Understanding Spatial Variation in Sweetcorn Production

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VG07035 – Understanding Spatial Variation in Sweet corn Production

Taylor *et al*., 2008

Australian Centre for Precision Agriculture
The University of Sydney

Project VG07035

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SYNOPSIS
A study of a sweet corn production system at The Lagoon, Bathurst, NSW was undertaken to determine if there was sufficient variation in sweet corn yield and quality to make Precision Agriculture (PA) practical in the industry. A large variance in yield and quality parameters was observed. The range in yield response was spatially coherent giving growers the option to manage the crop in management classes or site-specifically. The amount of nitrogen used in the system and the magnitude of yield variation provides some very obvious and easy approaches to cost saving through variable-rate fertiliser application. However, adoption of PA will be stilted if adequate support is not provided through variable rate fertiliser decision support systems. This requires models for crop growth to be adapted or developed. Preliminary modelling, with the spatial data set from this study, indicates that these models could be very effective in decision-making systems. The lack of a yield or quality sensor is also an issue as growers are unable to effectively determine the impact of any change in management.

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Media Summary

Stepping into Precision Agriculture in the Australian sweet corn industry

AUSVEG and HAL Ltd have recently funded an investigation into the viability of adopting site-specific crop management and Precision Agriculture in Australian sweet corn production systems. The study was conducted by The Australian Centre for Precision Agriculture at The University of Sydney. The study showed that the degree of variation in yield within a field was similar to that in other crops where site-specific crop management has been successfully adopted. At the study site near Bathurst, NSW, the yields at individual sites within three fields ranged from 6 to 30 $ton.ha^{-1}$. A large range in yield translates to a large range in input requirements by the crop at each site. This gives growers the opportunity to better manage inputs, particularly nitrogen, by variably applying fertiliser at each location in the field based on the yield potential. Some simple economic analysis showed possible savings in excess of $100 per hectare on nitrogen budgets. The opportunity for site-specific management was further increased by the presence of large spatial trends in crop yield which makes variable rate management easier.

The variation in cob quality was also measured. It was also unclear if the variance in cob quality was great enough for concern to the processing sweet corn industry. However the range in quality observed is likely to have an effect on the marketability of production in fresh market sweet corn production systems. The study showed that by manipulating yield it should be possible to optimise quality at each site in the production system. This could be done by varying management spatially in the fields.

Of the new technologies used by the researchers in the study, sensors that measure canopy and crop biomass in early and mid-season growth appear to be the most useful for any growers considering the move into site-specific crop management. Spatial crop modelling appears to be a potentially useful tool for site-specific management, if existing models can be successfully adapted and the correct input information, particularly information on plant density, can be cheaply and easily collected.

Precision Agriculture is viable in the Australian sweet corn industry and the opportunities exciting for improved management if the industry provides support to growers, particularly through decision-support systems.

Technical summary

For site-specific crop management (SSCM) to be viable a production system must exhibit a sufficient magnitude and spatial structure in crop response to make differential management economically feasible. The crop response may be a yield or quality response. Prior to committing to larger projects, a preliminary investigation into the variability within sweet corn production systems was undertaken. The intention was to quantify how variable crop response was, which spatial technologies are most applicable to variable rate management and how successful decision support systems to assist growers may be.

Both yield and quality attributes exhibit large ranges and spatial coherence. Yield in particular was spatially structured providing opportunities for SSCM. Quality attributes exhibited less spatial structure but enough to suggest that they could be managed spatially. The range in yield response (from 6 to 30 $ton.ha^{-1}$) in a uniformly treated production system, provides opportunities to better manage fertiliser. A simple economic analysis, based on applied nitrogen and possible yield response, shows potential savings on fertiliser of $122 - $243 per hectare in the three fields. This is without incorporating any spatial management. Further savings are possible when information from mid-season biomass sensors is included.

An analysis of the applicability and best way of constructing management classes was undertaken. Information from early and mid season canopy sensors provides the best data for constructing management classes. This indicates that current on-the-go variable-rate fertiliser systems, such as the N-sensor, Greenseeker and CropCircle, may be readily adapted to these production systems and negate the need for management classes. Information from soil sensors did not assist in agronomic decision making, possibly due to the presence of irrigation (removing issues associated with variation caused by variable soil moisture holding) and probable excess nutrition in the system. For any growers interested in investing in SSCM, a proximal canopy sensor or aerial image acquisition appears to be the best option (provided sufficient spatial agronomic support is available).

To be used effectively these variable rate fertiliser systems need decision support systems which in turn require good crop models to predict potential yield and fertiliser requirements. Preliminary modelling indicates that canopy sensor data, coupled with plant density data, does provide good predictions of yield. This data is preliminary but concurs with recent published information that looks at adapting maize crop models to sweet corn. It appears that information on plant density is a prerequisite for progress in this area. Non-destructive methods for measuring or estimating plant density are a priority. Modelling of the yield-quality interaction was also undertaken. The models indicate that quality, in this case cob length, can be manipulated by managing yield. This may be of more significance in the fresh market sweet corn industry.

The adoption of new technologies and methodologies is dependent on growers being able to recognise a positive return on investment. Without a yield or quality sensor at harvest it is difficult to quantify the effect of SSCM. The development/adaptation of yield sensors for a sweet corn harvester is a major step in making PA work in sweet corn. If a viable sensor is available/developed, the effect should be positive as the harvest is centrally contracted. Therefore, a few sensors will be able to service a large proportion of the industry. The vertical integration of the industry and interest by the processor, Simplot Australia, in SSCM means that advances in this area should be well received and adopted by growers.

Objectives of the Project

This project is an investigation to quantify the amount of variation in sweet corn production systems and the opportunities for future research and application of differential management strategies. The project has three main sections;

a) collection of spatial environmental data prior to crop production,
b) collection of spatial crop production information during the growing season; and
c) synthesis and data anlaysis of the environmental and crop data

Reporting for the project will be in two sections;

i) Quantification of the inter- and intra-field variation in crop growth and production (biomass, yield and quality attributes)
ii) Analysis and discussion of management options and economics associated with the observed variation.

Whilst this constitutes the final report for the completion of the contracted project VG07035, there will be a significant addendum to the report to be submitted by December 31, 2008. As indicated in Milestone 1 of VG07035 a research project is being undertaken on this data by a final year student in the B.Sc.Agr degree at The University of Sydney. The research project will investigate more thoroughly interactions between crop quality and the environmental data sets. A report on this work will be submitted as an addendum to this report.

Introduction, including review of literature

Sweet corn in Australia is grown for both the fresh and processed food market. In NSW the majority of corn grown for processing is done under licence to Simplot Australia Ltd. Production is strongly vertically integrated with Simplot being involved in the planting and harvesting of the crop. They also provide agronomic assistance to growers during the season. It is the grower's responsibility to manage the crop from sowing until harvest.

The profitability of the processed sweet corn sector relies on production efficiencies both on-farm and at the factory. The state production needs to be managed to ensure a regular supply of corn to the factory so that the factory operates optimal. New technologies are now available which assist growers in managing variation in their production system. Crop models and differential decision making are also being used to tailor production to specific quality parameters and improve timeliness of production. To date these technologies and methodologies, collectively termed 'Precision Agriculture', have not been used in the Australian sweet corn industry.

Despite the similarities with broadacre maize production, there has been very little published material on the application of precision agriculture to sweet corn. Precision Agriculture is a philosophy that seeks to improve the resolution (either spatial and/or temporal) of decision making. Generally this is in response to observe variance in production. The scientific literature has no reports of the level of yield and quality variation that is expected in an irrigated sweet corn production system. Therefore the first aim of this research was to establish how much variation in production occurs in the production system by measuring crop growth parameters during the season and yield and quality parameters at harvest. The hypothesis from discussion with growers, agronomists and from previous estimations was that yield variation is sufficient to warrant variable rate management, particularly fertiliser.

Variation in production provides opportunity for differential management however effective decision support systems are needed to translate variation into agronomic decisions. These decision support systems are often based on crop growth models. At the submission of this project there was no crop growth model for sweet corn. The first sweet corn crop model has recently been published by Lizaso et al., (2007), which was adapted from the CERES maize model. This model will provide a significant boost to any PA adoption. Another recent paper (Ma et al., 2007) provided another piece in the decision support puzzle by linking canopy responses to N rates. Sweet corn production relies on a large amount of side dressed fertiliser thus effective yield calibration models at side dressing, driven by canopy sensor data, will be able to deliver considerable production efficiencies and profitability.

Despite this link between canopy response and nitrogen requirement there has been no research into the best approach to differential management. Real-time on-the-go sensors are available for variable rate application of inputs (fertiliser) and have been used effectively in broadacre crops. Similarly, the management class (zone) concept has also been effectively applied in broadacre crops for management. The preferred approach i.e. the one that gives the most ‘bang for a buck’, is unclear in sweet corn production. This is the second aim for this project – to identify how management might be implemented given that production is variable. It is possible that yield and quality (and pssibly different quality parameters) may need different strategies for management. However until the drivers of variation are identified management is blind.

Gaining a greater understanding of how production varies, what drives the variationand possible management strategies should assist all members of the value chain. Growers should achieve improved production efficiencies which will produce a more uniform and predictable level of production. It should also reduce the environmental footprint of production (e.g. less loss of fertiliser to the environment) which is a social good. Improved production will also assist the processor with improved harvesting logistics as well as operating capacity within the factory.

Materials & methods

Site Selection

The project initially aimed at monitoring 5 fields of Sweetcorn at The Lagoon, near Bathurst, NSW. Two fields, Pivot 2-3 and Pivot 4-5, were scheduled to be early sown with the variety Challenger and the other three fields, Post Office, Pivot 1 and Bidgeribbin, to be late sown with the variety Punch. The difference in sowing dates did create problems with the mid-season sampling and the collection of crop biomass data (Cropcircle sensor and aerial imagery). When the biomass counts were taken (January 16-18) the Challenger crop was already beginning to tassel and had reached full canopy closure. However, the other three fields still had very open canopies. The problems associated with analysing imagery after full canopy closure lead the research team to focus more efforts at harvest on Post Office, Pivot 1 and Bidgeribbin fields. Mid-season tissue N analysis was also confined to these three fields.

All five fields received the same fertiliser treatment which consisted of;

i) 50 $kg.ha^{-1}$ urea pre-sowing (46% N)

ii) 240 $kg.ha^{-1}$ of NPK + Zn at sowing (15% N)

iii) 2 $L.ha^{-1}$ foliar NPK + Cu + Zn 30 days after sowing

iv) 200 $kg.ha^{-1}$ urea as a side dressing (46% N)

which is approximately 150-160 kg of nitrogen applied per hectare.

Part I - Quantification of variation in production

Data Collection:

Sensors

High resolution spatial data on soil and topographic variation was collected in September 2007 by performing an on-the-go survey with two soil sensors (Geonics EM38 and Geonics EM31) and a carrier-phase GPS receiver (Omnistar HP GPS). This provided information on the apparent electrical conductivity (EC_a) of the soil to two depths, 0 - 1.5 m and 0 - 6 m. The EC_a signal is affected by primarily by the clay content, clay mineralogy and moisture content of the soil. (The EC_a signal is also strongly affected by salinity when present. The EC_a data indicated that salinity was not an issue in this area.) The Omnistar HP-GPS data was used to map elevation (to an accuracy of < 20 cm) and geo-reference the EC_a data (accuracy < 10 cm). It was intended to collect soil information using a gamma-radiometer and an on-the-go pH sensor. Attempts to run these sensors were hampered by mechanical and weather problems.

A vehicle-mounted crop biomass sensor (CropCircle, Holland Scientific, Lincoln, NE, USA) was run over the paddocks from late December to late-January. Initially the sensor was mounted on a 4WD and run over three fields (Pivot 1, Bidgeribbin and Post Office) before the sensor was transferred to the fertilizer rig. The 4WD could not be run through Pivot 2-3 and Pivot 4-5 fields in late December due to the height of the crop. Sensor data was collected from all 5 fields during side-dressing from December 31 to January 8. After side-dressing, the CropCircle sensor was mounted onto the spray rig and run when the spray rig was operational. Unfortunately no useful information was gathered at this time. The biomass sensor information was geo-referenced with a Garmin GPS76 GPS receiver (95% CEP of < 15 m however it is generally more accurate when moving and a smoothing filter is applied).

A 4-band multi-spectral aerial image (1.8 m^2 pixels) of the 5 fields was taken on January 15^{th} by Specterra. The image was register with ground control points gathered when surveying with the EC_a sensors.

Manual Field Sampling.

Soil cores were extracted to a depth of 1 m in October 2007. The location of soil samples was determined using latin-hyper cube approach of Minasny and McBratney (2006) with the location coordinates, topographic and EC_a information collected in September as inputs into the model. This approach looks at the variation in the input variables (soil types and topography) and stratifies the samples to take account of the observed variation. The location coordinates were used to spatially distribute the samples across the 5 fields. Soil core locations were geo-referenced with the Omnistar HP-GPS.

Mid season crop measurements were taken from all 5 fields on January 16-18. Measurements consisted of plant counts (density) and measurements of plant height (to the top node on the primary culm) and were geo-referenced with a Gamin GPS76 receiver. Measurements at each point were taken within an area 2 m along the rows by 3 rows (row width was 0.75 m = 2.25 m). A width of 3 rows was used as it is half the seeding width (6 row planter). Measurements were taken from the inside to the outside row to compensate for variance in the 6-row planter[1]. In three of the fields (Bidgeribbin, Pivot 1 and Post Office) heights and counts of both primary and secondary culms were counted. A sub-sample of 60 plants, from several fields, which covered the range of heights measured were uprooted and brought back to Sydney to create a calibration between plant mass and plant height.

For the three late-sown fields (Bidgeribbin, Pivot 1 and Post Office), plant tissue samples were taken at silking to measure the nitrogen content in the plants. The whole leaf opposite the primary cob was sampled with 4-6 leaves taken per site. Again, sampling was done across three rows from the inside to the outside of the 6 row planter. Sites were identified from management classes formed from clustering the available plant (CropCircle and aerial imagery) and soil (topographic and EC_a) data (see the protocol of Taylor *et al.*, 2007). However, the final location of the sample was influenced by accessibility to the crop and usually confined to short distances (a minimum of 10 m) from easy access points such as irrigator swaths or pivot wheel tracks. Sample location was geo-referenced with a Garmin GPS76.

[1] Differential application of fertilizer at sowing across the planter was an issue in some fields.

