging software (Minasny *et al.*, 2005) and specific interpolation criteria derived for yield mapping (Taylor *et al.*, 2007). This interpolation provided wheat yield estimates for missing areas due to error removal and provided a grid of similar resolution to that of the Landsat imagery so that spatial comparison could be undertaken.

Because yield data was not available across all farms for all years, several processes were used to chose the calibration and validation datasets. For the majority of years (1998 to 2004), models were developed for each farm. Here, data from one farm was used in model development while data from the other two farms were used to validate its prediction accuracy. The exception to this was 1996, when only one dataset was available. As the fields in this datasets were of similar area, the data was randomly separated into calibration and validation sets in the proportions 70:30.

7.4.4 Comparison of wheat grain yield estimates and Landsat imagery

NDVI was calculated for all Landsat images. A cell by cell comparison was then used to relate specific NDVI values to the 25 by 25 metre interpolated wheat grid for each field. This provided a 1:1 mapping of each pixel NDVI value to an interpolated yield estimate. Empirical relationships between wheat yield and NDVI were then developed for each farm and image date. An assumption was made that all models should pass through zero, indicating that zero yield was associated with zero NDVI value.

The simple regression models were then applied to predict wheat yield from NDVI values of the validation farms for the corresponding image date. Three accuracy criteria were chosen to assess these predictions based on the differences between the modelled yield estimates and the corresponding interpolated yield estimates derived from continuous yield mapping. These criteria were the Root Mean Square Error (RMSE), the Coefficient of Variation of the RMSE (CVr) and the Nash-Sutcliffe Efficiency Criterion (E). These measures provide an insight into the magnitude and variation in the prediction error created by each of the models. The two later criteria allow for the comparison of prediction accuracy across models since they normalise the prediction error across varying yield distributions used in the validation process. The Nash Sutcliffe Efficiency Criterion (E) is defined as one minus the sum of absolute squared difference between the predicted and observed values normalised by the variance of the observed values (Nash and Sutcliffe, 1970). Values of E range between 1.0 (perfect fit) and $-\infty$. Here, a negative efficiency indicates that the mean value of the observed yield would have been a better predictor than the model (Krause *et al.*, 2005). Calculating this criterion for the calibration models is equivalent to the calculation of the R^2 value. These criteria were derived for both the calibration and validation phase of model development.

The above criteria show the overall effectiveness of the models. Another tool that can be used for model assessment is the visualisation of the relationship between the prediction error and the corresponding interpolated wheat yield measurements (Figure 41). Graphs of these estimates reveal important information about the ability of the model to predict the dependent variable in different ranges (Jain and Sudheer, 2008). The grey regions (Figure 41) show what might be seen as the prediction error tolerances across the yield spectrum. A greater proportion of data falling within these bands indicates a more suitable wheat prediction model. That is, extreme over-prediction of yield values in the lower yielding range means that areas of low yield will not be identified. Similarly, the underestimation of yield values in higher ranges means that these areas will be incorrectly highlighted as low-producing. The selection of the best performing model should therefore be based on the performance of all efficiency criteria as well as the spread of predicted values as revealed by the graphs.

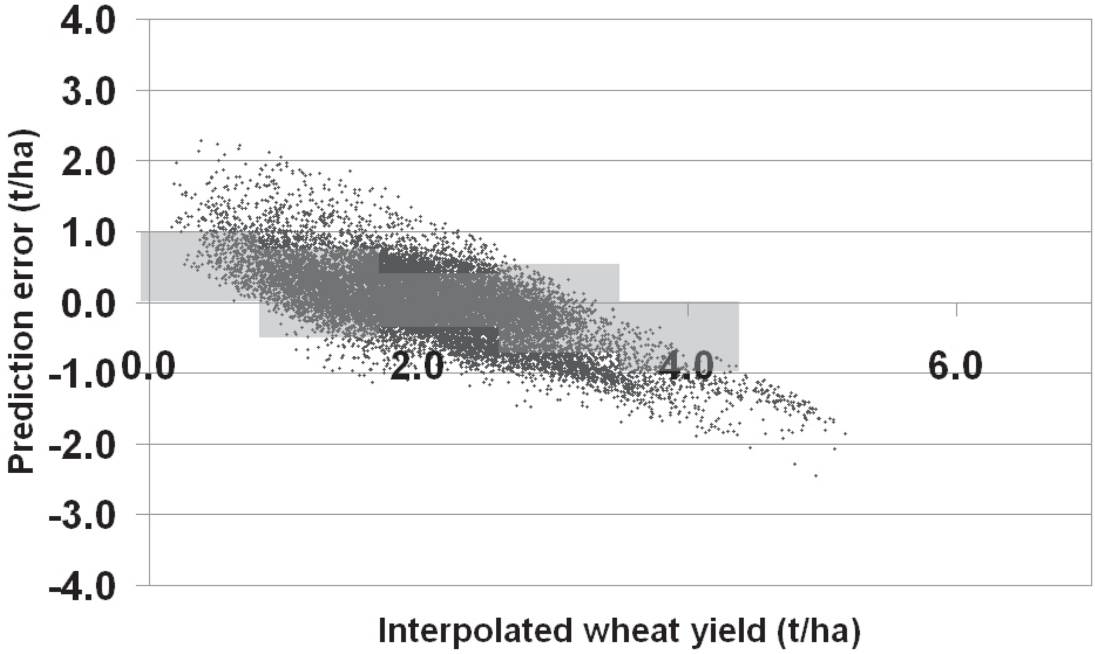

Figure 41 Prediction error (Y-axis) against the interpolated yield estimates (X-axis). Grey bands provide in indication of the prediction error tolerances in which data should fall for suitable model selection.

7.5 Results

7.5.1 Low rainfall scenario

For 2001, the early image (26/08/01) relationships (Figure 42) show a small statistical range of NDVI values, especially for Farm 3 where a clustered pattern of NDVI values is evident. The two week difference between the image dates showed a significant decrease in minimum, maximum and average NDVI values as well as an increase in the statistical range. Efficiency criteria for the calibration models (Table 14) across both image dates and years (shown in italics) illustrated moderate relationships between yield and NDVI in low rainfall years. For 2001, the strength of the yield-NDVI relationships for Farms 2 and 3 increased with acquisition date; this was similar to the results for all 2004 models (Table 14). Prediction efficiency measured by the Nash-Sutcliffe Efficiency Criterion (*E)* provided reliable yield-NDVI relationships with values between 0.11 and 0.44, while values for 2004 were slightly higher, between 0.18 and 0.64.

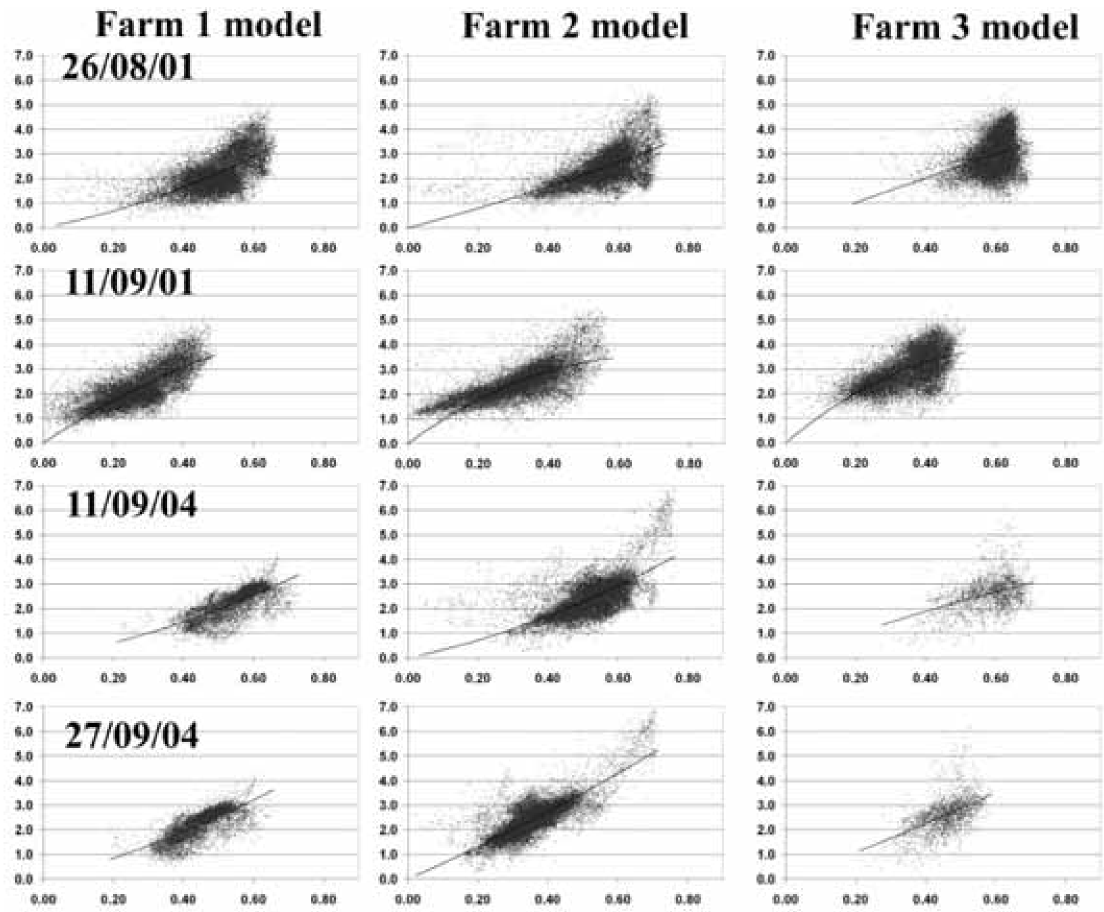

Figure 42 Regression relationships between Normalised Difference Vegetation Index (NDVI) (X-axis) and yield monitored wheat grain yield (t/ha) (Y-axis) for low rainfall growing seasons

