



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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Thesis abstract

Balancing sustainable agricultural production with environmental, social, cultural and community objectives under the uncertainty of the impacts of climate change on rural livelihoods has become an increasing priority worldwide. This may mean land-use patterns that have evolved over the last decades may be suboptimal. Environmental degradation but also economic opportunities for climate change mitigation from carbon sequestration may support alternative land-use scenarios. However, the majority of cost of such changes is expected to be borne by the landholder and adoption of alternative land uses will only occur if profit from traditional cropping practices is comparative to new options, namely, in areas where the economic opportunity cost is low.

Precision agriculture has shown that yield variation in fields can be substantial and here lies the potential that is explored in this thesis. Precision agriculture provides data with a spatial resolution that is fine enough to reflect the spatial variability within fields. If unproductive patches can be allocated to more environmentally friendly use, both the environment and farm economy may benefit. However, inherent problems exist with the technology and these need to be addressed before the information can be used in the decision making process. A preparation step in this thesis is therefore to evaluate a suite of targeted algorithms to remove a substantial amount of yield mapping errors.

This thesis examines the degree of spatial and temporal variability and estimates a potential range of economic opportunity costs that might be associated with reallocation of land to different use. Although dependent on the interplay between the spatial and temporal variability of yield and the price volatility of international commodity markets, a likely scenario shows that about 50% of the land may be taken out of production with only a 25% reduction in income.

Regional land managers do not have access to precision agriculture data because yield mapping data does not exist at a scale or temporal dimension required for regional analyses. This thesis shows that it is possible to create high resolution estimates of economic performance at a broad scale by extrapolating yield mapping data from early adopters to an entire study area using remotely sensed imagery over numerous seasons. This also has strong benefits for landholders who do not have long time series of yield

data. By using satellite remote sensing they may be able to leap frog the long phase of yield map archiving giving them the ability to make management and land use decisions sooner.

This thesis suggests that high resolution yield estimates combined with financial estimates of production can identify cropping areas with marginal income returns. This type of information may facilitate adoption of a mix of environmentally friendly land uses in the cropping landscape without significant financial repercussions to the grower. Additionally, the mapping of this information will 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.

Thesis executive summary

Balancing sustainable agricultural production with environmental, social, cultural and community objectives under the uncertainty of the impacts of climate change on rural livelihoods has become an increasing priority worldwide. In Australia, environmental degradation on the one hand, and economic opportunities for climate change mitigation from carbon sequestration on the other, mean that key environmental strategies, such as revegetation, may need to be considered in future land-use decisions if a resilient and sustainable grains industry is to be attained.

In comparison to the United States and Europe, little financial compensation is paid to Australian growers for environmental actions. Here, the majority of cost of conservation is expected to be borne by the landholder and adoption of alternative land uses will only occur if profit from traditional cropping practices is comparative to new options, i.e. in areas where the economic opportunity cost is low.

Current research into agricultural economic opportunity cost for land use trade-offs has major limitations. Studies are often non-spatial, which fail to distribute cost over different agricultural enterprises. Where spatial data does exist, the resolution is too broad for any on ground decisions to be made. In cases where high resolution data exists, its currency provides only an annual snapshot of land use and assigns production figures reported at a regional, farm or field level, hence potentially blurring the spatial yield variability that is apparent within a region due to rainfall, soil fertility and agronomic factors.

The major premise of this thesis, is that any feasibility analyses of land use change for environmental benefit, whether it is at the farm or regional scale, 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 thesis aims to develop relationships between remotely sensed imagery and wheat yield data from farms that have historically adopted yield mapping. Relating these two independent data sources enables the creation of high resolution estimates of wheat yield over the broad extent of the imagery and provides a means to overcome the adoption and information gap. High resolution estimates of opportunity cost at a broad scale can then generated from a gross margin analysis. In order to achieve this result, there are several key objectives that need

to be accomplished before the economic opportunity cost can be calculated and the methodology extended more widely.

The first objective of this thesis was to achieve accurate measurements of within field spatial yield variability by developing erroneous data removal routines after harvest records have been collected. This involved the creation of a batch software system which removed yield mapping errors based on a mixture of previously cited and newer methods proposed by the author. The software removes widely reported yield mapping errors such as start and end pass delays and short harvest segments. In addition, newer methods utilise 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.