Harvest data was collected in late February and early March. Harvest sampling was restricted to the three late sown fields. Samples were taken from the same area as the mid-season biomass samples (2 m by 3 rows) but not at the same location. The harvest sampling sites were manually selected based on the management classes formed from the mid-season crop biomass data and the pre-season soil data and by access to the field. At each sample site primary cobs and secondary cobs were picked into two separate bags. The sample site was geo-referenced with a Garmin GPS76 receiver. In the farm shed the primary cobs were roughly husked (to approximate the process within the harvester), individually measured for length and diameter and then collectively weighed on a per sample site basis. This provided data on yield (mass) and quality (cob length and cob diameter). The secondary cobs were also counted and collectively weighted for each sample site and the presence of large secondary cobs noted. Secondary cobs were not dehusked thus their weight includes some overestimation error from excess leaf material. Grain moisture was measured as another quality indicator. Grain moisture samples were taken from two fields (Bidgeribbin and Post Office) using the protocol of Simplot. This consisted of removing the grain from one side of the cob on a subsample of 15 cobs from each sample site. The grain was weighed wet before being placed in an oven and then weighed dry. The presence of any insect damage was also recorded for the 15 subset corn cobs at each sample site. For Pivot 1, time and oven space constraints did not permit this approach. Instead cob (grain) moisture was calculated by weighting a subsample of 15 whole cobs from each sample site, then drying and reweighing the entire cob.

Laboratory Analysis.

Soil Analysis

Soil cores were analysed in the laboratory for particle size distribution (clay, silt and sand %), pH and EC in both the topsoil (0-30 cm) and subsoil (60-90 cm) fraction. This was done using standard procedures from the Australian Soil and Land Survey manual (McDonald *et al*., 1990).

Midseason Crop Samples

For the whole plant samples collected, the roots of the plants were cut off and the height and fresh weight of the plants recorded on arrival back in Sydney (approximately 4 hours after collection). The plants were then oven dried and reweighed to obtain dry weights. This data was used to construct a transfer function to predict the above ground biomass from the plant height data (Appendix A). It was assumed that the response would be curvilinear but in fact was linear and there is no difference in analysing the height and fresh weight data.

The plant leaf tissue samples were immediately dried in an oven (60ºC). The leaves were then roughly crushed before a sub-sample (~40-60% of total mass) was placed in a coffee grinder and ground. The ground material was passed through a 40 micron sieve to form the final samples. Samples were sent to The Waite Institute in Adelaide where the samples were analysed for N using the combustion technique with an Elementar Instrument.

Data Analysis

Map production

The sensor data (soil and crop circle data) was collected as point data. The data was cleaned and then interpolated using local kriging (after the method of Taylor *et al*., 2007). A standard grid was used for all interpolations. The spectral data for each band of the aerial image (Blue, Green, Red and Near-Infrared (NIR)) was also extracted directly from the image to the same grid.

All data was imported into ArcMap 9.2 (ESRI, Redlands, Ca, USA) and displayed in raster format. This resulted in:

> 3 soil/landscape layers – EC_a-EM38 (0-1.5 m depth response), EC_a-EM31 (0-6 m depth response) and elevation
>
> 3 canopy response layers – CropCircle data from late December (All 5 fields) and early-mid January (3 fields only) and a multi-spectral aerial image (mid January)

The manual sample data – soil core data, midseason crop counts/heights, plant tissue N data and harvest yield and quality data were imported and displayed in a point (vector) form.

Spreadsheet Construction

For each sampling period (midseason biomass, plant tissue N at silking and harvest data) the respective data was paired with the georeferenced location from the Garmin GPS76. Locations were stored in both Latitude and Longitude (decimal degrees, WGS84) and Eastings and Northings (metres, WGS84 UTM Zone 55S). The interpolated response from the soil sensors, crop sensors and aerial imagery was extracted onto each sample location within ArcMap (ESRI, Redlands, Ca, USA). The management class in which the sample was located for each of the 6 management class models (see below) was also extracted in ArcMap. Since sampling was performed at different locations at the different sampling times a separate spreadsheet was constructed for the biomass, plant tissue N and harvest measurements. The final spreadsheets contained location data, the measurement data, imagery and soil sensor data and management class model data. The aerial imagery was extracted as 4 bands (blue, green, red and NIR) and converted into the Normalised Differences Vegetative Index (NDVI) [NDVI = (NIR-Red)/(NIR+Red)]. The Cropcircle data was recorded as NDVI. Where relevant, the data, e.g. the plant count data, was converted from plot units (4.5 m^2) into hectare units.

Non-spatial data analysis

The distribution of the manually sampled data at all times was plotted in JMP v7 (SAS Institute, Cary, NC, USA). The field means and coefficient of variation are provided in tabular form. A histogram plot of the data from each field is given in Appendix B.

Geostatistical analysis

Data from the three late sown fields were aggregated together. This was done to ensure there were sufficient data (> 100) for variogram analysis. Variogram analysis was performed using Vesper (Minasny *et al*., 2005) to identify any spatial dependency in the data. The Cambardella Index (Cambardella *et al*., 1994) and Mean Correlation Distance ((MCD) (Han *et al*., 1994) calculated from the variogram parameters to quantify the spatial response. These indices give an indication if an attribute is likely to have enough variation and enough spatial structure to permit variable rate management. (See Appendix C for a brief description of variogram analysis, the Cambardella Index and MCD).

The yield data was kriged onto the grid of the three survey fields (Post Office, Bidgeribbin and Pivot 1) using the global variogram option in Vesper. Data was imported into and displayed in ArcMap.

Management Class Analysis

Management classes were derived from the environmental (EC_a-EM38, EC_a-EM31 and Elevation) and crop canopy response information (CropCircle and aerial imagery). Three different approaches were tried

a) only using the soil and elevation information
b) only using the crop information, and
c) using all available information

All three approaches used the protocol of Taylor *et al*., 2007 in constructing the management classes. For each field, 2 and 3 management classes were defined. This gave six combinations for each field;

i) $Soil_2$
ii) $Soil_3$
iii) $Crop_2$
iv) $Crop_3$
v) All_2
vi) All_3

The sample sites for all manually collected crop data (midseason biomass measurements, harvest counts) were then allocated to the 6 combinations of management classes within each field. The effectiveness of the derived management classes was determined by calculating the amount of variation explained by the each management class combination using an ANOVA. Since sample size per management class is not equal the adjusted r^2 statistic was used to determine the amount of variation in crop response that was explained by the different management classes. To determine the best classes the adjusted r^2 values for the 6 different classes were ranked from 1 to 6 (with 1 being the highest r^2 value). The mean rank and the standard deviation of rank across all crop parameters was calculated and plotted after the method of Laslett *et al.*, 1987. This analysis was done for each individual field and on the pooled data from all three fields.

The best management class models ($Crop_2$ and $Crop_3$ – see results) were then used to identify differences in response between the management classes. This was done by using the management classes as a treatment effect in an ANOVA. The response for the manually sampled data at the three sampling times (midseason biomass, silking plant N and harvest) are presented in a table form with an indication of whether the response was statistically different between management classes. Differences can only be compared within management class models (e.g. $Crop_2$-Class 1 and $Crop_2$-Class 2) not between different models

Part II - Management Options

Within season management of crops is aided by decision support systems that are able to accurately predict yield and/or quality of a crop during the season. This permits growers to alter input rates to try and achieve the optimal return on production. In most cases the dominant inputs are fertiliser (N) and irrigation. Shortly after the commencement of this project the first adapted crop model for sweet corn production was published (Laziso *et al*., 2007). This model used plant density, fresh ear weight and dry ear weight as predictors for yield.

Two preliminary analyses of the ability to predict yield and quality in this production system were undertaken.

Yield prediction model

The first approach was to predict yield from the midseason NDVI and plant density data. This was an attempt to simulate how well midseason information could be used to predict final yield potential. When accurate predictions of final yield potential mid season can be made this information can be coupled with crop growth models to drive variable rate applications. In this production system both moisture (through irrigation and rainfall) and nitrogen (see results of plant tissue N analysis) were not considered to be limiting. Yield was assumed to have reached full potential given the environmental and managerial conditions of production.

Yield was predicted as both absolute and relative field values. The yield between Pivot 1 and the other two fields was statistically different (Table 3) therefore the yield within each field was standardised using the following equation.

$$\text{Relative Yield} = \frac{\text{Actual Yield - Minimum Yield}}{\text{Maximum Yield - Minimum Yield}} \qquad \text{Equation 1}$$

This allowed the model to be run at both the individual field scale and also on all the data aggregated across the production system. The NDVI data from the January Cropcircle measurements and the January aerial imagery were chosen as inputs into the model. The models were run with only one NDVI input at a time i.e. with either the Cropcircle or aerial NDVI but not together.

Yield and quality interaction model

The second modelling exercise was to construct a model which related the interaction between yield and quality in the production system. When quality premiums are a principal determinant of profitability it may be useful for growers to be able to influence quality by managing yield. If the yield potential is known (Model 1 above) then yield response may be managed through inputs to optimise quality.

Using the harvest data, a regression equation was established to predict both yield and quality. For this exercise cob length was chosen as the desirable quality trait to model. For both models the grain moisture % and plant density (at harvest) were used as inputs. For the yield model, cob length was also an input and, vice versa, for the quality model, yield was used as an input parameter. Harvest is usually governed by grain moisture therefore this quality attribute can be considered a constant at harvest (~70-80%). Plant density is set during establishment and cannot be altered by the grower (with the possible costly exception of plant thinning). Therefore by manipulating yield the cob length can be altered i.e., if a desirable cob length is known then the optimum yield goal for given plant densities can be calculated. For this model only absolute yield values were used.

Both modelling exercises were undertaken in JMP. Cross-validation has not been undertaken at this stage as the intention here is to investigate opportunities not provide definitive proof. Further work on this data set will examine the robustness of the models.

Results

Map Production

All maps, reports and data generated during the project are available through a WebGIS display portal at

http://rural-gis.usyd.edu.au/VG07035/

A copy of the full GIS, with all relevant database and image files, in an ArcMap (ESRI, Redlands, Ca, USA) platform is available from HAL (contact Helen Sargent for access). Selected layers are also shown in Appendix D.

Part I - Quantification of variation in production

Variation at the field-scale

Variance of within season crop growth

Mean plant counts were acceptable in all fields accept Bidgeribbin where the plant density in Bidgeribbin was sub-optimum and significantly lower than the other fields. For the early sown Challenger fields, the amount of variation in the fields was lower. This may be a consequence of measurement at a later stage in the season. The other three fields also exhibit a decrease in the CV of plant density at harvest (Table 3). Pivot 1 had the lowest level of variation in plant density of the three late-sown crops whilst Post Office and Bidgeribbin exhibited higher levels of variation in plant density (CV 28–36%). The pattern of variation observed in the plant density data was repeated in the mean height of the primary culms and plant fresh weight data. There was a significant difference in plant height between the two different sowing dates/varieties but not within varieties. This is an expected result. Although not significantly different, the mean height in Pivot 1 was greater than in Post Office despite Post Office being sown before Pivot 1. Bidgeribbin was the first of the three fields to be sown and had the highest mean plant height. The percentage of tillering in the three late sown fields was uniform (~35%) despite the differences in plant density. This may be a genetic effect given that moisture, nutrients and space (early in the season) are non-limiting.

Pivot 1 exhibits much lower variation in crop growth (plant density and plant height) than Post Office and Bidgeribbin.

Leaf Tissue N sampling.

Sampling for plant tissue N at silking revealed that all three fields had a plant tissue N % of ~ 3.5% with no statistical difference between the fields ($P<0.05$). The majority of data ranged from 3.2 % - 4% with only one location recording a value below 3.2 %. This sample point (2.7 % N) was located in a waterlogged region of Post Office. These plant tissue N values are high with the mean response in Bidgeribbin and Pivot 1 higher the accepted ranges quoted in the literature (2.6–3.50% in Reuter and Robinson (1997) and 2.76–3.50 % in Martin-Prével *et al*., (1984)). Once a physiological level of N in the plant tissue is reached (usually between 3-4 %) then there will be no further increase in plant tissue N % with increases in soil N and/or fertiliser (Shenker *et al*., 2003). This result indicates that there is sufficient (and more than likely excess) N in the system for crop production.

Table 1: Field mean, field standard deviation and field coefficient of variation (CV) of midseason measurements of plant density, plant height, plant fresh weight and tiller % for the 5 target fields in the survey.

Field	No. of Samples	Plant Density (‘000 plants/ha)			Primary Culm Plant Heights (cm)			Plant Fresh weights (ton/ha)			Tiller %
		μ	σ	CV	μ	σ	CV	μ	σ	CV	μ
Bidge-ribbin[§]	22	56.47[a]	20.36	36.05	123.47[a]	44.33	35.91	2.27	1.23	54.36	34.27
Pivot 1[§]	20	79.78[b]	12.44	15.60	104.09[a]	23.44	22.52	2.29	0.77	33.51	34.48
Post Office[§]	15	85.49[b]	23.87	27.92	96.27[a]	32.93	34.21	2.39	1.33	55.53	35.99
Pivot 2&3[†]	19	77.20[b]	10.87	14.08	209.91 [b]	46.36	22.08	4.18	1.18	28.25	ND
Pivot 4&5[†]	20	82.22[b]	10.04	12.22	203.04[b]	53.84	26.52	4.26	1.29	30.26	ND

[§]Variety Punch, late sowing
[†]Variety Challenger, early sowing
Different letters indicate significant differences (Tukey All Pairs test) within a field and a particular Management Class Models.
ND = No data collected

Table 2: Number of samples per field and mean field response to the results of plant tissue N analysis.

Field	Number of samples	Mean Leaf Tissue N (%)	Lower 95%	Upper 95%
Bidgeribbin	19	3.553[a]	3.446	3.660
Pivot 1	15	3.553[a]	3.433	3.674
Post Office	12	3.450[a]	3.316	3.584

Different letters indicate significant differences (Tukey All Pairs test) within a field and a particular Management Class Models.

Table 3: Field mean and field coefficient of variation (CV) of harvest measurements of primary cob yield, plant density, secondary cob yield and % of plants with secondary cobs for the 3 harvest target field. Mean yield values recorded by Simplot are given in brackets.

Field	No. of Samples	Yield from 1º Cobs (ton/ha)		Plant Density ('000 plants/ha)		Yield from 2º Cobs (ton/ha)		Plants with 2º Cobs
		μ	CV	μ	CV	μ	CV	%
Bidge-ribbin	61	19.08[a] (19.8)	23.90	64.70[a]	16.83	2.86[a]	50.83	67.00
Pivot1	26	22.62[b] (21.18)	15.45	83.33[b]	9.67	1.71[b]	43.78	63.08
Post Office	30	16.16[a] (16.4)	32.57	72.89[c]	15.12	2.73[a]	49.37	82.62

Different letters indicate significant differences (Tukey All Pairs test) within a field and a particular Management Class Models.