Efficiency criteria for the late August and September 2001 acquisition dates show moderate prediction capability, with the September image date providing better results. RMSE ranged from 0.57 to 0.75 t/ha for the August image and 0.51 to 0.65 t/ha for September. This error represented 21% to 28% of the average validation yield for all models across both dates. Prediction efficiency measured by the Nash-Sutcliffe Efficiency Criterion (*E)* provided reliable accuracies in some cases with values between 0.07 and 0.35 for August and 0.16 and 0.49 for September.

Table 14 Model and yield prediction efficiency criteria for Landsat imagery acquired for 2001 and 2004 - Root Mean Square Error (R), Coefficient of Variation of RMSE (CVr) and the Nash-Sutcliffe Efficiency Criteria (*E*). Values in bolded italics represent efficiency criteria for the calibration models.

		Farm 1 dataset			Farm 2 dataset			Farm 3 dataset		
Model	Date	R	CVr	*E*	R	CVr	*E*	R	CVr	*E*
F 1	26/08/01	***0.56***	***0.25***	***0.38***	0.58	0.24	0.23	0.69	0.23	0.07
F 2	26/08/01	0.57	0.26	0.35	***0.55***	***0.23***	***0.31***	0.75	0.25	-0.09
F 3	26/08/01	0.62	0.28	0.23	0.64	0.26	0.07	***0.68***	***0.23***	***0.11***
F 1	11/09/01	***0.50***	***0.23***	***0.35***	0.51	0.21	0.47	0.62	0.21	0.24
F 2	11/09/01	0.51	0.23	0.49	***0.50***	***0.20***	***0.44***	0.65	0.22	0.16
F 3	11/09/01	0.58	0.26	0.34	0.58	0.24	0.23	***0.57***	***0.19***	***0.37***
F 1	11//09/04	***0.42***	***0.19***	***0.47***	0.65	0.27	0.20	0.65	0.25	0.09
F 2	11/09/04	0.52	0.24	0.18	***0.56***	***0.23***	***0.40***	0.68	0.26	0.01
F 3	11/09/04	0.48	0.22	0.31	0.60	0.24	0.33	***0.62***	***0.24***	***0.18***
F 1	27/09/04	***0.39***	***0.18***	***0.55***	0.87	0.36	-0.44	0.67	0.26	0.05
F 2	27/09/04	0.97	0.44	-1.84	***0.44***	***0.18***	***0.64***	0.81	0.3	-0.40
F 3	27/09/04	0.51	0.23	0.22	0.63	0.26	0.26	***0.58***	***0.22***	***0.29***

The negative *E* for the Farm 2 model validated on Farm 3 highlights its poor prediction capability, suggesting that the average wheat yield value for the Farm 3 validation set would be a better predictor than the proposed model. The Farm 3 model had the lowest yield prediction error when compared to the other two models.

Validation of the 2004 models (Table 14) showed that the image acquired in mid-September was the best yield predictor for that year. RMSE for the models were below 0.68 t/ha or less than 26% of the average yield, while *E* values varied between 0.01 and 0.33. The model developed on Farm 3 was the best predictor across all acquisition dates when compared to the efficiency criteria of the other models.

The graphing of prediction error against the corresponding interpolated yield values shows where along the yield spectrum under or overestimation occurs. The relationships developed from the September image provided better prediction accuracy than those relationships developed with late August image. Overestimation was significant below 2 t/ha while values greater 3 t/ha were under estimated for the models developed with the late August acquisition date (Figure 43). The dispersion of prediction error decreased with the later image date, with the majority of error being less than 1 t/ha in the yield ranges below 4 t/ha for both Farm 1 (F1) and 2 (F2) models. The Farm 1 (F1) model provided the best yield prediction for 2001 but all models for this year had reasonable yield predictive capability.

The visualisation of yield prediction error in the mid September image shows the best prediction, with the late September image providing only marginal prediction capability. For the models developed on the earlier image acquisition date, the Farm 1 (F1) model under predicted yield values of 3 t/ha and greater (Figure 44) while the Farm 2 (F2) model over predicted most yield values. For the late September image, under prediction of yield was apparent with the Farm 1 (F1) model while yield was over estimated using Farm 2 (F2) model. The Farm 3 (F3) model was the better yield prediction model with less dispersion of prediction error when compared to the other model validations.

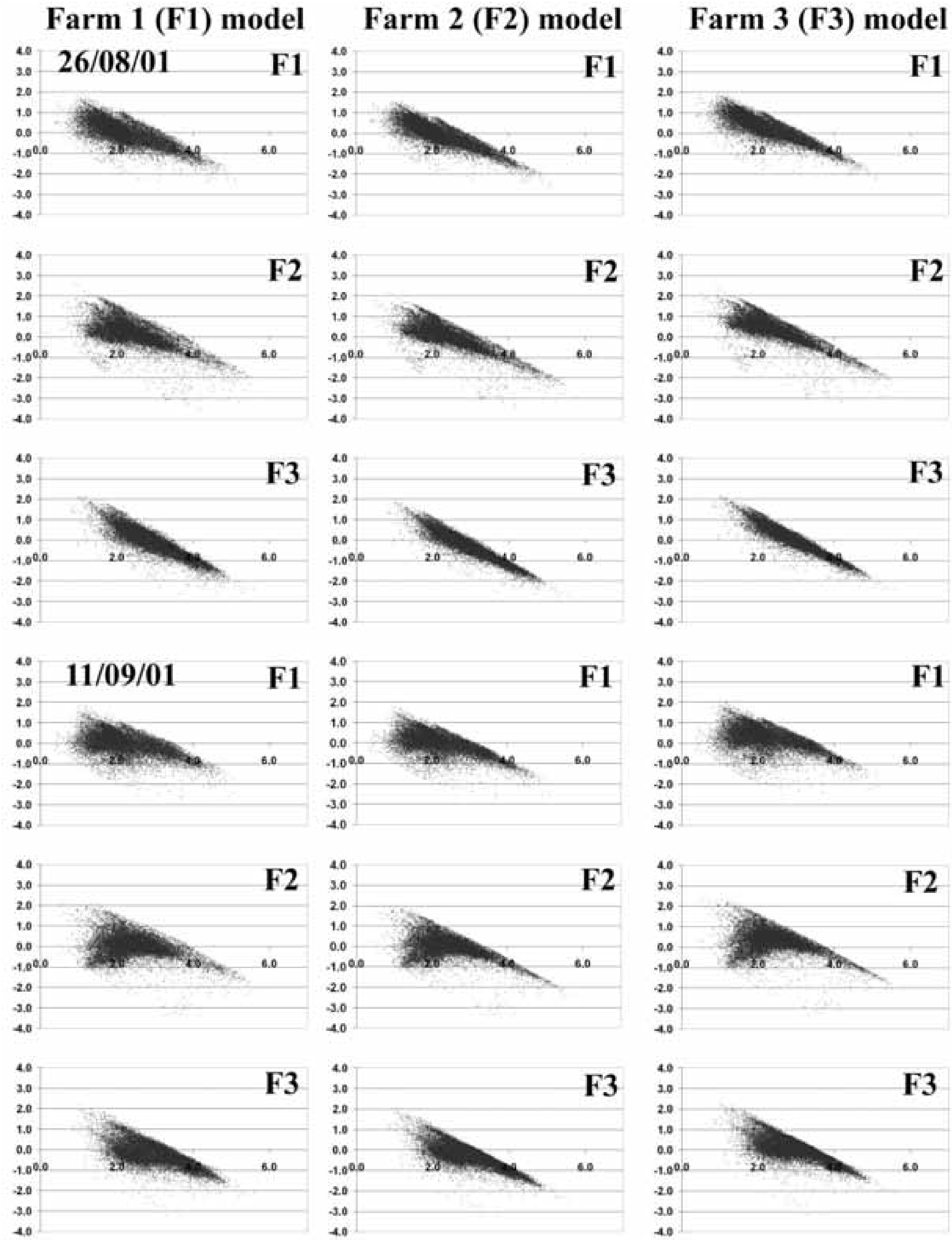

Figure 43 Yield predicted error (t/ha) (Y-axis) versus interpolated yield (t/ha) (X-axis) for the three wheat yield prediction models in 2001