In order to judge the overall error removal effectiveness of these methods, comparisons were made to results from two other less targeted statistical methods. For effectiveness of error removal, the criteria used for comparison were based on the reduction in standard deviation of yield caused by the removal of erroneous data. Each individual algorithm's effectiveness was also assessed by identifying its contribution to the overall reduction in standard deviation of yield. Both assessments were calculated over 183 independently selected fields. A further statistical and visual assessment was undertaken with a randomly selected field by spatially comparing local area yield variation within harvest paths and interpolated yield estimates between both raw and processed datasets.

Overall, the implementation of the algorithms reduced the standard deviation of the 183 yield files by an average of 26% (0.65 t/ha to 0.49 t/ha). This reduction was double that of less targeted error removal methods based on each yield file's statistical distribution. Assessment of the each algorithms effectiveness in removing specific yield mapping errors showed that the newly developed routines contributed to 57% of the total reduction in standard deviation. For the example field, results showed a 47% reduction in standard deviation and 11% increase in average field yield when the algorithms were implemented. The creation of interpolated yield maps from both datasets showed that the yield prediction error was significantly reduced in areas where specific errors were removed. This result further corroborated the effectiveness of the approach.

The second objective of this thesis was to utilise a 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. 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 one farm with a ten year datasets. 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. The methodology developed in this thesis will provide growers with an adaptive capacity to adjust to the constraints of volatile international markets and climate change by increasing the ability to specifically target portions of their land for alternative management without negative financial repercussions.

The third objective of this thesis was to assess the possibility of creating high resolution estimates of economic performance as used above at a broad scale. Creating high resolution estimates at this scale will overcome the 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 showed a root mean squared error of 0.72 t/ha, which was 31% of the neighbouring farms average yield.

Results of the regional gross margin analysis demonstrated that 90% of the income generated within the area of interest was produced by 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 at larger regions with longer time series seem necessary, results presented here show that there is the potential to improve overall economic returns by selectively reassigning land use.

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 six seasons reviewed, four 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.

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Upon finishing the last formatting changes, I can reflect on the passage of time that has me where I am today. It has been a rewarding but often trying time, with progress often two steps forwards one step backwards. Nevertheless, as the majority of my life experience has shown me, persistence does pay off.

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Declaration

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

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Gregory Maxwell Lyle

Publications, awards and research projects arising from this thesis

Refereed publications

Lyle, G and Ostendorf, B. (2005) Drivers and determinants of Natural Resource Management Adoption at the farm scale. In Zerger, A. and Argent, R.M. (eds) MODSIM 2005 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, December 2005, pp. 170-176. ISBN: 0-9758400-2-9.

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Lyle, G, Ostendorf, B (*Under Review*) The effectiveness of post processing routines to remove erroneous yield mapping errors. Submitted to *Precision Agriculture* as at 17th April 2010.

Lyle, G, Bryan, B and Ostendorf, B (*Under Review*) Identifying the spatial and temporal variability of economic opportunity cost in Mediterranean grain growing regions. Submitted to *Agriculture, Ecosystems and Environment* as at 23rd February 2010.

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Land use planning for sustainable production systems. NRM Research Alliance and the Department of Water, Land and Biodiversity Conversation, South Australian government. January 2009 – September 2009.

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Proportion of contribution by author

This section is a declaration of the extent of each author's contribution to the refereed papers arising from this thesis. The extent of each author's contribution is quantified for each of three categories: conceptualisation, realisation and documentation. Finally, each author gives permission for the paper containing their contribution to be included in this thesis.

Percent contribution and permission to include paper in thesis: Lyle, G and Ostendorf, B. (2005) Drivers and determinants of Natural Resource Management Adoption at the farm scale. In Zerger, A. and Argent, R.M. (eds) MODSIM 2005 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, December 2005, pp. 170-176. ISBN: 0-9758400-2-9.

	Conceptualisation	Realisation	Documentation	Signature
Lyle, G.	80%	80%	80%	_____
Ostendorf, B.	20%	20%	20%	_____

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Bryan, B.A.	5%	10%	10%	_____
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Ostendorf, B.	10%	10%	5%	_____

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