Table 4: Field mean and field coefficient of variation (CV) of harvest quality measurements of cob diameter, cob length, grain moisture and insect damage for the 3 harvest target field

Level	Number of sites	Cob Diameter (mm)			Cob Length (mm)			Grain Moisture (%)		Insect damage
		μ	CV	Site σ	μ	CV	Site σ	μ	CV	%
Bidge-ribbin	61	53.82[a]	5.15	5.34	189.73[a]	6.46	21.24	75.46	3.40	66.34
Pivot 1	26	52.82[a]	4.76	4.86	181.55[b]	6.11	20.87	73.02‡	1.75‡	NR
Post Office	30	48.98[b]	10.54	6.09	173.72[b]	11.09	25.15	75.85	4.46	57.95

Site σ is the mean standard deviation of the measurements at each site (not the variance between sites within the field)

‡ based on whole cob measurements not subsamples of grain cut from cob.

Different letters indicate significant differences (Tukey All Pairs test) within a field and a particular Management Class Models.

Variance of Yield measurements

The yields measured by hand sampling across the three fields ranged from 5 - 30 $ton.ha^{-1}$, with all fields 18-20 $ton.ha^{-1}$. Pivot 1 field exhibited less variation in yield than the other two fields (Table 3) but still had a yield range of 18 $ton.ha^{-1}$. Pivot 1 yield was significantly higher than the other two fields but there was no significant difference in the yield between Post Office and Bidgeribbin. The CV of yield was highest in Post Office. The range of CVs observed in this study is similar to values obtained in other grain crops where Precision Agriculture has been applied (Pringle *et al.*, 2003). This indicates that the magnitude of variation in sweet corn yield is sufficient for site-specific management.

Plant density was measured at harvest as well as mid season. Bidgeribbin again exhibited the lowest plant density at harvest and was below the target population density. It was significantly different ($P<0.05$) to the Pivot 1 plant density but not to the plant density in Post Office. This contrasts with the midseason results and is a due to an increased plant density estimation in Bidgeribbin and decreased estimation in Post Office at harvest. For each individual field the plant densities recorded at harvest were not significantly different ($P<0.05$) to the plant density densities recorded midseason (analysis not shown). While the mean plant density in each field was not significantly different there was a marked decrease in the variation in plant density (CV) between midseason and harvest. The CV of plant density at harvest was approximately half that observed midseason. This indicates that the crop is capable of compensation and produces a more uniform plant density towards the end of the growing season (NB. This does not necessarily equate to more uniform production). The pattern midseason of Pivot 1 having the lowest variation in plant density was repeated at harvest.

The (lost) yield from immature 2º cobs was significantly higher in Bidgeribbin and Post Office. Very few 2º cobs were of sufficient size to be processed thus 2º cobs can be considered wasted energy by the plant. The ratio of 1º to 2º cobs was calculated and found to be significantly higher in Post Office. Bidgeribbin and Pivot 1 exhibited a similar response to this ratio. There was a weak negative relationship in Pivot 1 and Post Office ($r = -0.38$ and $r = -0.50$) between plant density and the ratio of 1º to 2º cobs, however this was not observed in Bidgeribbin ($r = -0.13$).

(Histograms of distributions of yield parameters in each field are given in Appendix B.)

Variance of Harvest Quality measurements

Bidgeribbin and Pivot 1 had similar CVs for cob dimensions (diameter and length) (Table 4). The variation in cob dimensions in Post Office was greater (~ twice the CV of the other fields) and mean dimensions were lowest. The range in quality attributes was large. Within field ranges were 12 – 21 mm for cob diameter and 50 – 75 mm for cob length with Post Office exhibiting the largest range for both properties.

Variation in the quality parameters that determine the harvest date (in this case grain moisture) tend to be less variable as harvest logistics aim to minimise this variation. The CV of grain moisture was lower in Pivot 1, however, whether this is a result of the alternative grain moisture measurement technique, the more uniform crop production in Pivot 1 or an external factor is unclear. For grain moisture the mean and CV between Post Office and Bidgeribbin was similar. Ranges in grain moisture of 5 – 10% were observed in all fields, with Bidgeribbin exhibiting the largest range.

(Histograms of distributions of quality parameters in each field are given in Appendix B.)

Spatial Data Analysis

Table 5 presents the variogram parameters for the harvest measurements. Variograms are displayed in Appendix E.

Table 5: Variogram parameters and calculated spatial indices of harvest yield and quality parameters for the 3 target field combined. (N = 113 with the exception of grain moisture N = 73)

Harvest Parameter	C_0	C_1	*a* (m)	Adjusted *a* (m)*	Model type	Cambard-ella Index	MCD
Yield 1º (ton.ha^{-1})	2.15	19.37	76.61	229.83	exponential	9.97	25.86
Yield 2º (ton.ha^{-1})	0.52	1.47	197.70	197.70	spherical	25.96	54.89
Ratio 1º:2º cobs	0.01	0.03	236.10	236.10	spherical	25.03	66.38
Plant Density ('000s ha^{-1})	57.64	74.88	380.30	380.30	spherical	43.50	80.58
Cob Diameter (mm)	3.49	4.26	26.08	78.24	exponential	45.03	5.38
Cob length (mm)	51.21	121.40	32.24	96.72	exponential	29.67	8.50
Grain Moisture %†	4.587	2.157	336.4	336.4	spherical	68.02	40.35

* The range needs to be adjusted for the different model types. The range in a spherical model is approximately 3 times that of an exponential model. Range has been standardised to the equivalent spherical range

† Only 73 samples from Bidgeribbin and Post Office were available for this analysis. The grain moisture samples from Pivot 1 were analysed using a different protocol and considered incompatible for this analysis

The yield (primary (1º) cobs, secondary (2º) cobs and ratio) parameters show a strong spatial pattern (low Cambardella index and high MCD). The plant density exhibits a moderate Cambardella Index value with a high MCD values which also indicates that it has a strong spatial pattern. The cob dimension quality parameters exhibit less spatial structure with lower ranges (distance over which the data are auto-correlated) which are reflected in low MCD values. Grain moisture exhibits an intermediate Cambardella and MCD value.

Crop parameters with strong spatial patterns are more conducive to variable rate management as they tend to give larger, more coherent management classes. The table above indicates that site-specific management of yield (and drivers of yield) using variable rate technologies will be easier (from a technological aspect) than managing quality traits. However, the table does not give any indication of the ease with which these drivers of yield can be identified or remedied. If a valid agronomic solution to management the variation is not possible then having a good spatial structure, which allows ease of implementation, is redundant.

The grain moisture exhibits some potential for spatial structure however it does have limited samples (N = 73). A strong spatial structure in grain moisture would be beneficial to assist in differential harvesting strategies.

Variation explained by Management Class models

The amount of variation in the midseason and harvest crop counts that could be explained by the 6 different management class models was assessed by ANOVA. In this analysis the management classes are considered as treatment effects. A tabulated list of adjusted r^2 values for each management class model and each crop measurement from the ANOVA is given in Appendix F. These results were used to construct the mean rank by standard deviation of rank plot (Figure 1). In Figure 1 it is clear that the management classes derived from the crop sensor data ($Crop_2$ and $Crop_3$) are the best models for explaining variation in the midseason and harvest measurements(low mean rank and low standard deviation). Bidgeribbin and Post Office management classes were the most reliable (lowest mean rank and lowest standard deviation). Pivot 1 crop-based classes were less reliable (higher mean standard deviation of rank) which may be expected in a more uniform crop. The management classes derived only from the soil data did not perform well (high mean rank) and were more variable in response (high mean standard deviation).

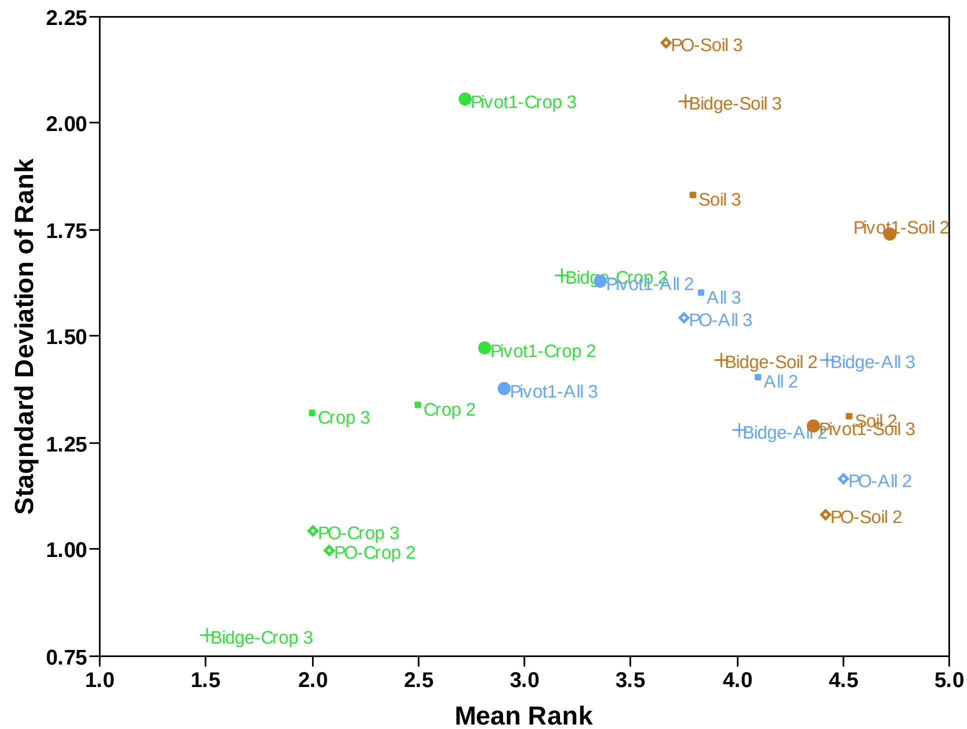

Figure 1: Plot of Mean Rank against Standard Deviation of Rank after ranking the response of the 6 management classes derived from the sensor data in explaining variation in the manually sampled crop data

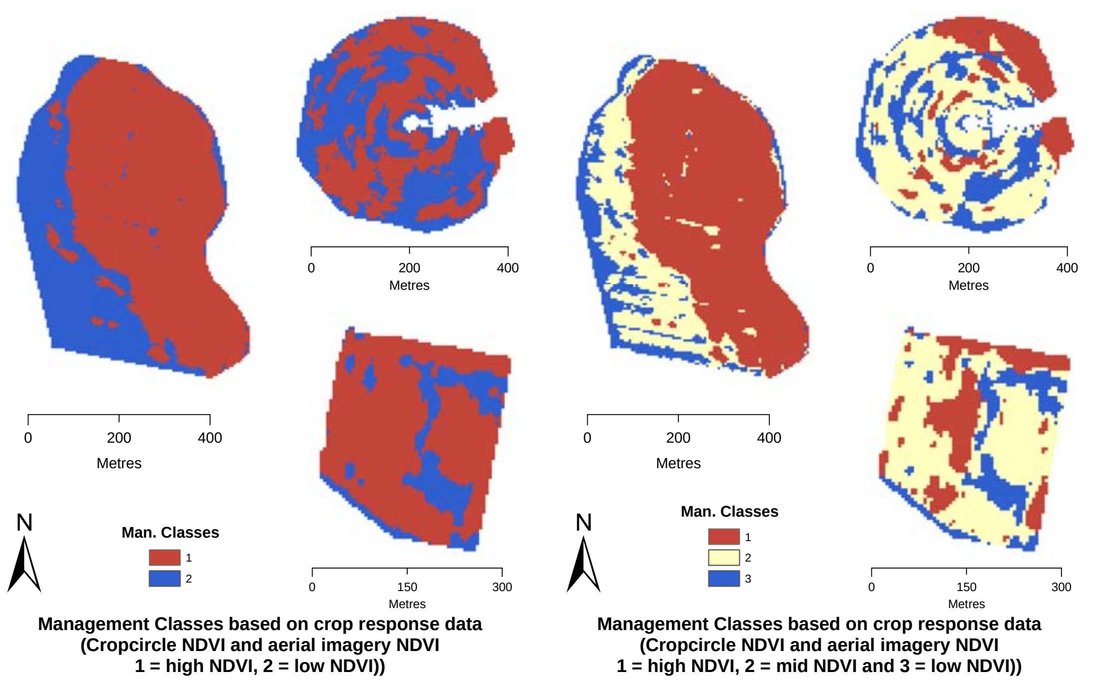

Figure 2: Management Class maps for the 3 fields where harvest samples were taken. The $Crop_2$ and $Crop_3$ model maps are shown. Management class maps for other models are shown in Appendix G.

Figure 2 presents the $Crop_2$ and $Crop_3$ management class maps for the three fields. As well as considering the amount of variation explained, management class maps need to be coherent enough to permit variable rate machinery to adjust to crop response. Rapid changes in rates is feasible in the current system as operations (sowing, fertiliser) are done on narrow (6 row or 4.5 m swaths). Even with this narrow implement width it is likely that all the $Crop_3$ maps, particularly for Pivot 1, would need to be simplified (Figure 2). The $Crop_2$ maps for Bidgeribbin and Post Office show very strong patterns which would be easy to manage. The management class maps for the other models ($Soil_2$, $Soil_3$, All_2 and All_3) are shown in Appendix G. The smooth nature of the soil maps (data), compared with the crop canopy data, produce more coherent management classes. However, as shown above and in Appendix G, these models do not explain the observed variation in the manually collected crop data.

Variation in midseason biomass measurements between management classes

Across all three fields there was a trend with the highest midseason NDVI classes having the highest plant density and the tallest plant heights, i.e. plant establishment was better and plant growth rates higher in management class 1 (higher NDVI). Only in the Pivot 1 field was the difference in mean plant density and mean plant height not significantly different, however the trend was present. Tillering percentages were not significantly different between the $Crop_2$ classes in any field however the trend of more tillers in management class 1 was constant. This link between more fertile soil and moisture availability and increased tillering percentage has been know for a long time (Dungan *et al*., 1958). Better plant establishment and growth tends to initiate more tillers however once canopy closure is reached tillers tend to dieback.

Variation in Plant Tissue N % between Management Classes

Table 7 shows the mean response in plant tissue N between the $Crop_2$ management classes in the three target fields. Within each field there was no statistical difference in plant tissue N % between the $Crop_2$ Management Classes. Again, the mean plant tissue N in the management classes was high given accepted limits and N is not limiting in any of the management classes. Whilst there was no statistical difference between the management classes (possibly in part to insufficient sample size), in all three fields there was a trend of management class 1 (higher NDVI) having a higher mean plant tissue N response. This was also observed in the $Crop_3$ model (data not shown). The reason for this is unclear and may be due to the more advanced physiological stage of growth.