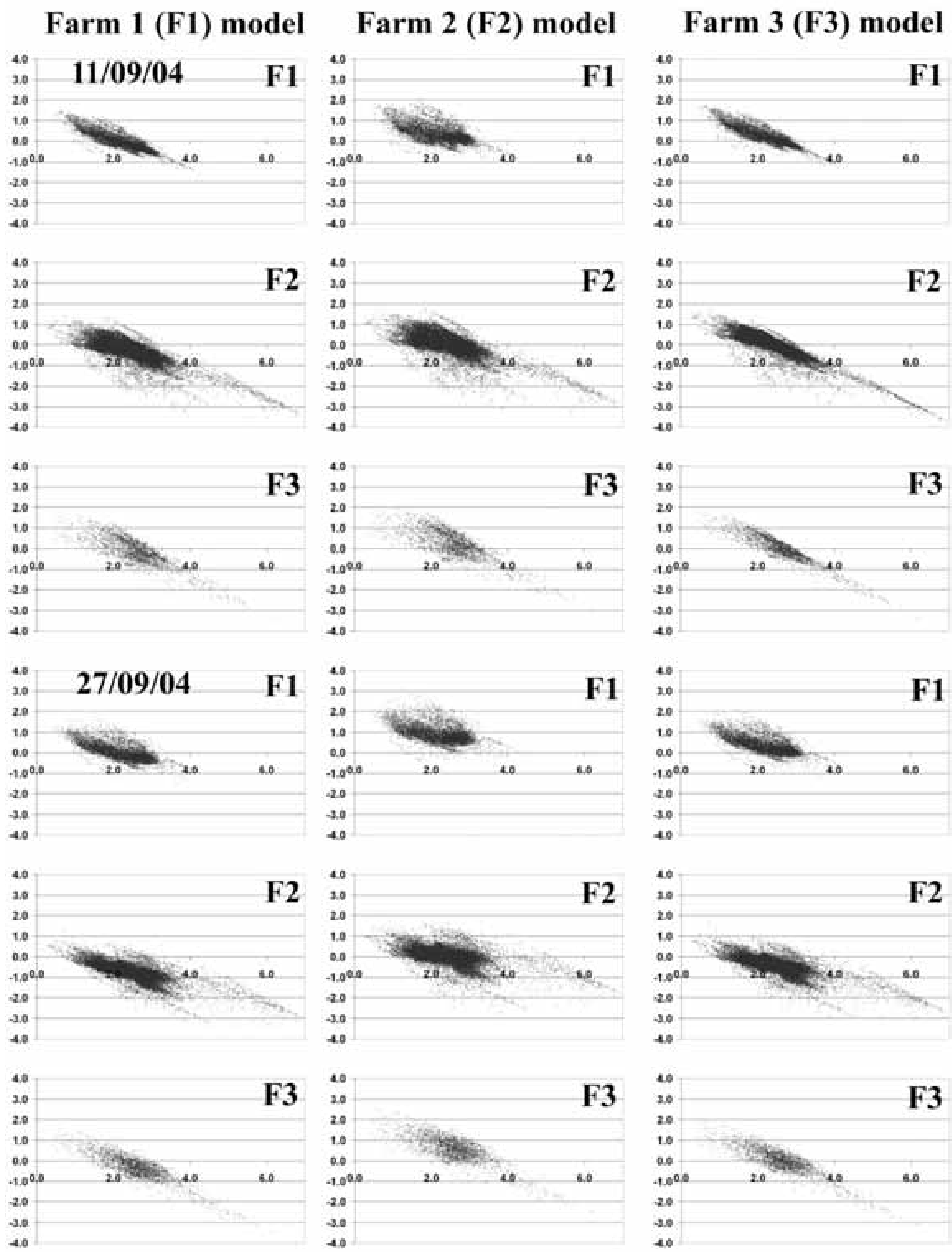

Figure 44 Yield predicted error (t/ha) (Y-axis) versus interpolated yield (t/ha) (X-axis) for the three wheat yield prediction models in 2004

7.5.2 Medium rainfall scenario

A good relationship (E = 0.69) was established between yield and NDVI for the mid-September image for 1996 (Figure 45). For 1998, the yield-NDVI relationships with images taken in late August and mid-September were poor, with NDVI values increasing between the acquisition dates. This later acquisition date slightly weakened the yield-NDVI relationship in the Farm 1 model and slightly strengthened the Farm 3 model (Table 15). The clustered pattern of NDVI values evident in 1998 also manifests itself in 2003 on Farms 1 and 3. Movement from mid-September to the early October image shows an increase in the range of NDVI values but also a decrease in their magnitude. For each model this caused an increase in strength of the relationship between yield and NDVI, except for the Farm 3 model.

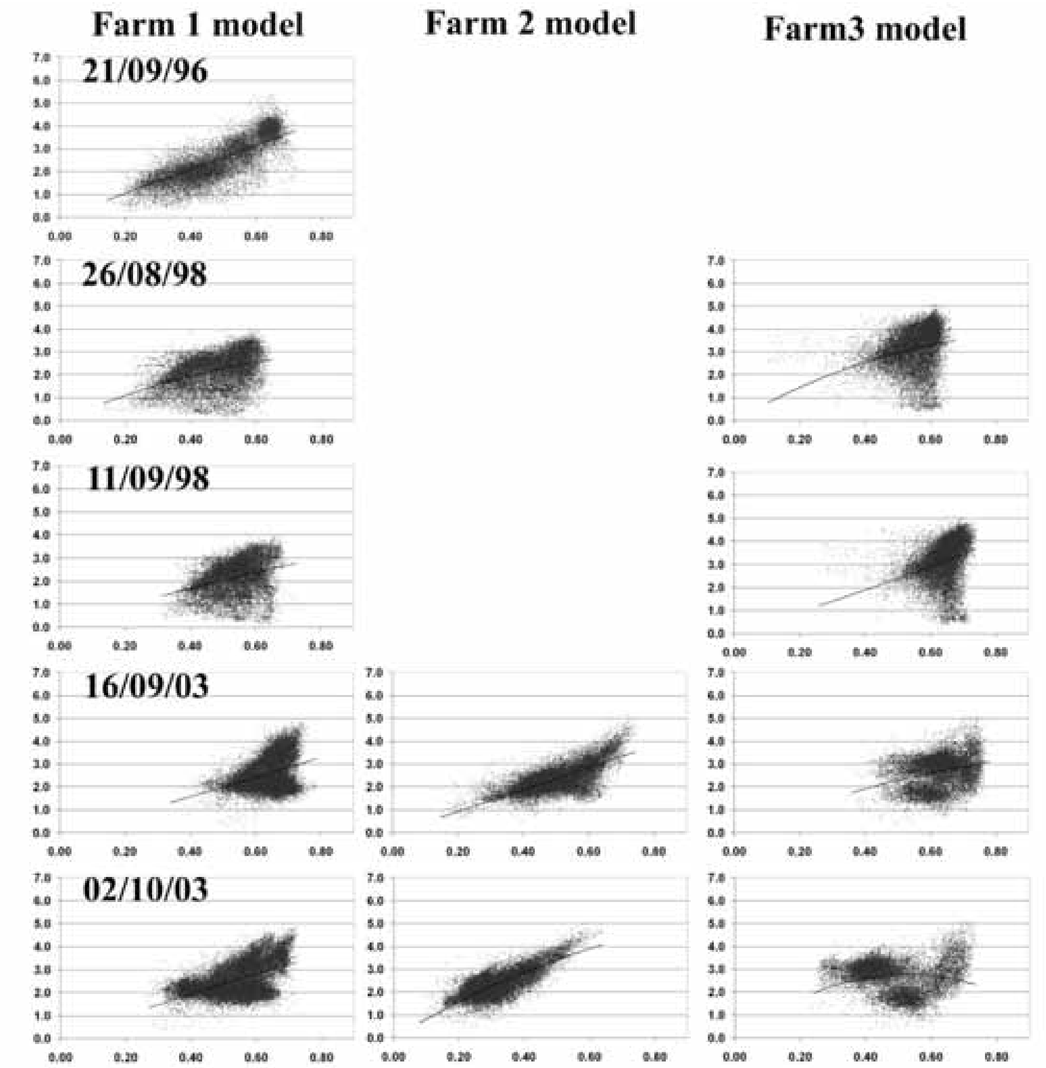

Figure 45 Regression relationships between Normalised Difference Vegetation Index (NDVI) (X-axis) and yield monitored wheat grain yield (t/ha) (Y-axis) for the medium rainfall growing seasons

High prediction accuracy was achieved for the 1996 model with RMSE of 0.54 t/ha, a CV(RMSE) of 20% and an *E* values of 0.64. Independent validation of the 1998 models (Table 15) showed poor predictions with high RMSE and CV(RMSE) and low to negative *E* values for both image dates. For models developed in 2003, the mid-September image provided the best models for yield prediction, with the Farm 3 (F3) model performing the best across the efficiency criteria. Validation of the models developed in October showed poor yield prediction capacity even with the subsequent increase in strength of the yield – NDVI relationships.