Table 6: Mean response in midseason plant density, plant height and tiller % for the management classes from the $Crop_2$ and $Crop_3$ models for each of the three fields

Field	Man. Class Model	Man. Class ID	Number of samples	Area (ha)	Mean NDVI (Aerial image January)	Mean Plant Density ('000s.ha^{-1})	Mean Plant Height (cm)	Tiller %
Bidgeribbin	$Crop_2$	1	12	17.77	0.59^{a}	67.59^{a}	66.41^{a}	35.36^{a}
		2	10	8.54	0.45^{b}	43.11^{b}	42.52^{b}	32.95^{a}
	$Crop_3$	1	10	16.76	0.60^{a}	69.33^{a}	68.09^{a}	37.12^{a}
		2	9	6.12	0.52^{a}	55.06^{b}	53.77^{b}	32.84^{a}
		3	3	3.43	0.28^{b}	17.78^{c}	19.11^{c}	29.00^{a}
Pivot 1	$Crop_2$	1	12	7.30	0.61^{a}	82.59^{a}	50.76^{a}	36.90^{a}
		2	8	6.52	0.54^{b}	75.56^{a}	40.95^{a}	30.86^{a}
				.				
	$Crop_3$	1	6	2.93	0.61^{a}	82.22^{a}	51.25^{a}	33.62^{ab}
		2	7	7.17	0.61^{a}	80.95^{a}	48.81^{a}	40.53^{a}
		3	7	3.72	0.53^{a}	76.51^{a}	41.08^{a}	29.19^{b}
Post Office	$Crop_2$	1	10	6.08	0.60^{a}	96.00^{a}	49.36^{a}	39.67^{a}
		2	5	1.77	0.41^{b}	64.44^{b}	31.22^{b}	28.64^{a}
				.				
	$Crop_3$	1	5	1.89	0.64^{a}	103.56^{a}	55.89^{a}	39.20^{ab}
		2	6	4.58	0.57^{a}	86.67^{ab}	43.72^{ab}	41.42^{a}
		3	4	1.38	0.36^{b}	61.11^{b}	27.00^{b}	23.85^{b}

Different letters indicate significant differences (Tukey All Pairs test) within a field and a particular Management Class Models.

Table 7: Mean Leaf N % for the management classes from the $Crop_2$ model for each field.

Field	Man. Class ID	Number of Samples	Plant Tissue N %
Bidgeribbin	1	8	3.65[a]
	2	11	3.48[a]
Pivot 1	1	9	3.59[a]
	2	6	3.50[a]
Post Office	1	7	3.60[a]
	2	5	3.24[a]

Different letters indicate significant differences (Tukey All Pairs test) within a field for the $Crop_2$ model.

Variation in Harvest parameters between Management Classes

In Bidgeribbin, the $Crop_2$ management classes showed a big difference in yield (5.87 $ton.ha^{-1}$). The greater yield in Class 1 came from both a statistically larger ($P<0.05$) plant density and cob size (diameter). The mean class yields in the $Crop_3$ model showed the prevailing trend of a lower mean NDVI midseason producing lower plant densities, smaller cob size and lower mean yields at harvest, however, the difference in yield and quality measurements at harvest between Class 2 and Class 3 was not significantly different. The grain moisture data indicates that the high yielding zones in Bidgeribbin are less mature (higher grain moisture %) than the low yielding zones.

In Pivot 1 there was no significant difference in yield or plant density between the management classes for both the $Crop_2$ and $Crop_3$ models. This again reflects the uniform nature of production in this field. For both models, the management class with the lowest midseason mean NDVI did produce the lowest yield reflecting a decrease in cob size. There was a significant difference in grain moisture between the management classes although the difference was not large (1.15 %). However this was the only significant difference in grain moisture observed with the $Crop_2$ and $Crop_3$ management classes in the three fields. (NB. MC 2 and 3 in All3 are sig different as well)

The Post Office field exhibited the biggest yield difference in the $Crop_2$ models (9.23 $ton.ha^{-1}$). Whilst yield was significantly different between management classes the grain moisture was not and the difference in the mean grain moisture between the $Crop_2$ classes (2.08%) is elevated by one outlier (89% moisture). If this outlier is removed the difference between the means of the two classes is 0.01%. The low NDVI areas (Class 2) were slower to establish (with lower mean height – data not shown), however have reached the same level of maturity as the remainder of the field. This accelerated maturity comes at a cost of lower yield from fewer and smaller cobs.

Table 8: Mean response in yield, plant density, cob diameter and grain moisture for the management classes from the $Crop_2$ and $Crop_3$ models for each of the three fields

Field	Man. Class Model	Man. Class ID	Number of samples	Area (ha)	Mean NDVI (Cropcircle January)	Mean Yield (ton/ha)	Mean Plant Density ('000s.ha^{-1})	Mean Cob Diameter (mm)	Mean Grain Moisture (%)
Bidgeribbin	$Crop_2$	1	31 (30)	17.77	0.60^{a}	21.96^{a}	69.17^{a}	55.39^{a}	76.03^{a}
		2	30 (30)	8.54	0.43^{b}	16.09^{b}	60.07^{b}	52.19^{b}	74.87^{a}
	$Crop_3$	1	27 (26)	16.76	0.61^{a}	22.32^{a}	69.62^{a}	55.68^{a}	75.87^{a}
		2	25 (25)	6.12	0.47^{b}	17.12^{b}	61.42^{b}	52.80^{b}	75.36^{a}
		3	9 (9)	3.43	0.37^{c}	14.77^{b}	59.01^{b}	51.03^{b}	74.51^{a}
Pivot 1	$Crop_2$	1	16 (15)	7.30	0.57^{a}	24.19^{a}	82.22^{a}	53.75^{a}	72.56^{a}
		2	10 (10)	6.52	0.45^{b}	21.28^{a}	85.11^{a}	51.32^{b}	73.71^{b}
	$Crop_3$	1	8 (7)	2.93	0.59^{a}	23.84^{a}	82.77^{a}	53.08^{a}	72.69^{a}
		2	10 (10)	7.17	0.54^{b}	23.25^{a}	82.44^{a}	54.06^{ab}	72.83^{a}
		3	8 (8)	3.72	0.44^{c}	21.95^{a}	85.00^{a}	50.99^{b}	73.55^{a}
Post Office	$Crop_2$	1	23 (18)	6.08	0.53^{a}	19.93^{a}	76.13^{a}	50.78^{a}	75.26^{a}
		2	7 (7)	1.77	0.41^{b}	10.70^{b}	62.22^{b}	43.03^{b}	77.34^{a}
	$Crop_3$	1	9 (9)	1.89	0.56^{a}	20.99^{a}	74.32^{a}	51.84^{a}	75.53^{a}
		2	15 (10)	4.58	0.50^{b}	19.01^{a}	76.88^{a}	49.98^{a}	74.87^{a}
		3	6 (6)	1.38	0.40^{c}	9.88^{b}	60.74^{b}	42.14^{b}	77.94^{a}

Different letters indicate significant differences (Tukey All Pairs test) within a field and a particular Management Class Models.

Part II – Investigation of management options

Midseason Prediction of Yield

Table 9 shows the results of yield predictions based on mid season NDVI data and a knowledge of plant density. Predictions with both sets of NDVI data (CropCircle and aerial imagery) produced reasonable fits to the individual fields (r^2 0.40 - 0.75). Bidgeribbin provided the best model fits and Pivot 1 the worst. The poor fits in Pivot 1 are probably due to the lower variability in response making prediction harder. The global yield prediction model – using the data from all three fields – explained about two-thirds of the variation in the yield response. Standardising the data to a relative yield value within each field and then running the global model produced did not improve the predictions. There is a lot of potential noise in both the manual crop measurements and sensor data which are propagated through the models. When this is taken into account these model fits are very encouraging.

Table 9: Adj r^2 and RMSE of absolute yield prediction from NDVI and plant density (at harvest) data (using sample data) and relative yield for combined data set

Field	Number of Samples	Model A$^{\ell}$		Model B$^{\Diamond}$	
		Adj. r^2	RMSE	Adj. r^2	RMSE
Bidgeribbin ($ton.ha^{-1}$)	61	0.75	2.30	0.75	2.27
Pivot1 ($ton.ha^{-1}$)	25	0.50	2.75	0.40	3.00
PO ($ton.ha^{-1}$)	30	0.61	3.76	0.68	3.27
All ($ton.ha^{-1}$)	116	0.66	3.10	0.64	3.16
All (Relative Yield %)	116	0.57	15.83	0.53	16.59

$^{\ell}$ Model inputs are Cropcircle NDVI (January) and plant density
$^{\Diamond}$Model inputs are Aerial image NDVI and plant density

Yield predictions based only on the NDVI were also performed (data not shown) and these produced much poorer fits (r^2 0.05 – 0.53 for the individual field fits). Knowledge of plant density appears beneficial to accurate yield prediction. Plant density is correlated with the NDVI data in Bidgeribbin and Post Office ($r = 0.4 – 0.6$) but not in the more uniform Pivot 1 field. With multi- or hyper-spectral sensors it may be possible to use a combination of other vegetative indices to estimate plant density quasi-independently of NDVI. This is certainly an area that warrants further investigation and for the multi-spectral aerial image can be done with the current data set.

As an aside, the NDVI values were also standardised to a relative NDVI values within each field by substituting NDVI for yield in Equation 1. This was done to examine the effect of (small) differences in sowing dates and crop development between the fields. NDVI is influenced by both the number of plants and the size of the plants, therefore crops at the same density and chlorophyll content at a more advanced stage will produce higher NDVI values. The CropCircle sensor also took several days to collect data which may further increase the error due to crop size on the NDVI measurements. The substitution of a relative NDVI for the actual NDVI in the combined data model (all three fields) did not improve the model fit. For fields sown over short (1 week) time frames standardising NDVI does not appear to be beneficial for modelling. This is supported by the lack of significant difference in mean plant height between the fields (Table 1).

Modelling yield, quality and plant density.

The plots of the global model fits and the regression equations for both the yield and quality models are shown in Figure 3 and Equations 2 and 3. The fits for individual fields are shown in Appendix H. The global models have a very good (r^2 0.90 and 0.78).. The stability of this relationship needs to be tested over time and across more fields. However, these preliminary results indicate that quality is related to the yield – plant density interaction and by manipulating yield it may be possible to optimise quality.

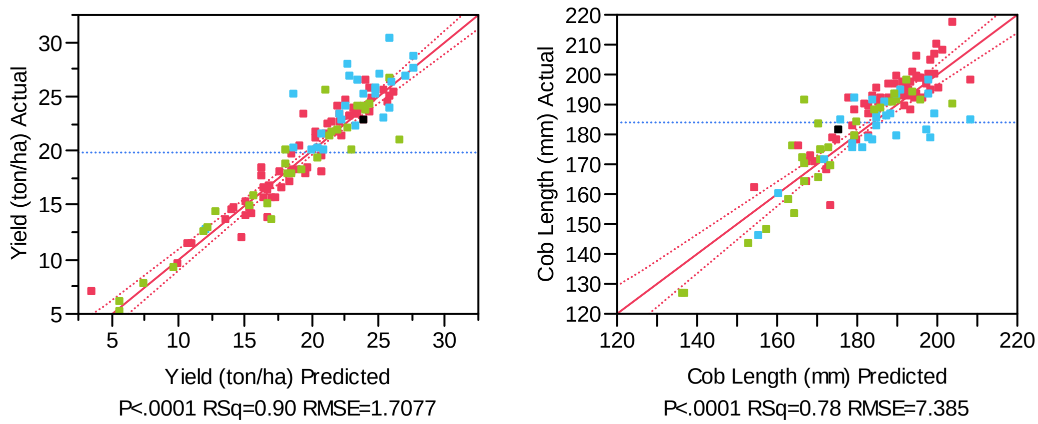

Figure 3: Regression model fits of actual vs. predicted Yield (ton.ha^{-1}) (left) and Cob length (mm) (right). Colours indicate fields; Red – Bidgeribbin, Green – Post Office and Blue – Pivot 1.

Yield (ton/ha) = -39.99 + 0.30*Plant Density +0.20*Cob Length + 0.016*Moisture %

Equation 2

Cob Length (mm) = 191.93 + -1.13*Plant Density + -0.056*Moisture %p + 3.83*Yield

Equation 3

Some (simple) economic analysis of N fertiliser.

Nitrogen was uniformly applied and totalled ~151 kgN.ha^{-1} across the growing season (23 kgN.ha^{-1} pre sowing, 36 kgN.ha^{-1} at sowing and 92 kg.ha^{-1} sidedressed). The cost of this, assuming it is all applied as urea (46% N), at a cost of \$900 ton, is (0.151/0.46) * 900 = \$295 ha^{-1}.

The results of the N analysis of leaf tissue collected at silking indicate that most plants across all fields had excess N levels (> 3.25 %) in the plant tissue. Only one site, associated with a waterlogged area in Post Office, had a plant tissue N level that was low (2.6 %) but not limiting to production. This indicates that N is being over applied in the system. Further anecdotal evidence of excess N is provided by the aerial imagery of Post Office. At sowing there was a differential application of N across the six rows of the planter due to problems with fertiliser distribution in the planter. This produced variable plant growth early in the season across rows. This would expect to be seen as striping in the high resolution aerial imagery if the crop was truly short of N during emergence. However no striping is discernible in the aerial imagery in Post Office.

Measured yields across the paddocks ranged from 6 – 26 ton.ha^{-1}. On average, a 17 ton crop in the Central-West of NSW requires 220 kg of N (Wright *et al*, 2005). Assuming a linear function, this equates to 13 kg N per ton of sweet corn produced. The uniform application of N on the fields was ~ 155 kgN.ha^{-1}, therefore any site that yielded under 12 ton.ha^{-1} had excess N applied even before the pre-sowing soil available N is accounted for. There were 15 (of 123) sites where this occurred.

The value of 220 kgN.ha^{-1} is an average for the district. The plant tissue N results indicated that even in the high yielding areas of the three fields N is non-limiting at silking. From this it can be assumed that there is sufficient N in the system to produce a crop of ~ 26 ton (26.5 ton being the highest recorded yield level in the lowest yielding field, Post Office). The yield means (from Simplot (Evan Brown *pers. comm.*)) for the three fields were 16.4 ton (Post Office), 19.8 tons (Bidgeribbin) and 21.2 ton (Pivot 1). Therefore, on average, there is sufficient N to produce a further 9.6, 6.2 and 4.8 tons of corn in the respective fields. This equates to a N excess of 125, 81 and 62 kgN.ha^{-1} for the three fields (or 270, 175 and 135 kgUrea.ha^{-1}) which equates to an additional unnecessary cost of production of $243, $158 and $122 ha^{-1} for Post Office, Bidgeribbin and Pivot 1 respectively. NB. This cannot be considered as total wastage as some of the N will be stored in the soil for future crops, but this is an upfront extra 'capital' input which will depreciate i.e. N will leach out of the root zone. It also has some environmental implications and possibly costs.