The 1996 model showed high prediction errors in the lower yield range, with decreased error in the medium to high range of yield (Figure 46). For 1998, the Farm 1 model showed considerable over-estimation of yield in the lower yield range for both image dates (Figure 47). For the Farm 3 model, similar overestimation of wheat yield was apparent across all measured yield values.

Prediction errors for the Farm 1 (F1) and Farm 3 (F3) models developed in mid-September 2003 were lower than for models developed in October. September models had only marginal predictive power with both models having similar distributions. The Farm 2 model overestimated yield at lower measured values. Of the models developed in October, those using the Farm 1 model under estimated yield, while the Farm 2 model over predicted yield. The Farm 3 model provided mixed results with better predictive capacity when validated against the Farm 2 dataset.

Table 15 Model and yield prediction efficiency criteria for Landsat imagery acquired in 1998 and 2003 – Root Mean Square Error (R), Coefficient of Variation of RMSE (CVr) and the Nash-Sutcliffe Efficiency Criteria (E). Values in bolded italics represent efficiency criteria for the calibration models.

		Farm 1 dataset			Farm 2 dataset			Farm 3 dataset		
Model	Date	R	CVr	*E*	R	CVr	*E*	R	CVr	*E*
F 1	26/08/98	***0.66***	***0.30***	***0.16***	*	*	*	1.11	0.36	-0.62
F 3	26/08/98	0.93	0.43	-0.67	*	*	*	***0.85***	***0.27***	***0.05***
F 1	11/09/98	***0.67***	***0.31***	***0.11***	*	*	*	1.04	0.33	-0.43
F 3	11/09/98	0.81	0.37	-0.27	*	*	*	***0.84***	***0.27***	***0.08***
F 1	16/09/03	***0.64***	***0.25***	***0.10***	0.57	0.24	0.097	0.69	0.26	-0.009
F 2	16/09/03	0.80	0.31	-0.43	***0.43***	***0.18***	***0.48***	0.73	0.27	-0.13
F 3	16/09/03	0.66	0.26	0.03	0.46	0.19	0.41	***0.66***	***0.25***	***0.08***
F 1	02/10/03	***0.58***	***0.23***	***0.26***	0.90	0.38	-1.30	0.92	0.34	-0.79
F 2	02/10/03	1.2	0.47	-2.22	***0.39***	***0.17***	***0.56***	1.11	0.42	-1.62
F 3	02/10/03	0.71	0.28	-0.13	0.46	0.19	0.41	***0.74***	***0.28***	***-0.17***

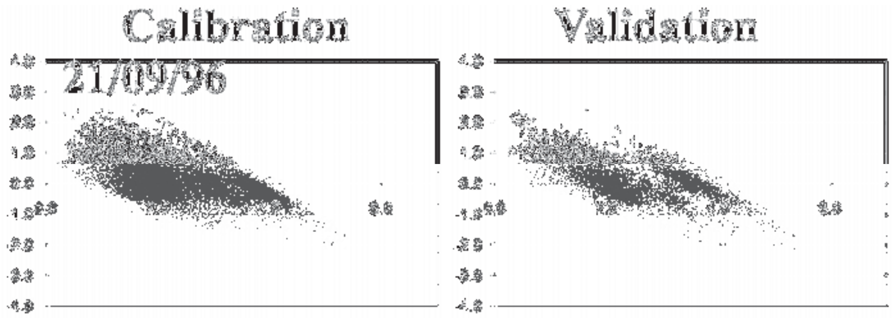

Figure 46 Yield predicted error (t/ha) (Y-axis) versus interpolated yield (t/ha) (X-axis) for the wheat yield prediction model in 1996

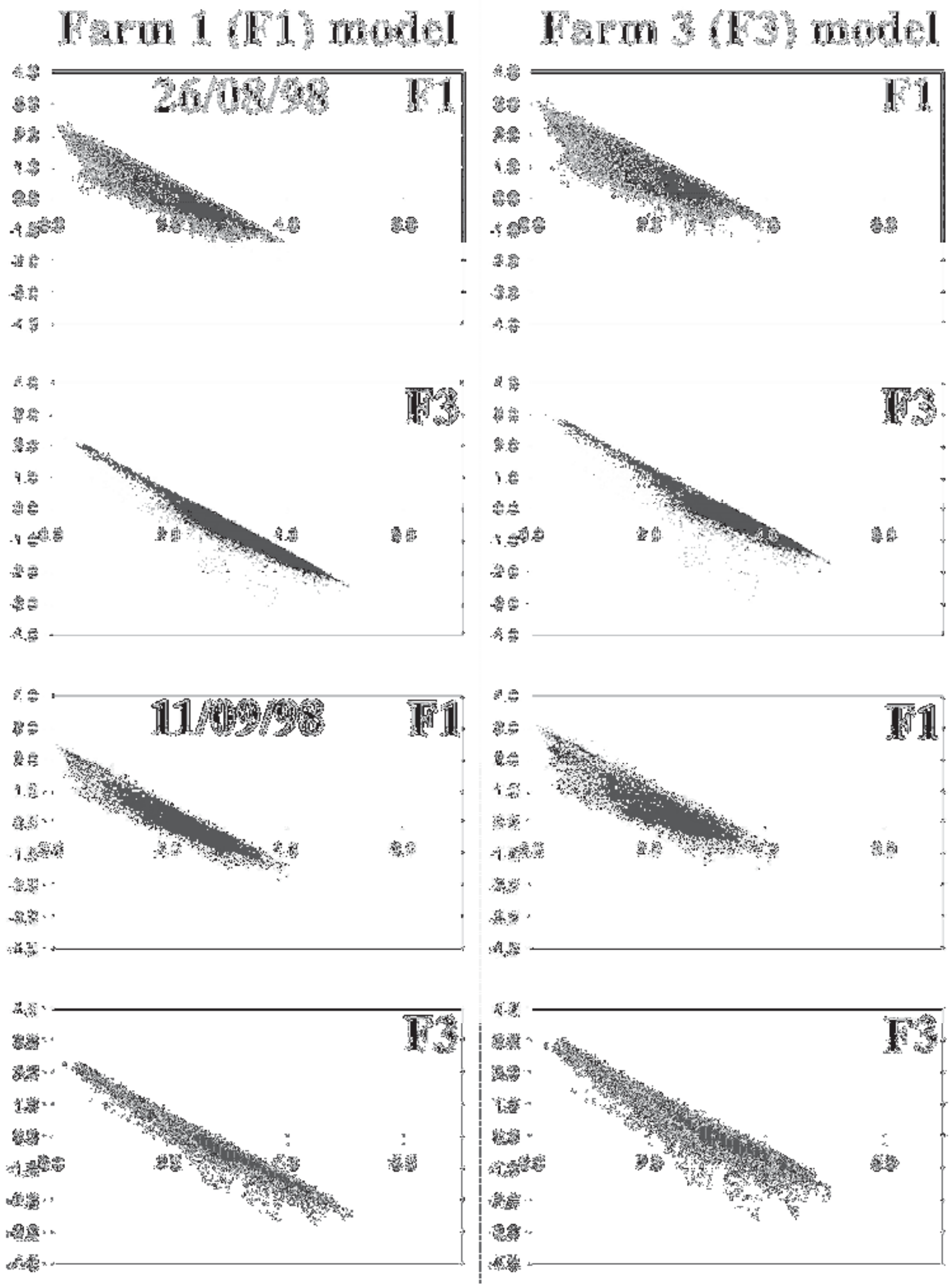

Figure 47 Yield predicted error (t/ha) (Y-axis) versus interpolated yield (t/ha) (X-axis) for the two wheat yield prediction models in 1998