Discussion

Is there sufficient variation to warrant site-specific or management class-specific management?

The yield coefficient of variation for the three fields is similar to that observed in other grain crops where PA has been successfully implemented. The mean yield is generally higher than other (dryland) grain crops where PA has been implemented however the large range of yield values within fields (14 – 20 ton.ha^{-1}) indicates that there is plenty of potential to adjust management away from uniform applications.

The analysis presented in this report has focused on total yield. During data collection at harvest, the dimensions of each primary cob at each sample location were measured. This will allow for a more rigorous analysis of actual vs. marketable yield at each sample site by culling any undersized cobs. From both the producer and processor perspective it is the marketable yield which is of greatest importance. Unfortunately, individual cob mass was not recorded at harvest due to time constraints. However the % of marketable cobs can be calculated and an estimation of yield based on a relationship between diameter, length and mass can be made. (This analysis forms part of the honours work that will be completed in November 2008.) The expectation with this analysis is that high yielding areas will have low rejection rates while poor yielding areas will have high rejection rates. The result of this will be an increase in yield variation.

Mean quality parameters at each site also exhibited large ranges and opportunities to manage differentially. Apart from insect damage, Simplot Australia Ltd does not have stringent guidelines for cob dimensions. Sweet corn destined for the fresh market has more emphasis on cob size. In general, average cob dimensions were less than the preferred dimensions by Simplot Australia Ltd (cob length 195-205 mm, cob diameter 53-55 mm) for all three fields. Further analysis of the implications of observed variation in quality for a fresh food market will be provided in the addendum. There was no spatial pattern associated with insect pressure and this was poorly explained by all management class models.

The large variation observed in both yield and quality parameters indicate that a uniform management system is sub-optimal in this production system. One of the prerequisites for successfully implementing precision agriculture is the presence of a sufficient magnitude of variation. In this production system this appears to be true. These results indicate opportunity for PA in sweet corn but other growers will need to verify the magnitude of variation in their production system independently. The large variation in the canopy sensed data (both aerial and proximal) that mirrors the variation in production may provide a tool to gauge within-field variation in other systems. However, this data will need some ground-truthing to verify the local response.

The three fields exhibited different levels of variation in yield and quality with Pivot 1 being more uniform. It is more likely that investment in PA and VRT in Post Office and Bidgeribbin would have a higher return on investment as there is more variation to manage.

Management Classes and variable-rate management

One of the objectives of this project was to evaluate the usefulness of management classes as a tool for differential management. Whilst it is usually best to have some end-of-season production data, such as yield maps or quality maps, experiences in Australia and overseas have shown the value on high resolution soil maps derived from on-the-go soil sensors. The sensors used in this study measure the apparent electrical conductivity of the soil (EC_a). This soil property is an indication of the amount of clay (higher clay % = higher EC_a), soil moisture (more moisture = better conduction = higher EC_a), salinity when present (more charge in the soil solution = higher EC_a) and clay mineralogy (more surface charge = higher EC_a) in the soil. There are also other soil properties that have a smaller effect on EC_a (organic matter, soil temperature, soil pH) and are not considered here.

Deriving management zones from only soil sensor is not optimal but is often required when existing high resolution production data, particularly yield maps, are not available, as is the case in this study. The output from EC_a sensors can be used to identify where soil moisture is or is likely to be held (i.e. where the clay is). In dryland situations, the ability to store soil moisture often drives productivity thus the EC_a data has been very useful in understanding maize yield response and deriving management classes. Elevation data can also provide information on where water is expected to be in the landscape and previous studies (Kravchenko and Bullock (2000) and Kaspar *et al.* (2003)) have shown that much of the variation in dryland maize yield can be explained by elevation and slope effects.

In this study, the management classes derived only from soil sensor and elevation information ($Soil_2$ and $Soil_3$) did not appear useful for differential crop management. In Bidgeribbin and Pivot 1 both $Soil_2$ and $Soil_3$ models explained very little of the variation observed in yield and quality. In Post Office the $Soil_2$ model was ineffective but the $Soil_3$ model did explain some of the variation in yield and quality. However the $Soil_3$ model was only superior to the other models in explaining the variation in cob diameter and length and performed poorly on the other harvest parameters.

In contrast the $Crop_2$ and $Crop_3$ management classes based only on the NDVI data (CropCircle and aerial imagery) explained 10 – 25% of the variation in yield with the worst response in Bidgeribbin (Appendix F). In actual values this translated to a 5.9 $ton.ha^{-1}$ difference in Bidgeribbin and a 9.2 $ton.ha^{-1}$ difference in Post Office between the $Crop_2$ classes (Table 8). These differences are large enough to warrant class-specific management at least. Even though crop response was more uniform in Pivot 1 and there was no significant difference in yield between the classes, the $Crop_2$ and $Crop_3$ models were able to discriminate significant differences in quality. However this is not significant from a premium/discount perspective for processed sweet corn. The $Crop_2$ and $Crop_3$ models did not explain differences in harvest quality in Bidgeribbin or Post Office (Appendix 6 and Table 8).

The $Crop_2$/$Crop_3$ models were also successful in identifying differences in growth midseason (Table 6 and Appendix F) in Bidgeribbin and Post Office. There were significant differences in plant density and height between classes which will have implications for potential yield goals and within-season management. If different classes have different mean densities and development stages then midseason management should be altered to accommodate the current and future needs of the plant given its growth/yield potential. Pivot 1 did not show significant differences to the $Crop_2$/$Crop_3$ models midseason (and did not show significant yield differences at harvest).

When the soil and crop data were joined (All2 and All3) there was no benefit gained in explaining the variation in crop production. Some attributes performed better with the All_2/All_3 models but the trend was not consistent and these models performed worst than the $Crop_2$/$Crop_3$ models on average (Figure 1).

In these three fields crop production and variation in crop production is best gauged from a direct measurement of the plant (canopy) midseason. The ability to irrigate has eliminated much of the variation in crop production that can be directly attributed to variation in soil moisture holding capacity. In fact, with the wet summer in 2007/08, it is a problem with waterlogging, which is not as easily mapped with soil sensors, that drives much of the variation, particularly in Post Office. Soil fertility also seems to be sufficient (as measured by plant tissue N %) to not introduce any variation in production.

The good results associated with the midseason canopy data indicate that an on-the-go system to variably apply mid-season inputs (fertiliser or irrigation) will be applicable and perhaps more relevant in these production systems than pre-defined soil-based management classes. The preference for canopy sensor-based decision making does not totally exclude management classes or soil information. Management classes based on yield information, rather than just soil information, may yet prove to be useful. This approach is stifled in the interim until reliable harvest sensors are available. Once a calibration between crop production and mid-season canopy response is developed then additional information either on management classes or site-specific soil properties may be useful to further refine and improve the decision support system.

There appeared little difference in information value between the aerial image and the CropCircle data. Both have advantages and disadvantages. Aerial imagery is less flexible with timing and relies on an external contractor, whilst the CropCircle can be run at anytime that suits the grower and run multiple times during early growth. However aerial imagery requires little post-processing to create images while the CropCircle data needs interpolation to produce maps. The turn around time for both is similar however the interpolation requires more skills and support. CropCircle is a larger capital cost up-front with little on-going cost whilst imagery incurs a cost every year for collection. Growers need to investigate which approach best suits their production and local agronomic support base.

Crop modelling for sweet corn

Crop modelling is an important tool for crop management and even more so for site-specific crop management. Crop models form the basis for many decision support systems. As indicated above, the canopy sensor data provided the best discriminator of variation in midseason and harvest production. The fits of the yield regression models (Table 9) derived from the midseason canopy sensor data and harvest plant density data support this. Being able to reliably predict yield (or at least yield potential) midseason provides valuable information for any decision support system associated with midseason crop management.

The technology to perform on-the-go VRT of fertiliser or irrigation already exists. These VRT systems can be driven by either real-time information, from a tractor mounted canopy sensor fed directly into a decision support system, or from a prescription map derived from previously collected data from proximal or remote (multi-spectral aerial/satellite imagery) sensors. Whether real-time or prescription-based, these systems are only as good as the decision support system (DSS) that runs them.

Sweet corn crop models are poorly developed compared to other cereals, however much of the knowledge within existing cereal crop models appears to be transferable. This has recently been illustrated by Lizaso *et al*., (2007) who have adapted the CERES crop model for sweet corn. The different production environment in Australia does not make these results directly transferable to Australia however it does open the possibility for adaptation of existing Australian models (e.g. APSIM) for sweet corn with a minimal time and cost expense. The data from this small study shows that effective field and global models can be generated from plant density and canopy response data. There is an opportunity to expand on this to develop meta-models, using complex crop models (like APSIM) and site-specific crop/soil data, to drive DSSs. These meta-models have the ability to make the output from complex models accessible to on-farm situations. This has already been done at a field-scale in the grains industry with Yield Prophet®. The development of a fertiliser or irrigation decision support system based on canopy and biomass sensors is certainly an area for the industry to pursue if they wish to continue in down the PA path. Without this support, variable-rate decision making is difficult. A similar caution to the North American sweet corn industry has been recently expressed by separate work in the U.S.A. (Ma *et al.*, 2007).

The first modelling exercise in Part II looked purely at the ability of midseason knowledge to predict yield with the intention of adjusting inputs to optimise yield. The second approach was to model how yield and quality interacted. These regression models are only a preliminary step but illustrate how plant density, quality and yield interact. Quality parameters need to reach minimum threshold values for the sweet corn to be marketable. Equation 2 can be used to estimate a desirable yield goal for given quality attributes. Alternatively, if potential yield is known, as a result of midseason measurements and crop models, then the final quality (dimensions) of the sweet corn can be predicted. Models such as these permit economic analysis and risk management planning for growers. This is becoming increasingly important as the cost of inputs rises.

As indicated in the results section the robustness of these models are yet to be tested by bootstrap/jack-knife methods or application into independent production system. The data within this project can be cross-validated internally but any future work needs to ensure that models are robust enough for different agronomic regions or alternatively develop region-specific models. The temporal (seasonal) stability of the models also needs to be evaluated. If these models are only field-, farm- or season -specific then their applicability is limited and growers will need to focus on on-farm experiments to develop their own models for DSS.

Missing links (technological and methodological) to implement precision agriculture in sweet corn.

For site-specific crop management to be effective growers must be able to quantify the response within the production system. Without quantifying yield and/or quality it is difficult to put dollar figures on the cost/benefits of variable rate management. Without this dollar figure most farmers are reticent to invest in new technologies. The sweet corn industry is harvested by only a few combine harvesters. The priority is to get some form of yield sensor onto these machines. Measuring quality is more difficult but it may be possible to do using digital image analysis to measure cob length and cob diameter. In both cases the preferred option would be to adapt and calibrate existing, reliable sensors rather than build new systems. The cost of this should be relatively small for each partner if shared between the growers, processor and peak industry body. (Some thoughts on yield and quality sensors are given in Appendix

This work and that of Lizaso *et al*., (2007) indicate that plant density is a key driver in production and in modelling production. Two priorities in this area are a) to ensure more even planting and germination and b) to be able to measure plant density.

a) Even planting: The sweet corn crop in NSW is contract planted. It is know that as variation in plant density increases then yield decreases even though the mean density remains constant. All possible efforts need to be made to ensure that the contract planter is running optimally. The additional of RTK-GPS auto-steer will help minimise errors in row spacing between runs. There was a large variation in plant densities observed in this production system however the soil EC_a data from this study did not show strong soil effects on plant establishment. There may be differences in soil types that lead to variable soil crusting or variable top soil moisture which may need to be differentially managed to ensure even emergence. The soil core results (to be delivered in the addendum report) may shed further light on this.

b) Measuring plant density. To make crop models effective, a measurement or estimation of plant density appears preferable. The mid-season NDVI identified significant differences between the $Crop_2$ management classes. However NDVI integrates both number of plants, size of plants and chlorophyll content of the plants therefore cannot be used to directly estimate plant density unless plant size is even (which, from the plant height data, it is not). There are alternative vegetative indices that can be constructed from multi-spectral data and it may be possible to use a combination of indices to extract plant density from sensor data. Little work has been done in this domain, particularly in sweet corn. There has been some work in wheat which examined the coefficient of variation in spectral response as a measurement of plant density (Arnall *et al*, 2004). Alternatively, a plant density sensor could be used based on mechanical or optical measurement. Radar based sensors for measuring plant density have been reported (Paul and Speckmann, 2004) but are not in common use. Cost could be an issue with these sensors if a large market is not available. For either approach further work is required. The ability to measure plant density site-specifically or class-specifically is an important step in achieving effective variable rate management.

As indicated elsewhere in this report the absence of effective crop models is a issue with successful adoption of VRT.

As an irrigated crop, variable rate irrigation (VRI) is also a potentially cost saving technology. VRI systems exist, particularly for pivot and linear systems. There is already investment from HAL and other sources into these systems. Again, the engineering aspects of VRI are well understood and commercial systems are available. The primary bottleneck in adoption is attaining sufficient spatial resolution in application and in decision-making. Research into soil and canopy-based sensors to determine plant water status is underway and the sweet corn industry should keep abreast of this research to facilitate adaptation to sweet corn.

Lastly, the data from this study and results from Lizaso *et al*'s (2007) modelling indicate a that yield and quality are linked and can be manipulated to optimise quality. This is likely to be more relevant in the fresh market (compared to the processed market) but is any area of research that can be explored so that site-specific management can be used to produce a more uniform (saleable) crop quality.

Other issues…

If not soil, then what is driving variation?

The sensor derived soil data did not provide much help in identifying what soil factors where influencing production. There are certainly more issues to be explored here to better understand what is driving production. Is there an N excess effect in the crop? What is driving variable plant establishment apart from known crusting and waterlogging effects? Is there variation that is attributable to management variation instead of environmental variation? These issues need to be discussed by the grower and local agronomist – such discussions are key to any successful PA program.

There were certainly some interesting agronomic observations from the management class data. The high yielding Class 1 in Bidgeribbin actually returned a higher mean grain moisture % than Class 2. This was in contrast to the other two fields. This indicates that the higher yielding area in Bidgeribbin was less mature than the lower yielding area. Class 2, on the sandier slopes, was slower to establish but achieved maturity (at a lower yield potential) than Class 1. If the aim is uniform maturity (and quality), what implications does the faster growth rate in Class 2 have for sowing dates and/or sowing rates? Or implications for fertiliser strategies between classes? In Pivot 1, plant establishment was much more uniform between classes. The difference in NDVI mid-season indicated a difference in quality, not yield potential. In this case a DSS is need to assist with quality (not yield) management during side-dressing.

How much N is enough?