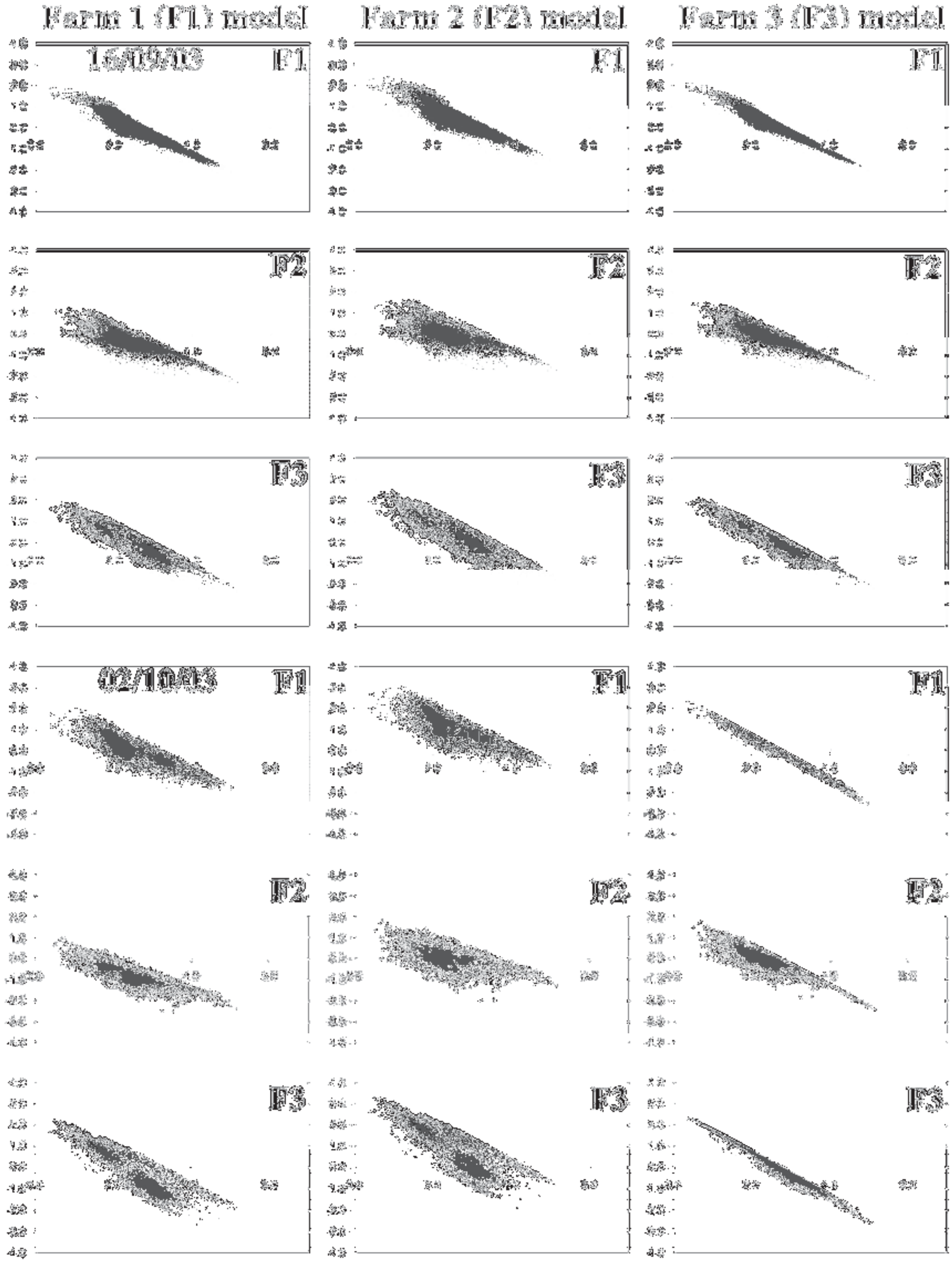

Figure 48 Yield predicted error (t/ha) (Y-axis) versus interpolated yield (t/ha) (X-axis) for the three wheat yield prediction models in 2003

7.5.3 High rainfall scenario

For 1999, a similar pattern of yield-NDVI distributions was evident across all selected image dates and prediction models (Figure 49). The strength of these relationships (Table 16) stayed constant for the Farm 1 model (E =0.45 to 0.48), peaked in early September (E = 0.12 to 0.37) for the Farm 2 model and decline over the selected time period (E = 0.51 to 0.28) for the Farm 3 model.

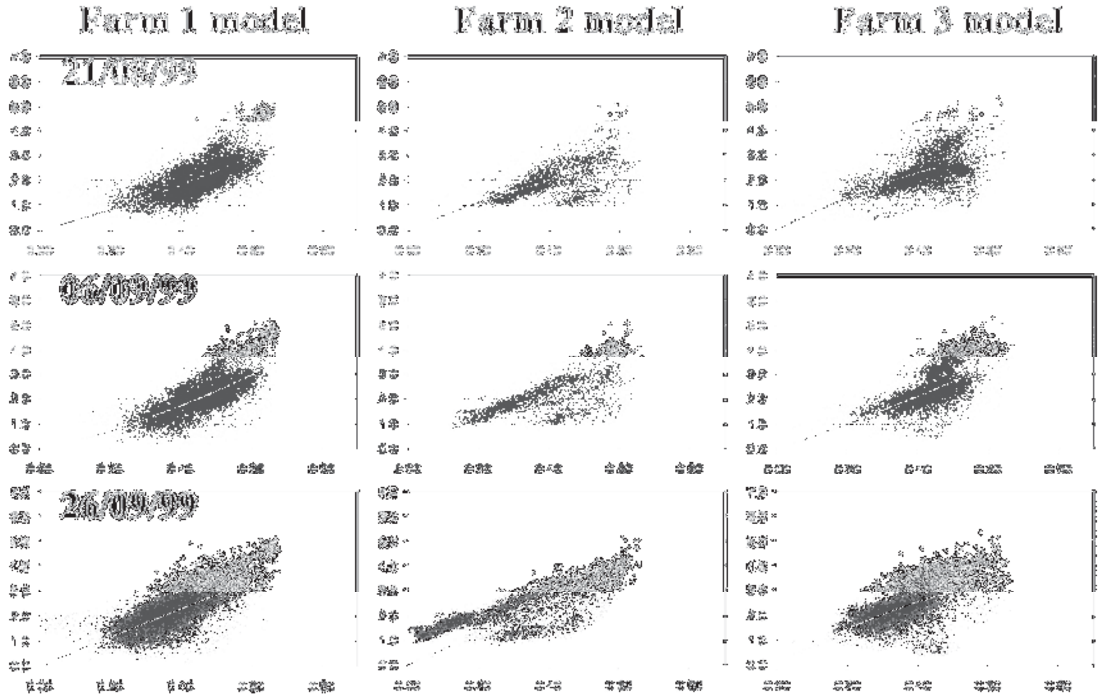

Figure 49 Regression relationships between Normalised Difference Vegetation Index (NDVI) (X-axis) and yield monitored wheat grain yield (t/ha) (Y-axis) for1999 high rainfall growing season

For the 1999 models, those developed in August were the most reliable predictors (Table 16). Models developed in early September showed consistent prediction efficiency, with the Farm 2 and 3 models showing similar predictive accuracy. Models developed later in September were weaker but still accurate with the exception of the Farm 1 model's prediction of Farm 2 data (E = -0.21).

Visual inspection of the prediction error showed the Farm 1 model provided the greatest prediction error variability in the August and early September images. The Farm 2 and

Farm 3 validation graphs show similar patterns with overestimation and underestimation in the yield range below 2 t/ha and above 3t/ha in the August image. Overestimation and underestimation was more apparent in the lower and higher yielding measurements of the Farm 2 model when compared to validation of the Farm 3 model for the early September image. Greater over and under prediction of yield values was apparent in the yield models developed from the late September image.

Table 16 Model and yield prediction efficiency criteria for Landsat imagery acquired for 1999 - Root Mean Square Error (R), Coefficient of Variation of RMSE (CVr) and the Nash-Sutcliffe Efficiency Criteria (E). Values in bolded italics represent efficiency criteria for the calibration models.

		Farm1 dataset			Farm 2 dataset			Farm 3 dataset		
Model	Date	R	CVr	*E*	R	CVr	*E*	R	CVr	*E*
F 1	21/08/99	***0.64***	***0.30***	***0.45***	0.63	0.31	0.19	0.75	0.32	-0.03
F 2	21/08/99	0.53	0.25	0.39	***0.60***	***0.29***	***0.28***	0.70	0.30	0.11
F 3	21/08/99	0.64	0.30	0.17	0.67	0.32	0.11	***0.64***	***0.35***	***0.51***
F 1	06/09/99	***0.53***	***0.26***	***0.48***	0.69	0.33	0.04	0.72	0.31	0.05
F 2	06/09/99	0.63	0.30	0.28	***0.56***	***0.27***	***0.37***	0.64	0.27	0.27
F 3	06/09/99	0.66	0.32	0.20	0.62	0.30	0.24	***0.61***	***0.26***	***0.34***
F 1	29/09/99	***0.53***	***0.25***	***0.45***	0.77	0.37	-0.21	0.69	0.30	0.14
F 2	29/09/99	0.67	0.31	0.12	***0.66***	***0.32***	***0.12***	0.65	0.28	0.22
F 3	29/09/99	0.59	0.28	0.30	0.69	0.33	0.04	***0.63***	***0.27***	***0.28***