The nitrogen analysis presented is a very simple approach to N economics with a few simple assumptions. However it illustrates that significant savings per hectare can be achieved, particularly at side-dressing. The relative yield prediction model could be used to assign rates based on the NDVI response at side-dressing, for example a decision in Post Office of not applying N on the low NDVI class (Class 2 with yield of 10.7 tonnes) would have saved 1.7 ha by 200 kg urea @ \$900 ton^{-1} = \$306 (or \$180 ha^{-1}). However for robust decision support systems more work needs to be done in the area of crop response and crop modelling.

Other recent studies have reported that nitrogen application in sweet corn is excessive. Shenker *et al* (2003) found that applying only 45% of the recommended N produced no significant yield loss. Over a three year study Ma *et al*. (2007) found no significant increase in yield from increasing N rates above 100 kg.ha^{-1} and for two years no benefit from increases above 50 kg.ha^{-1}. It is possible that these short term studies may be influenced by residual N stores in the soil, however this is further evidence that over application of N is common in sweet corn production systems. Since nitrogenous fertiliser is now a major cost, and a major potential pollutant, growers should be more cautious in application.

Strip or variable rate in-field trials of different nitrogen rates should be adopted by growers to tailor N requirements for their production systems. Protocols for on-farm experimentation are now being widely published (e.g. Whelan et al., 2005) and can easily be adapted to sweet corn production.

Technology transfer

The main technology transfer is through the WebGIS portal where all the data is displayed. Two Milestone reports have been generated which are again available through the WebGIS page

The WebGIS can be accessed at http://rural-gis.usyd.edu.au/VG07035

The soil sensors were displayed at a local field day in collaboration with DPI NSW.

There have been no formal publications from the project yet – mainly due to its short timeline (9 months). The large data set derived from the project should facilitate at least 1 journal and 1 conference paper. The current intention is to publish the results of the variation and the management class analysis in a journal. The results from the crop modelling will be prepared as a conference paper. Another paper (journal or conference) should arise from the senior research project which focuses on quality and soil interactions.

The preparation of magazine article for the AUSVEG industry magazine will commence at the submission of this report.

The chief investigator did intend to present the results to Simplot and growers at the post-harvest meeting, however a change of date precluded this. The information is now being directed through Simplot's Field Services Manager, Mr Evan Brown.

Recommendations - scientific and industry

The application of precision agriculture technologies to sweet corn is in its infancy. However, the physical similarities between sweet corn and maize production systems means that much of the technology required to implement PA in sweet corn systems already exists and can be adapted. The challenges in technological adoption lie in areas where the production system differ, principally in harvesting where maize harvests grain (kernels) whilst sweet corn harvests whole cobs. Industry needs to invest in the adaptation or development of harvest sensors for both yield and quality. Without this information implementation of PA will be stilted.

Of the existing technology canopy sensing sensors appear to be the most useful technology for sweet corn producers to drive variable rate management. In systems where neither moisture nor nutrient is limiting than an actual measurement of the canopy just prior to or during the application of within season inputs provides the best information on yield potential. Spatial information on soil variation appears to be of less importance during the initial stages of PA adoption. However this information may be come more important as a covariate in decision making particularly pre-sowing nutrient levels.

For canopy sensors to be most effective the signal needs to be translated into a decision. There are several successful commercial applications available however the decision support systems are developed for North American/European maize systems. For the decision support to work in Australia the tools need to be adapted a) for sweet corn and b) for Australian conditions. This will necessitate development/refinement of crop models. Immediate investment in this area is needed to ensure successful adoption of canopy sensors.

The large range in observed yield indicate that canopy sensors could be used crudely but effectively using intuitive agronomic knowledge of the farm systems. This could be done without either validating yield (harvest sensors) or a decision support system for VRT. One commercial proximal canopy sensor and an aerial image were used in this study. An investigation of the advantages of other canopy sensors and study of the optimal timing for sensing would assist growers who are keen to begin with a simple system.

Nitrogen application appears to be excessive in the sweet corn production system. Trials should be undertaken to determine how fertiliser inputs can be better optimised. This could be done in the traditional plot-trial method but would be better served using PA technologies and methodologies.

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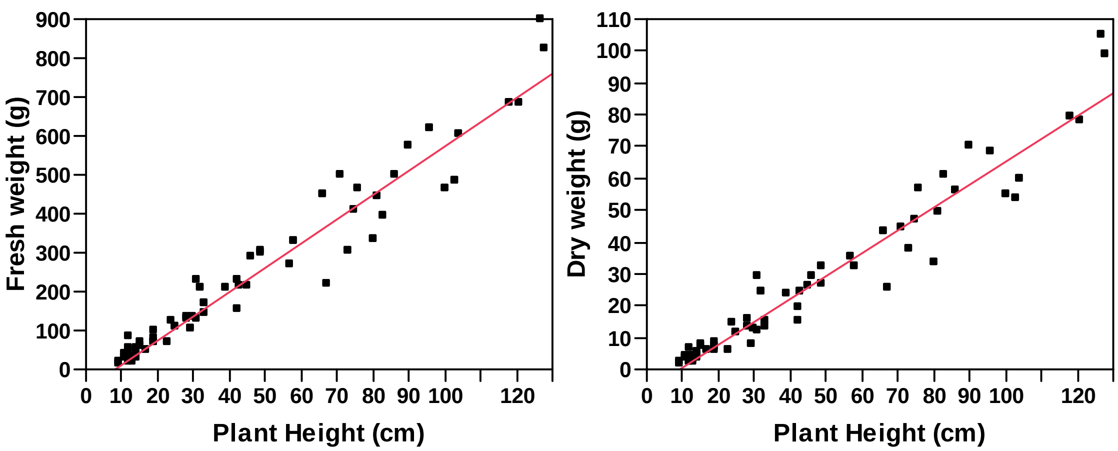
Appendices

APPENDIX A: Plant Height vs. Plant mass (Fresh and Dry)

Non-destructive sampling of plant biomass midseason was performed by measuring the height of plants to the top node of the primary culm. A sub-sample of 60 plants from the production system that covered the range of observed plant sizes were destructively sampled. The whole plant was harvested (including a root ball with soil). Plants were immediately transported to a lab (~4 hours after sampling) where the roots were removed. Individual plant heights (to the top node on the culm) and plant fresh weight were recorded. Plants were then dried in a drying oven (65ºC) before being weighted for dry weight.

A linear regression analysis was performed to determine the relationship between plant height and plant biomass (both fresh weight (FW) and dry weight (DW)).



FW (g) = -48.98861 + 6.2189861*Height

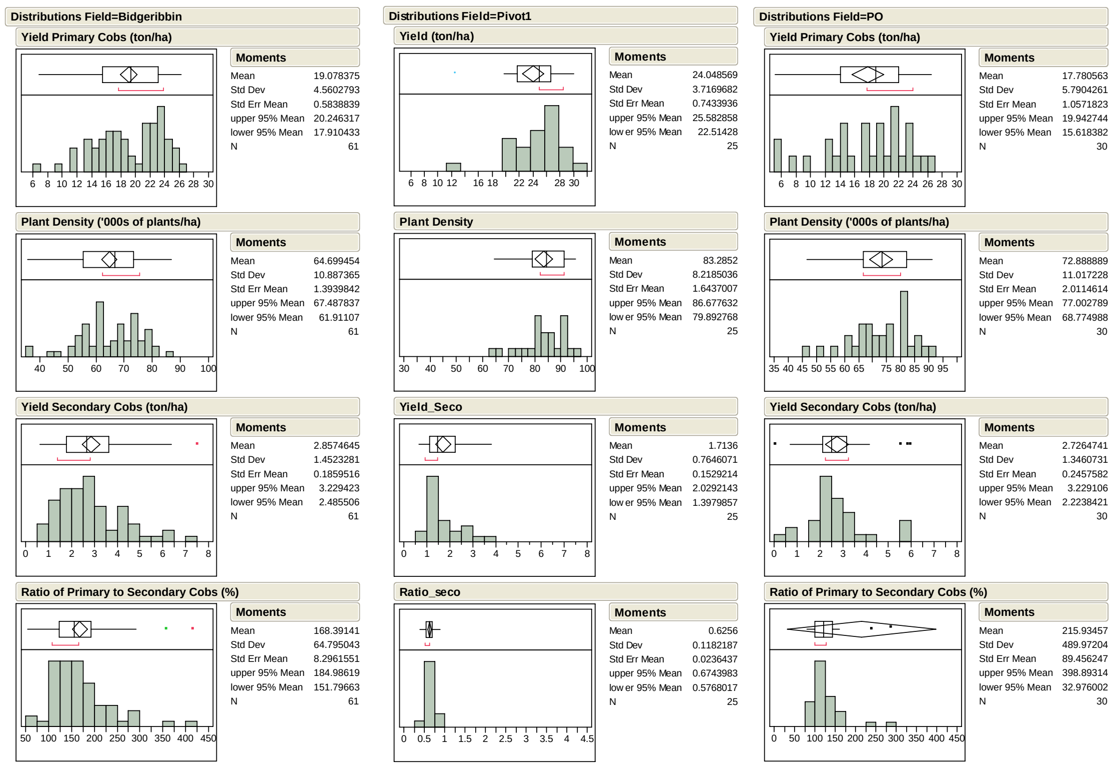
DW (g) = -6.549706 + 0.7158581*Height

Good linear fits were obtained for both FW and DW (r^2 = 0.95 and 0.94 respectively). This gave us confidence to convert the plant height data into a prediction of fresh and dry biomass. This was achieved using the plant count data (plant density) at each sample location.

This sampling covers a range of plant heights (10-120 cm) and was performed just prior to Nitrogen side-dressing of the crop. Measurements of plant height provide a good non-destructive method of estimating crop biomass.

APPENDIX B: Distribution of manually sampled harvest data

Distribution of Harvest Yield Data

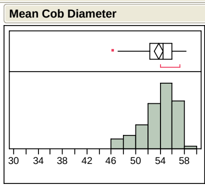


NB: Post Office ratio has one outlier not shown (one site had 28 primary cobs and only 1 secondary cob)

Distributions of Harvest Quality Data

Distributions Field=Bidgeribbin

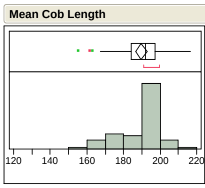
Mean Cob Diameter



Moments

Mean	53.818021
Std Dev	2.7732317
Std Err Mean	0.3550759
upper 95% Mean	54.528279
lower 95% Mean	53.107764
N	61

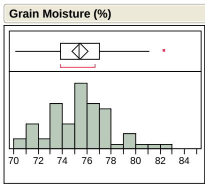
Mean Cob Length



Moments

Mean	189.72734
Std Dev	12.26137
Std Err Mean	1.5699076
upper 95% Mean	192.86762
lower 95% Mean	186.58705
N	61

Grain Moisture (%)

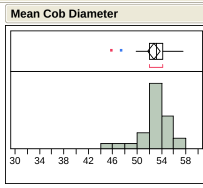


Moments

Mean	75.456536
Std Dev	2.5624277
Std Err Mean	0.330808
upper 95% Mean	76.118481
lower 95% Mean	74.794591
N	60

Distributions Field=Pivot1

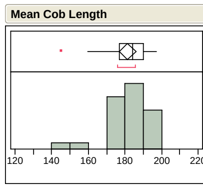
Mean Cob Diameter



Moments

Mean	52.818717
Std Dev	2.5160008
Std Err Mean	0.4934284
upper 95% Mean	53.834952
lower 95% Mean	51.802482
N	26

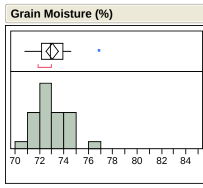
Mean Cob Length



Moments

Mean	181.54596
Std Dev	11.099328
Std Err Mean	2.1767574
upper 95% Mean	186.02907
lower 95% Mean	177.06284
N	26

Grain Moisture (%)

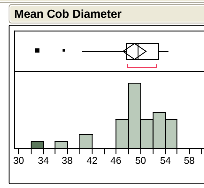


Moments

Mean	73.023404
Std Dev	1.2755386
Std Err Mean	0.2501537
upper 95% Mean	73.538605
lower 95% Mean	72.508203
N	26

Distributions Field=PO

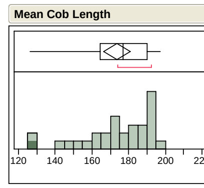
Mean Cob Diameter



Moments

Mean	48.975155
Std Dev	5.1615606
Std Err Mean	0.9423677
upper 95% Mean	50.902513
lower 95% Mean	47.047796
N	30

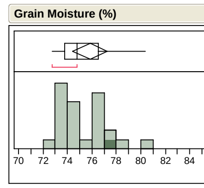
Mean Cob Length



Moments

Mean	173.72292
Std Dev	19.259343
Std Err Mean	3.5162589
upper 95% Mean	180.91448
lower 95% Mean	166.53136
N	30

Grain Moisture (%)



Moments

Mean	75.849089
Std Dev	3.3797967
Std Err Mean	0.6759593
upper 95% Mean	77.2442
lower 95% Mean	74.453977
N	25

APPENDIX C: Introduction to Variogram Analysis

For spatial data sets , where each data has a know location (x,y coordinate) then the theoretical spherical variograms can be calculated using the global variogram function in Vesper® (Minasny *et al*., 2005) and the variogram parameters (nugget variance (c_0), sill ($c_0 + c_1$) and the range (a)) that define the variogram can be recorded..

The c_0 value estimates the amount of variance at a lag distance of 0 m and is a function of stochastic effects and measurement error. The c_1 value estimates the amount of auto-correlated variance in these data and contributes with c_0 to define the sill ($c_0 + c_1$) or the total amount of variance in these data. The range defines the distance over which data are auto-correlated i.e. the distance at which the sill is reached.