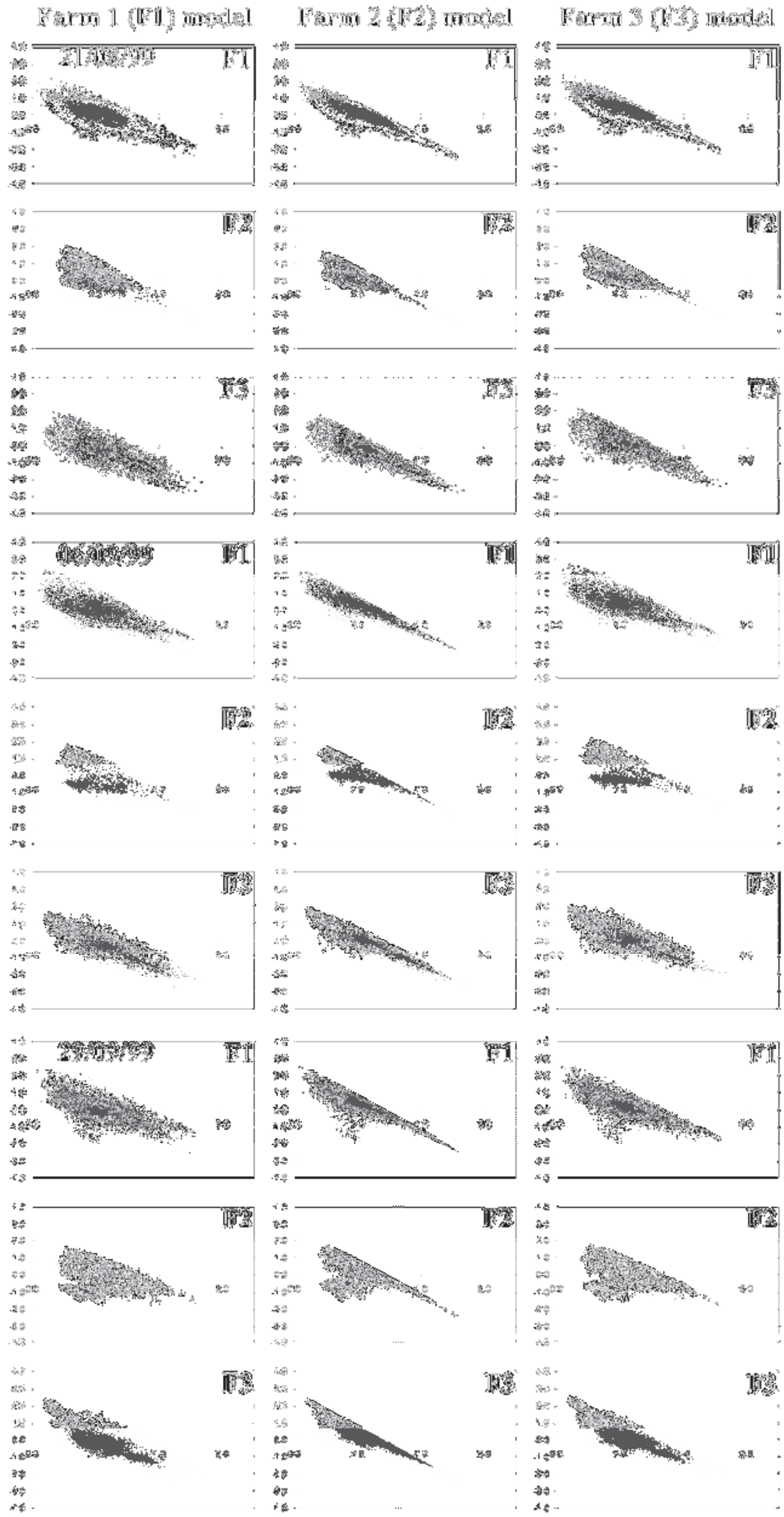

Figure 50 Predicted wheat yield minus observed wheat yield (t/ha) (Y-axis) versus observed wheat yield (t/ha) (X-axis) for the three wheat yield prediction models in the 1999 high rainfall growing season

7.6 Discussion

The automated sensing of grain yield every 1 to 3 seconds provides estimation of grain yield easily and accurately over large areas. Development of empirical models between this data and a spatially corresponding remotely-sensed vegetation index gives us the ability to predict yield at a resolution and extent defined by the sensor's measurements. Extrapolation of these models to other fields using satellite imagery can then create high resolution spatial estimates of wheat yield over broad areas.

Lobell *et al.*, 2003 suggests that accurate wheat yield predictions are possible using only one image, provided the image is acquired towards the middle of the growing season when most wheat crop canopies are fully developed. This study provides further evidence of this conclusion, provided the models have been developed and tested on a variety of farms where the variations in crop phenology, field planting dates, timing of herbicide and nutrient applications, cultivars and the influence of different soil types on plant growth are all apparent. However, the selection of the optimal model may require analysis of more than one image within a month in order to identify the trend (decreasing or increasing) of prediction accuracy.

The remote sensing approach taken in this study has received some criticism (Reeves *et al.*, 2005), on the basis that wheat yield is contained in storage organs and is very sensitive to adverse meteorological conditions at critical growth stages, principally flowering and grain filling. This means that the above ground biomass may be high and quantified using NDVI but the actual grain yield may not be commensurately large (Gomez-Macpherson and Richards, 1995). Pest infiltration, disease or lodging that occurs late in the season when grain is forming is also unpredictable (Labus *et al.*, 2002). These situations therefore limit the use of regression models developed with imagery acquired at anthesis (September) and when the final grain yield was measured (November or December).

We found, however, that of the six seasons reviewed, four showed moderate prediction accuracy with mid-September being the optimal time for image acquisition. The high rainfall year 1999 was not limited by rainfall and therefore provides a better representation of the best potential prediction efficiencies (Table 16). Acceptable prediction accuracies were still attained with earlier or later image acquisitions for this growing season. This high prediction accuracy was also apparent for the 1996 medium rainfall year; the model provided good predictions, but this conclusion is limited to analysis of only one image and a lack of additional validation data. For the dry seasons, mid to late August provided moderate prediction capability whereas mid-September to October saw the relationships start to break down. Even with low seasonal rainfall the yield-NDVI relationships may still hold because of varietal changes in wheat which lengthen greening periods in dry years due to better water use efficiency (Condon *et al.*, 2002; Turner and Asseng, 2005; Christopher *et al.*, 2008).

The years with medium rainfall scenarios (1998 and 2003) had the least accurate predictions of yield. For 1998, limited prediction was derived from a clumped pattern of NDVI values (Figure 45) acquired in late August and September. Inspection of the wheat yield NDVI relationships suggests that the NDVI values are still increasing with less variation in NDVI values apparent in the later image. This is also reflected in the year's efficiency criteria (Table 15) with improvement in model accuracy between the both image dates. The wet conditions in June – July which characterised this growing season may have affected biomass production at the acquisition time but this phenomenon needs to be reviewed further. For 2003, poor yield predictions were achieved with the mid September and early October images.

Because adoption of yield mapping technology has been limited in many agricultural regions, it was the aim of this study to test the reliability of yield predictions made by a model developed on one farm over other farms in the region. We have shown that most models provided stronger predictions than average yield values for the farm. For future studies, greater prediction power may be provided by models based on pooling and random selection of yield data to form the calibration and validation sets, rather than the stratification of yield data by farm. This type of model will encompass the spatial variation of wheat yield, biomass production, soil type, agronomic management and rainfall more thoroughly than prediction models based solely on one farm.

Sadler *et al.*, 2007 suggests that the conclusions based on model inferences are only as good as the accuracy of the model. Comparison of RMSE measured within this study with those reported in the literature shows that our errors are slightly higher. Validation with yield data aggregated to the district scale revealed RMSE values of 0.25 and 0.35 t/ha (Rudorff and Batista, 1991; Patel *et al.*, 2006) while a Root Squared Difference of 0.2 t/ha was reported in an early Australian study (Smith *et al.*, 1995). Wheat yield estimated through crop modelling and extrapolated to Landsat imagery underestimated yield, on average, by 0.5 t/ha and 0.9 t/ha when compared to in-field measurements (Duchemin *et al.*, 2008). Comparisons between yield predicted from three different sensors (multispectral radiometer mounted on a ground based platform, an aerial based platform and high resolution IKONOS imagery) and wheat yield measured by a plot combine harvester derived RMSE values of 0.47, 0.51 and 0.53 t/ha respectively (Reyniers *et al.*, 2006a; Reyniers and Vrindts, 2006b). RMSE differences between our study and these published results may be the consequence of use of coarser resolution validation datasets collected at the district level and higher resolution validation data measured at the plot level.

The choice of model accuracy and efficiency criteria gave further insight into the predictive capabilities of each model. The use of the CVr allows for the comparison of RMSE for each model across the variety of validation sets based on their variations in average yield. This has not been done with previous studies and therefore limits their comparison. Of greater reliability in understanding the predictive power of the regression models was the use of the Nash-Sutcliffe efficiency criterion (E). The efficiency criteria showed that most models had practical prediction accuracy and validation of the models showed moderate prediction power. However, this criterion has been shown to have several disadvantages, particularly with the calculation of squared values which tend to overinflate large prediction errors (Legates and McCabe, 1999; Krause *et al.*, 2005; Criss and Winston, 2008; Jain and Sudheer, 2008).

The graphical display of prediction error against the corresponding interpolated yield values provides further information on the applicability of the models, which cannot be shown through the other model efficiency criteria. For example, the 1996 model had good efficiency criteria. However, through inspection of the error vs. yield plots, high prediction error could be identified in the lower yield ranges. Caution must then be taken when making decisions using data at the lower end of the range. This information is not shown by the other model efficiency criteria. Overall, this technique showed that the models tended to overestimate and underestimate wheat yields in particular yield ranges within the validation datasets. This is an important criterion in model selection when the other efficiency criteria are similar. The overestimation of yield within lower ranges therefore poses empirical limitations when trying to spatially target areas where land use alternatives may be economically comparable to traditional wheat cropping. In terms of precision agriculture management, depending on the management strategy undertaken, this degree of prediction error may not be as limiting. Growers who prefer a zone management strategy might only require accuracy of the mean yield for a zone (Sadler, 2007). Those who adopt variable rate applications will require greater accuracy in the estimation of yield. Further research is needed into how the selection of the model with different overestimations and underestimations of wheat yield will affect the applicability to economic returns and also precision agriculture management decisions.

This study has shown that robust yield-NDVI models can be created to make accurate estimates of yield over a variety of different seasons. The next step is to extrapolation these models over regional areas via the associated NDVI values to identify the pattern of spatial yield variability for a number of seasons. The association with financial estimates of agricultural production can help quantify the economic opportunity cost associated with a change for one land use to another. However, several limitations of this type regional analysis are currently evident. This study has not taken into account other crops types that are present in wheat farming systems as break crops. These crops may not have the same yield-NDVI relationships due to plant physiology differences. The use of crop rotations may also limit predictions, especially where wheat is not the major crop in the agricultural landscape. The major methodological constraint to our approach is the availability of data. The methodology relies on access to historical yield mapping data and the availability of nearly cloud free images during anthesis within the agricultural region. These may pose limitations to this application of this methodology elsewhere.

7.7 Conclusion

We have shown the range of prediction accuracies for empirical relationships to predict wheat yield over low, medium and high rainfall years using wheat yield data collected by combine-mounted yield monitors and Landsat NDVI. Furthermore, we have tested the sensitivity of predictions to imaging date within the growing season. Overall, imagery acquired in mid-September showed stronger relationships and prediction accuracies when compared to those derived in late August, late September and early October. Of the six seasons reviewed, four gave moderate prediction accuracies, with low (2001 and 2004) and high rainfall years (1999) providing very good prediction accuracies. Good relationships were drawn from the model developed in 1996, although model assessment was limited by the availability of yield data within the region at that time. Marginal yield predictive capacity was obtained with the 2003 model. Accuracy of the 1998 model was the poorest, with average regional wheat yield estimates proving better yield predictors. For the years where the simulation of yield was poor, the associated range of yield and NDVI values in both calibration and validation datasets measured across each farm can be seen as the limiting factor.

These results show that robust wheat yield prediction models can be created over differing rainfall seasons. The validated models can then be applied to satellite imagery to derive spatially varying estimates of wheat yield and economic performance that are both broad in extent and high in resolution. The physical dimensions of this information will help inform decisions by both growers and policy makers on agronomic management, business viability and regional environmental objectives.

7.8 Acknowledgements

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Chapter 8: Discussion

8.1 Bringing it all together

The potential adversities and opportunities that come with climate change and the environmental degradation caused by agricultural practices in the Australian grains industry has caused a change in the way we think about the industry and its interaction with the environment. Emphasis is now placed on achieving economic, social and environmental outcomes referred to as the triple bottom line. Government, regional and industry organisations are using various instruments of influence to exert pressure on grain growers to implement better on-farm natural resource management (NRM) practices. Past strategies aimed at influencing the grower by appealing to their land stewardship and altruisms have proved worthwhile, as evidenced by increasing grower understanding of NRM problems. However, there has been a failure to deliver significant on-ground changes. Research into the adoption of NRM has suggested that the major factors that influence uptake are farm income, education and future farm planning. Other factors, such as individual farmer and social characteristics, have been identified as less important.

A study by Gallopín (2002, pp. 361-392 in: Gunderson, L.H. and Holling, C.S. (eds.), *Panarchy: Understanding Transformations in Human and Natural Systems*, Island Press, Washington) suggests that decision making processes for sustainable development are hampered by (1) a lack of political willingness, (2) a deficiency in understanding of environmental problems and their consequences and (3) the insufficient adaptive capacity (both financial and social) to act on the changes needed in the realm of physical possibility. This characterisation of the decision domain provides a useful model of the NRM adoption situation in Australia. The authors suggest that the pressure groups identified above will drive the willingness and understanding of future growers perceptions; whereas capacity is solely left to the individual grower. Here any decision to undertake NRM is based on uncertainty of the consequences of this adoption. Theoretically, the application of precision agriculture technology into this area can reduce the uncertainty in the decision making process by being able to quantify the effect of land use change on grower income. This additional information is collected at a high resolution at a scale in which NRM decisions are made. By accessing this information, the “farms capacity to change” should be examined ahead of the grower's capacity to adopt if the grower's uncertainties about NRM practices are to be diminished. Precision agriculture can estimate the opportunity costs associated with NRM adoption and further help in the understanding of the degree to which a farm can adopt NRM practices.

This thesis has followed several defined steps to travel from a high resolution measurement of wheat yield to regional scale estimates of economic performance.

8.1.1 Generating accurate yield mapping data

A necessary precursor to the establishment of high resolution estimates of yield was a thorough review of the accuracy of yield mapping. The measurement accuracy of this technology has been reported to range from 95-99.5% based on certain types of harvest situations. Straying from these conditions will produce erroneous yield estimates. Numerous studies have highlighted the existence of these errors, their sources and have proposed post processing methods and software to remove these outliers. However, none are comprehensive. The thesis characterised four types of yield mapping errors associated with yield monitoring from the literature. These reflected issues associated with combine harvester dynamics, the continuous measurement of grain yield and moisture, the position of the harvester, and the harvest operator. Methods to remove these errors have ranged from simple thresholds to complex routines that incorporate harvest position and local yield variation. The benefits of applying these filters have shown reductions in the statistics of yield variation and the prediction variance estimated from interpolation techniques. Using 183 independently selected yield files from Western Australia, the thesis highlighted the statistical characteristics of raw yield files and proposed extensions to current methods to remove errors associated with harvester speed, narrow finishes, harvester turns and overlaps.

The reviewing of the yield mapping error literature and the identification of potential extensions to the error removal process provided the basis for the first objective of the thesis. This objective involved the creation of yield error removal software to enable the batch processing of yield datasets from a variety of yield mapping proprietary systems. This removes the laborious process of investigating each file individually to remove yield mapping errors. This software incorporated 10 algorithms which identified and removed yield mapping errors based on previously cited methods, such as start and end pass delays and short harvest segments. In addition, newer methods that utilised positional information, harvest track search filters and thresholds to target specific erroneous data associated with harvester speed changes, yield fluctuations and harvest turns and overlaps were also implemented.

The criteria used to judge the effectiveness of error removal was the reduction in standard deviation of yield of the raw yield data. Overall, the implementation of the methodology reduced the standard deviation of yield by 26% (0.65 t/ha to 0.49 t/ha). This reduction was double that of the less targeted, statistical based, error removal methods. Assessment of each of the algorithms effectiveness in removing specific yield mapping errors showed that the newly developed routines contributed to 57% of the total reduction in standard deviation. This result provides strong evidence of the effectiveness of the approach taken.

8.1.2 Estimating spatial and temporal economic performance on farm

A major barrier to land use change decision making on farm is the lack of economic information of the current cropping enterprise. Currently, data is not at an appropriate spatial scale, spatial resolution and temporal dimension for informed decisions to be made. With the development of software that provides fast and accurate creation of yield measurements, the second objective of this thesis could be achieved. This second objective focussed on the utilisation of an historical archive of yield mapping datasets to assess the spatial and temporal consistency of economic performance on farms. A gross margin financial analysis was undertaken using wheat yield data from three farms within Western Australia. Farm 1 had 10 years of data while farms 2 and 3 had five and six years respectively. Drought years were removed and a total of 156 fields for Farm 1, 48 fields for Farm 2 and 82 fields for Farm 3 were analysed. Spatial analysis of the datasets consisted of identifying the income to area percentage on each farm. This identified the amount of area associated with high and low income generation, and reflects the proportion of area that may be taken out of current production and used for environmental benefits. To understand the income consistency over time, a spatio-temporal analysis was conducted on Farm 1. A scenario analysis, based on the minimum, medium and maximum returns over the ten year period, was then used to derive a range of economic opportunity costs under our selected gross margin assumptions.

Similar income to area ratios were found on three farms, with 30% of farm income derived from 50% of each farm's area. However, the areas that generated the lowest percentage of income were temporally inconsistent due to field rotations. Temporal analysis of a farm with a cropping area of 2,924 hectares (ha) showed that 12-19% (343–543 ha) of production areas consistently produced in the bottom 40-50% of farm income while 37-49% (1093-1430 ha) of the cropping area always produced over these thresholds. The economic opportunity costs ranged from $172-$404 per ha and $195-$444 per ha, respectively, depending on the chosen financial returns scenario. Such information improves grower capacity to adjust to the constraints of volatile international markets and climate change by identifying portions of their land that could be managed differently without negative financial repercussions.