The parameters from the variogram analysis can be used to calculate the Cambardella Index (Cambardella *et al*., 1994) and Mean Correlation Distance (MCD) (Han *et al*., 1994)

The Cambardella Index

$$\text{Cambardella Index} = \frac{c_0}{c_1 + c_0} \bullet 100$$

where		c_0 = nugget, $c_0 + c_1$ = sill,
and	<25	= Strong spatial dependency
	25–75	= Moderate spatial dependency
	<75	= Weak spatial dependency

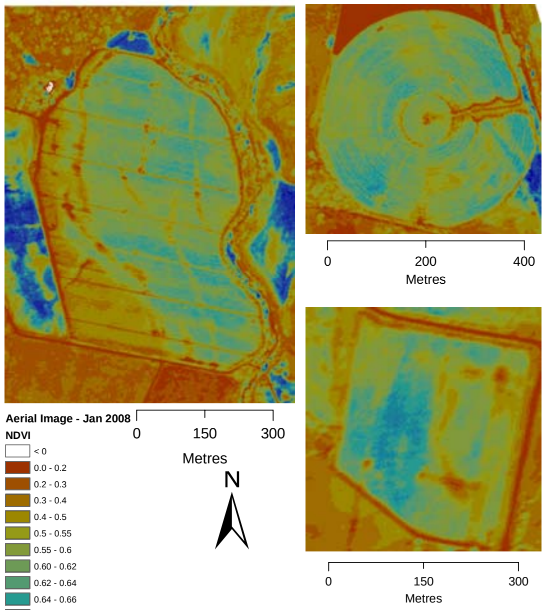
The Mean Correlation Distance (MCD)

$$\text{MCD (m)} = \frac{3}{8} \bullet \frac{c_1}{c_0 + c_1} a$$

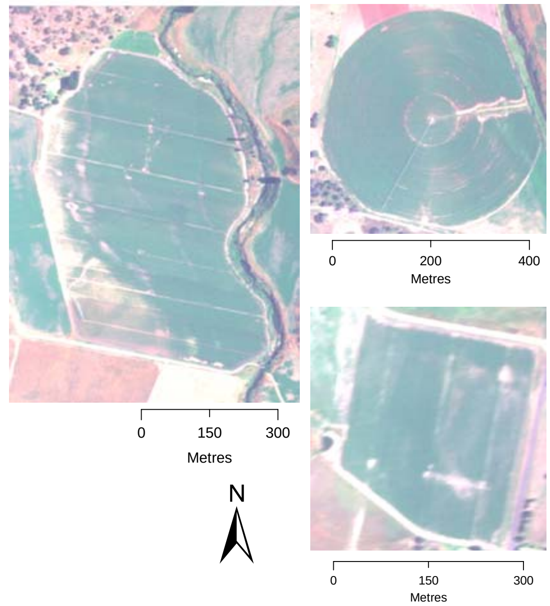
where c_0 = nugget, $c_0 + c_1$ = sill, a = range

Both the Cambardella Index and MCD provide some indication of the spatial structure in these data. The Cambardella Index is a ratio between the nugget (c_0) and the sill ($c_0 + c_1$) thus measures the amount of variance in these data that is auto-correlated and potentially manageable. Although no account is taken in the index of the range parameter smaller values are indicative of a stronger spatial structure (Han *et al*., 1994). The MCD is an empirical index, calculated in metres, that was originally derived for soil properties. The MCD includes the range of the data, as well as the ratio between the nugget and sill, to provide an estimate of the distance over which these data are auto-correlated. The greater the MCD the greater the spatial structure.

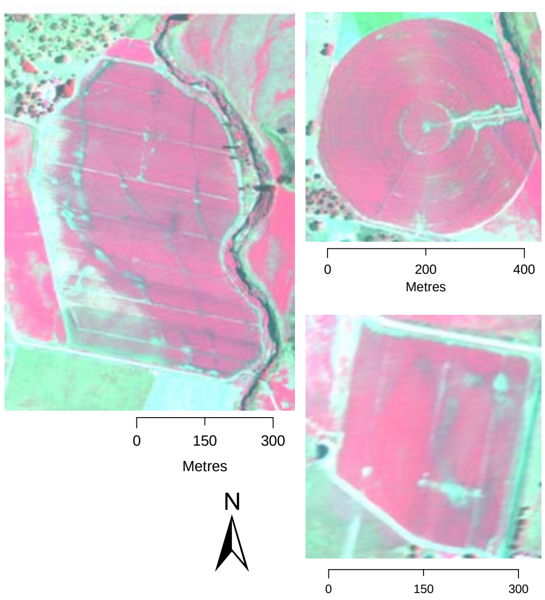
APPENDIX D: Maps of data



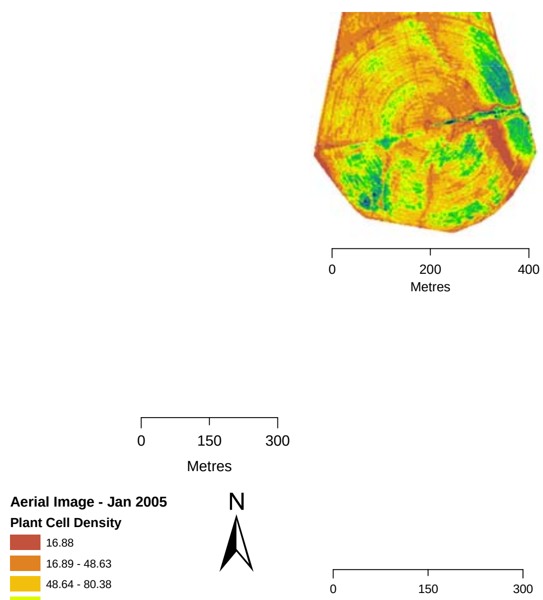
Normalised Differences Vegetation Index maps derived from multi-spectral aerial imagery taken January 15th 2008.



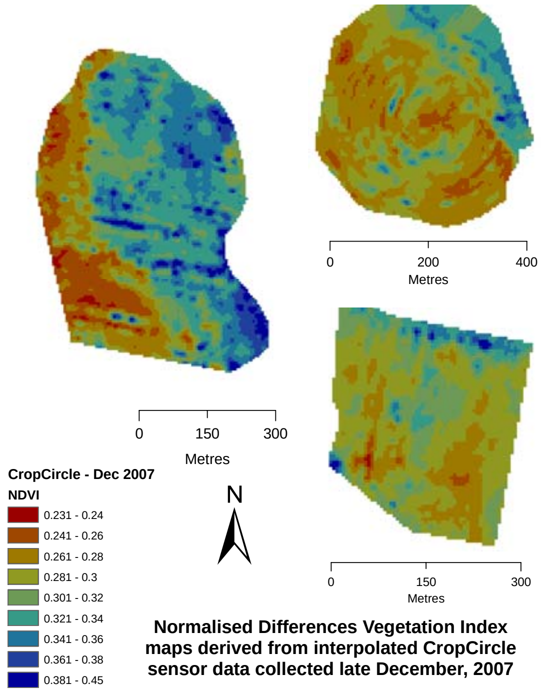
True colour aerial imagery taken January 15th 2008



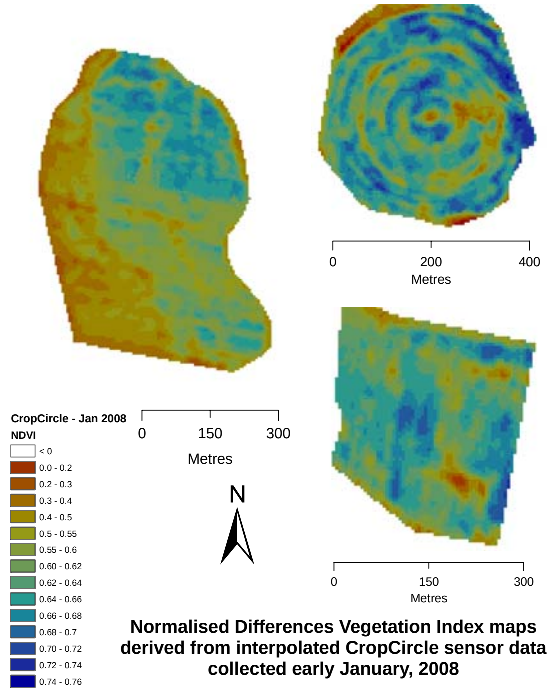
False colour aerial imagery taken January 15th 2008 (Green, Red, NIR bands)



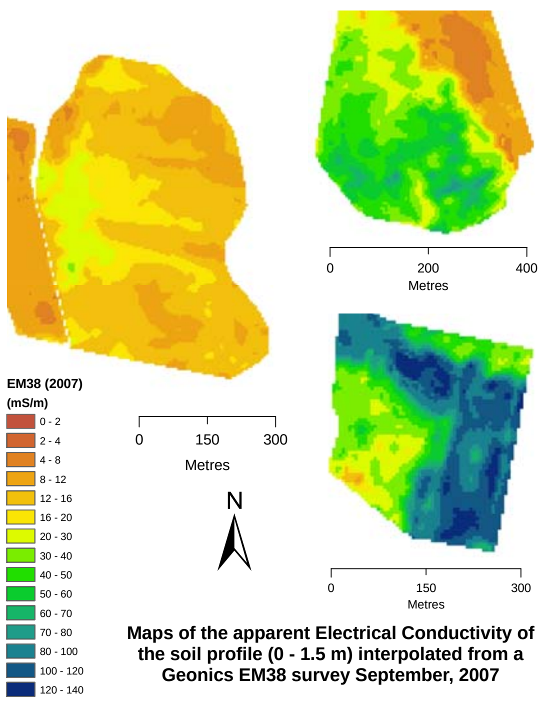
Plant Cell Density map from aerial image taken January 2005. (NB. No data collected for Post Office or Bidgeribbin in 2005)



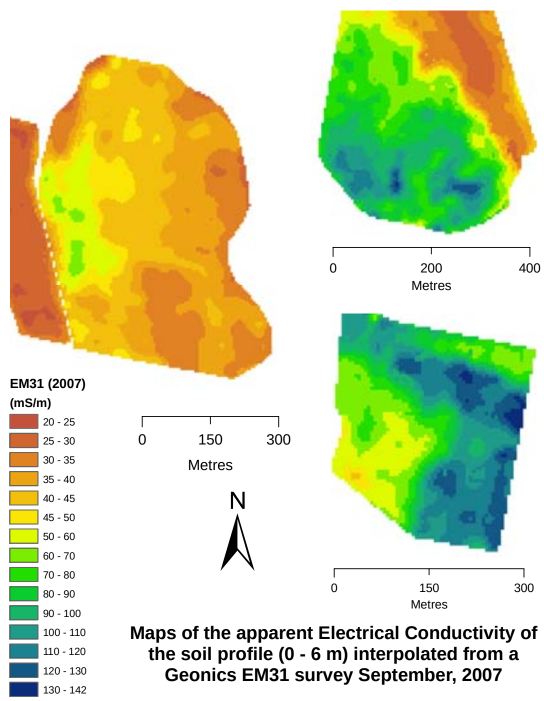
Normalised Differences Vegetation Index maps derived from interpolated CropCircle sensor data collected late December, 2007



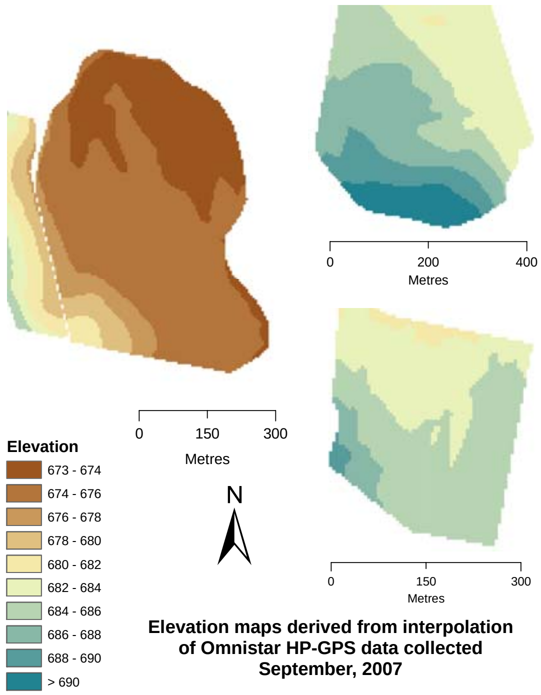
Normalised Differences Vegetation Index maps derived from interpolated CropCircle sensor data collected early January, 2008



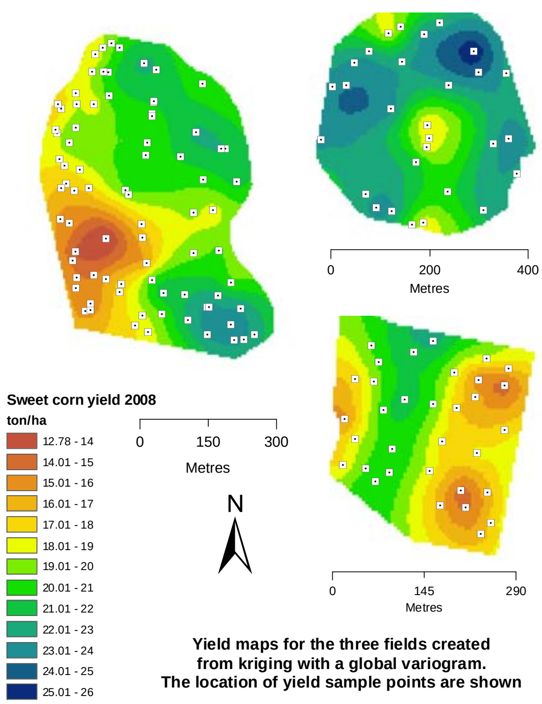
Maps of the apparent Electrical Conductivity of the soil profile (0 - 1.5 m) interpolated from a Geonics EM38 survey September, 2007



Maps of the apparent Electrical Conductivity of the soil profile (0 - 6 m) interpolated from a Geonics EM31 survey September, 2007



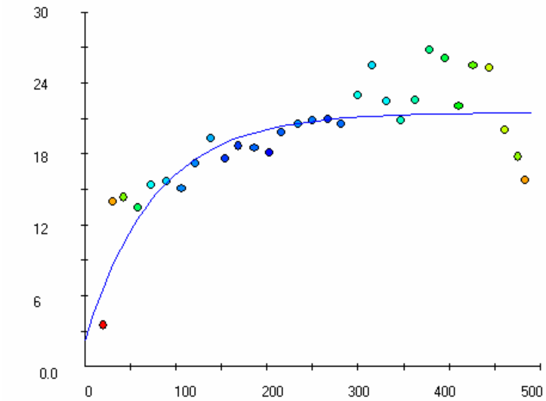
Elevation maps derived from interpolation of Omnistar HP-GPS data collected September, 2007



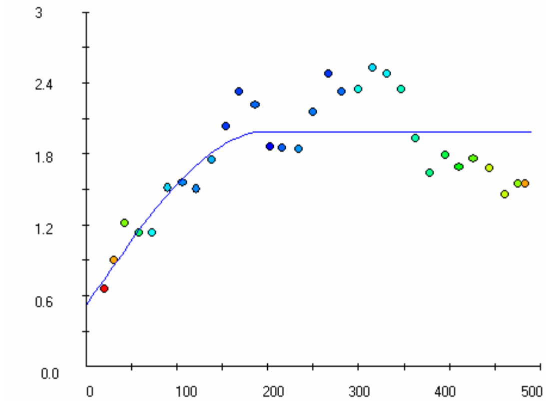
Yield maps for the three fields created from kriging with a global variogram. The location of yield sample points are shown