8.1.3 Estimating regional wheat yield from satellite imagery

The thesis was able to quantify economic opportunity costs at a high resolution by identifying a methodology of spatial and temporal consistency of economic performance of the cropping area. A clear outcome of this research is that resolution matters. These results suggest that feasibility analyses of land use change at farm and regional scales should be conducted with a spatial resolution that is fine enough to reflect the spatial variability observed from yield mapping. This methodology relies on yield mapping data being available. Unfortunately, adoption of yield mapping has been low in agricultural areas of Australia. To circumvent this data availability issue, the thesis contained the third objective to assess the possibility of generating high resolution estimates of economic performance at a broad scale from satellite remote sensing. Creating high resolution estimates at this scale reduces this limitation due to moderate adoption of yield mapping technology by Australian growers. This objective relied on the ability to extrapolate yield mapping data from at least one farm to the entire study area using remotely sensed imagery. To link these two datasets, the normalised difference vegetation index (NDVI) derived from Landsat 7 ETM+ imagery was derived and was compared against the yield mapped estimates. This index is a well established measure of green biomass and has been found to be related to wheat yield. To reflect crop specific yield NDVI relationships, the wheat fields were identified on the satellite image using a supervised classification. The ability to spatially discriminate crop type and the strength of the wheat yield NDVI model was tested over eight in-season images taken in 1999. The accuracy of wheat yield prediction was then validated by applying the model to an independent neighbouring yield mapped farm.

By applying a range of gross margin scenarios, we can derive an indicator to identify the economic value of land at sub-field scale which then allows identification of areas of marginal cropping value. This information provides an indication of how much land can be devoted to revegetation and quantifies the economic trade-off needed for this substitution to take place across the study region.

Late September imagery provided the best crop type discrimination accuracy while the relationship between wheat yield and NDVI was reasonable across the month of September, with early September providing the strongest relationship. Validation of the yield prediction model estimates for a neighbouring farm was successful and showed a root mean squared error of 0.72 t/ha, which was only 31% of the neighbouring farms average yield.

8.1.4 Estimating regional economic performance

Results of the regional gross margin analysis demonstrated that 90% of the income generated within the area of interest was produced by only 55-74% of the wheat growing area. This proportion depends on the cost-price scenario. Areas that made a financial loss or marginal monetary return equated to 27-44% of the study area, indicating that trade offs providing increased environmental benefits may be possible with minimal income loss in a relatively large section of the land. Although further analysis of larger regions with longer time series seem necessary, results presented here show that there is the potential create economic information from growers who are early adopters of yield mapping technology and archived satellite imagery. This type of information may help improve the economic returns of growers within a region by selectively reassigning land uses based on financial comparison and justification.

8.1.5 Assessing the accuracy of wheat yield predictions over time

The final objective of the thesis was to test the strength of the wheat yield prediction models over six different growing seasons. Objective three showed that it was possible to create empirical models that predict the spatial distribution of wheat yield from NDVI imagery for a particular growing season. However, the timing and distribution of rainfall will significantly affect wheat crop establishment, growth and potential yield within a season and thus will be reflected in both the acquired NDVI estimates and grain yield mapping. Therefore further investigation was needed to determine if this type of relationship holds for different growing seasons.

Fourteen Landsat images between August and September were acquired for six years. These years were classified into six different rainfall scenarios based on bi-monthly measurements of precipitation over the growing season. Empirical relationships between NDVI and the wheat yield data for each farm were developed for each image date acquired between August and September. Yield prediction models developed on one farm were then validated against yield data on the two other farms.

Over all seasons, model assessment confirmed that the best in season wheat yield prediction accuracies were achieved with imagery acquired in mid September. Of the 6 seasons reviewed, 4 showed very reasonable prediction accuracy with low and high rainfall years providing the highest prediction accuracies. Medium rainfall years showed marginal to poor prediction results due to little variation in both wheat yield and NDVI values. Given the predicted effects of climate change on grain season rainfall, further investigation into the relationships for such years is required. Overall, the strength of the relationship is surprisingly high given variations in crop phenology, field planting dates, occurrence of weeds and timing of herbicide applications, the influence of different soil types on plant growth and temporal occurrences such as pest infestation or frost damage which often occur after image acquisition. These factors appear to average out at broad scales.

Overall, the results demonstrate that over years with differing rainfall, wheat yield can be predicted from Landsat derived NDVI images and yield maps. However, timing of the image acquisition appears to be critical in order to obtain good relationships given that cloud cover is a major impediment to the selection of optimal imagery dates.

In summary, the thesis has shown that a large proportion of area within fields produces marginal income returns and hence could be assigned to a different land-use without significantly large economic opportunity cost. This demonstrates the potential for an income-neutral change towards higher environmental outcomes of cropping activities. Opportunities for further income generation will depend on the potential returns from the alternative land use and may increase the adaptive capacity of the farm business to deal with volatile international commodity markets and the potential constraints of climate change.

The thesis provides a proof of concept for a methodology that may facilitate a more informed adoption of other more environmentally friendly land uses in the cropping landscape. Regional managers will have the opportunity to view information, which otherwise would only be available to individual landholders. Maps of economic potential for change can be derived at an unprecedented level of detail. Such maps can act as a critical sounding board between the land holder and the catchment manager where conflicting objectives of economic and environmental outcomes can be compared.

Additionally, the creation of pattern of past yield performance may enable non or recent adopters of yield mapping technology to leap frog technology adoption. It would provide the equivalent of long-term yield map archives so that management and land use decisions can be made sooner.

Clearly, the approach is limited by the low predictive capability in medium rainfall years or the availability of cloud free images during peak season and further research is necessary to arrive at an operational level. However, the results presented in this thesis suggest that the approach may provide the basis for improved decision support and reduce resistance to change towards a more resilient and sustainable grains industry.

8.2 Future research

This research has highlighted gaps in the knowledge base. Below are discussion points that warrant further investigation.

- The creation of a multi-temporal dataset of yield across sub fields, fields, farms and large regions can filter into a multitude of scenario or trade off modelling projects that could include the:
    - adaptability and vulnerability of farms and regions to future climate change
    - potential adoption, feasibility and financial repercussions of introducing more environmentally friendly land uses into the agricultural system , such as woody perennials
    - targeting of areas for enhancing biodiversity and environmental objectives.
- Yield mapping data provides annual estimates of profitability across the farm. But in order to make robust long term business decisions, the inclusion of whole farm financial modelling is required. Only by taking on such a broad viewpoint which incorporates business considerations as well as farm financial constrictions can we understand the feasibility of a change in land use.
- Current research to define the spatial and temporal consistency of yield suggests that the number of years needed for a robust analysis should be greater than six, particularly for the dominant crop type, wheat. For most growers, the time period for this collection would be greater than 10 years due to annual crop rotations. The access to historical yield values based on extrapolated yield-NDVI relationships will provide a potential source of information to close this time gap. Further investigation is also needed into the interaction of other crop types with the definition of the spatial and temporal pattern of wheat yield.
- A major constriction to previous research has been the cost of imagery particularly from the Landsat sensor. With the decision by the United States Geological Survey (USGS) to provide all previous and future Landsat data for free, this cost issue is no longer a significant barrier. The combination of this imagery archive with early adopter data means that yield-NDVI information may be available from the mid 1990's for certain parts of the Australian dry land agricultural region.

There are also a number of technical improvements that may be incorporated:

- The automation of the post processing algorithms means that the processing of large datasets can now be done quickly and accurately. But there is a lack of a systematic analysis of thresholds and search radii that should be used to minimise the impact of removing so called “good” yield data.

- Currently, the processing step from post processed dataset to an interpolated yield map is too laborious and time consuming. An automated routine that streamlines the interpolation process may be needed before any large regional analysis is carried out.
- This study was based on a 625 square kilometre area for which field boundaries had been manually digitised. These boundaries were used to discriminate crop types with the fields. For larger regional studies, the digitising of each field boundary within the regional may be unfeasible. An alternative way to discriminate crop types within a region may be by identifying the spectral characteristics of different crops during the growth season. This could be done using imagery with a higher temporal measurement capability.
- For creation of the yield estimates over larger regions further research should be conducted into the within season temporal issues associated with yield–NDVI relationships. Certain problems will exist when yield data from one or two farms is associated with NDVI estimates taken in different regions which are physically further away. Areas further away will have differences in sowing dates which are associated with different breaks in the growing season. This will determine which crop growth stages are being measured within an image.
- Further conceptual testing of the estimated yield values from the NDVI images is needed. This will need to involve growers and grower groups to determine whether the derived annual yield variation reflects what is conceptually known on ground within the region. These tests should involve growers who are early adopters, recent and also non-adopter of yield mapping technology.