APPENDIX E: Variograms of Harvest yield and quality parameters

Primary Yield



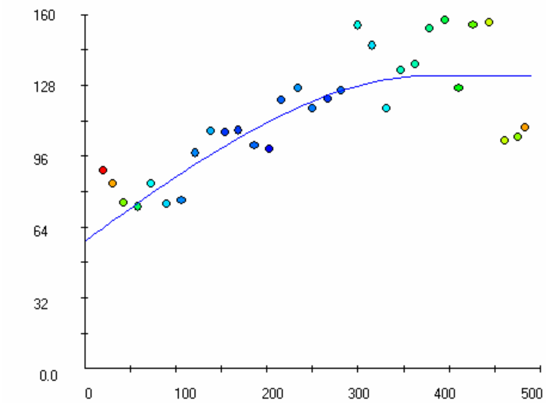
Secondary Yield



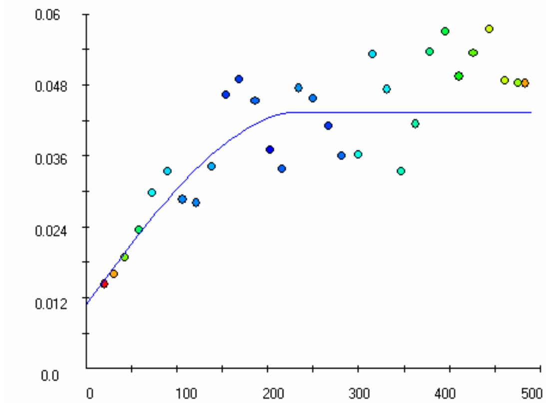
Variogram Parameters

	C_0	C_1	Range	Model
Yield 1º	2.146	19.37	76.61	exponential
Yield 2º	0.5167	1.474	197.7	spherical

Plant Density



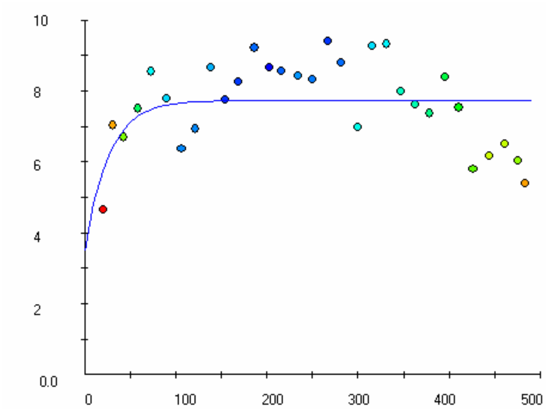
Ratio primary:secondary cobs



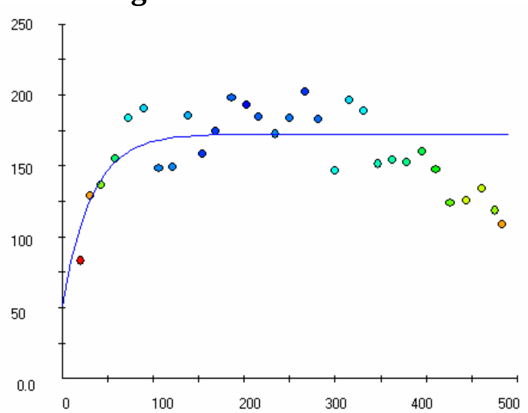
Variogram Parameters

	C_0	C_1	Range	Model
Density	57.64	74.88	380.3	spherical
Ratio	0.01087	0.03256	236.1	spherical

Cob Diameter



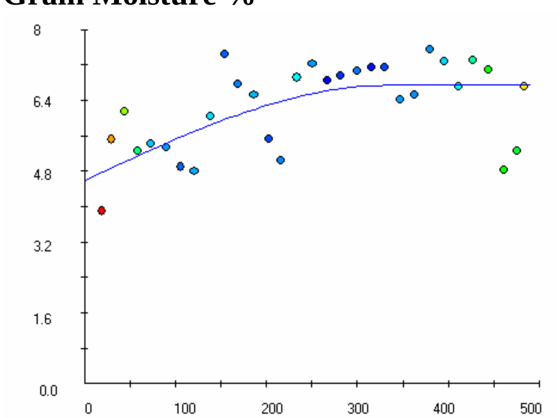
Cob Length



Variogram Parameters

	C_0	C_1	Range	Model
Cob Diameter	3.485	4.255	26.08	exponential
Cob length	51.21	121.4	32.24	exponential

Grain Moisture %



Variogram Parameters

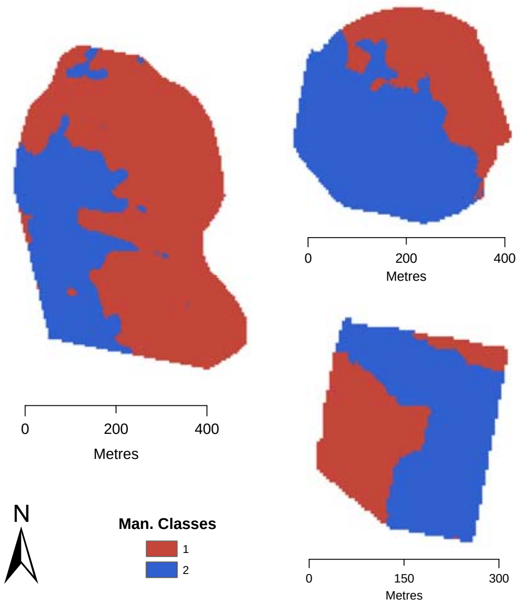
	C_0	C_1	Range	Model
Grain Moisture (73 samples)	4.587	2.157	336.4	spherical

APPENDIX F: Management Class response to Midseason and Harvest samples

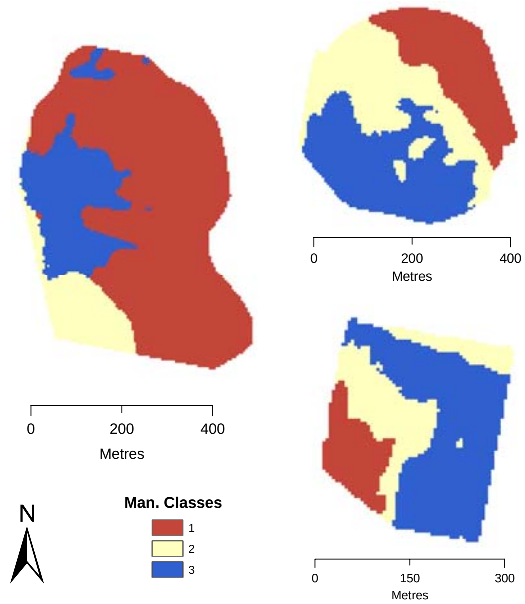
Field	Management Class	Plant Density Midseason)	Plant Height	Tiller %	Cob Length	Cob Diameter	Yield (1^o Cobs)	Yield (2^o Cobs)	Grain Moisture %	Insect Pressure %	Plant Density Harvest	Ratio 1^o to 2^o Cobs	Leaf Tissue N
Bidge-ribbin	$Soil_2$	10.1	-2	-4.8	-0.2	-0.1	-1	-0.7	0.8	4.9	-1.1	-1.1	-5.5
	$Soil_3$	6.5	0.9	-10.3	2.3	2.2	-0.7	-2.2	3.2	7.1	2.1	-2.5	-0.3
	$Crop_2$	*34.5*	*34.1*	-4	-1	-0.9	5	-1.2	-1.3	-1.1	0.3	-0.4	*10.5*
	$Crop_3$	**67.8**	**63.3**	-4.6	3.7	4	*10.7*	0.4	2.7	3.8	4.6	0	3.9
	All_2	*34.5*	*15.7*	-4.6	-1.3	-1.3	2.8	-1.2	-0.9	-0.6	-0.7	-1.2	-3.8
	All_3	*31.8*	*13.6*	-5.2	-1.1	-1.4	-1.5	-0.8	0.1	1.1	-1.4	-2.3	*15.9*
Pivot 1	$Soil_2$	*23*	***40.4***	-5.5	-2.2	-2.9	-2.2	-3.2	-3.7	.	-3	-2.4	-6.1
	$Soil_3$	5.4	*17.8*	3.3	1.4	-0.6	4.6	-3.4	7.8	.	2.2	-4.7	4.5
	$Crop_2$	3	*17.5*	5.9	*26.4*	*26.4*	*19.2*	5.3	4	.	23	*22.2*	2.6
	$Crop_3$	-7.2	8.1	*19.8*	*27.6*	*27.1*	*14*	2.8	-3.8	.	*28.7*	*19.1*	6.5
	All_2	*11.1*	**33.1**	-5.6	*24.6*	*25.3*	*15.5*	5.6	-6.4	.	*23.4*	*18.1*	-4.4
	All_3	*10.4*	***42.8***	-3.4	*22.4*	*23.1*	*12.1*	1.9	*13.7*	.	*25.4*	*15.4*	6.5
Post Office	$Soil_2$	***37.1***	*23.2*	1.4	-1.9	-2.7	-3.1	-3.2	-2.5	-2.9	-2.6	-2.9	-4.8
	$Soil_3$	*21.9*	*28.8*	-3.3	*14.6*	*15*	*21.4*	2.4	-4.7	-4.9	8.6	1.4	-16.3
	$Crop_2$	***37.1***	***30.7***	*14.7*	2.7	3.8	*24.2*	*22.5*	0	-2.3	5.2	*18.9*	*26.2*
	$Crop_3$	***42.1***	**53.7**	***32.2***	3.1	3	*19.4*	*21*	*23.6*	*11.3*	-1.6	*10.9*	*18.7*
	All_2	***37.1***	*23.2*	1.4	-2.4	-3	-1.5	-2.8	-2.5	-2.5	-3.1	-3.2	-4.8
	All_3	***38.8***	*20.4*	-2.3	6.1	3.1	*12.1*	0.4	2.7	2.4	-3.3	-0.1	-6.5

R2 values (percentage of variation explained) for different Management Class Models across a range of crop measurements.

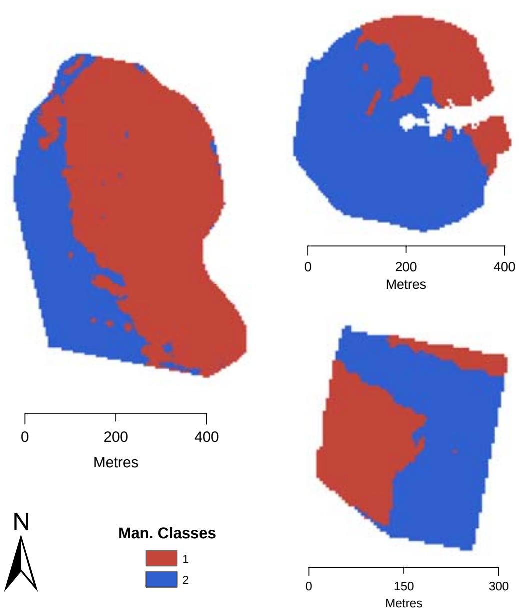
APPENDIX G: Maps of Management classes derived from Soil and Soil+Crop data



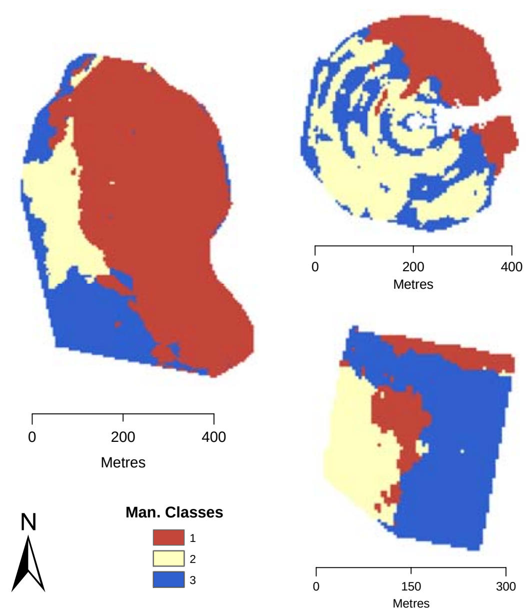
Management Classes based on soil sensor data (Geonics EM38 and EM31 and RTK-GPS elevation 1 = low ECa, 2 = high ECa)



Management Classes based on soil sensor data (Geonics EM38 and EM31 and RTK-GPS elevation 1 = low ECa, 2 = mid ECa, 3 = high ECa)



Management Classes based on all sensor data (Geonics EM38 and EM31, RTK-GPS and NDVI (Crop Circle and aerial imagery, 1 = high NDVI, 2 = low NDVI)



Management Classes based on all sensor data (Geonics EM38 and EM31, RTK-GPS and NDVI (Crop Circle and aerial imagery 1 = high NDVI, 2 = mid NDVI, 3 = low NDVI)

APPENDIX H: Results of regression analysis

a) Yield Models

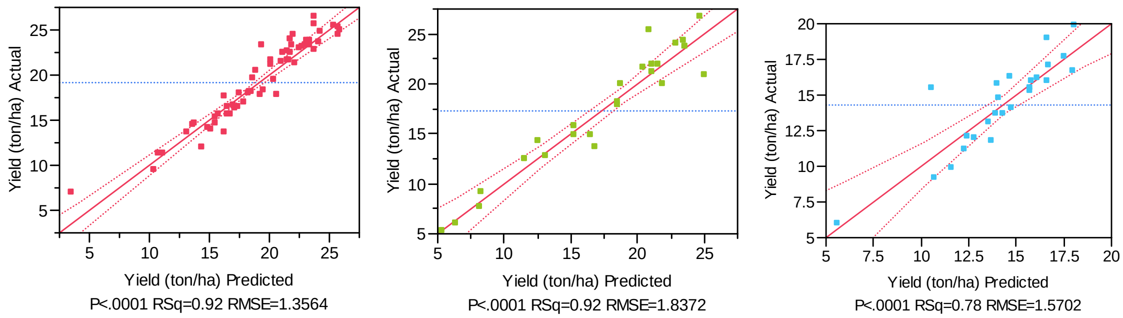


Figure H1: Plots of model fits and model parameters for prediction of yield using cob length, plant density and moisture content. Plots show left -Bidgeribbin (red), centre – Post Office (green) and right - Pivot 1 (blue)

Regression equations for prediction of yield for the three fields:

Bidgeribbin

Yield (ton.ha^{-1}) = -45.902 + 0.287*Plant Density + 0.208*Cob Length (mm) + 0.091*Moisture %

Post Office

Yield (ton.ha^{-1}) = -32.676 + 0.221*Plant Density + 0.213*Cob Length (mm) + -0.033*Moisture %

Pivot 1

Yield (ton.ha^{-1}) = -36.427 + 0.250 * Plant Density + 0.156*Cob Length (mm) + 0.0216365132313533 * Moisture %,

b) Quality Models

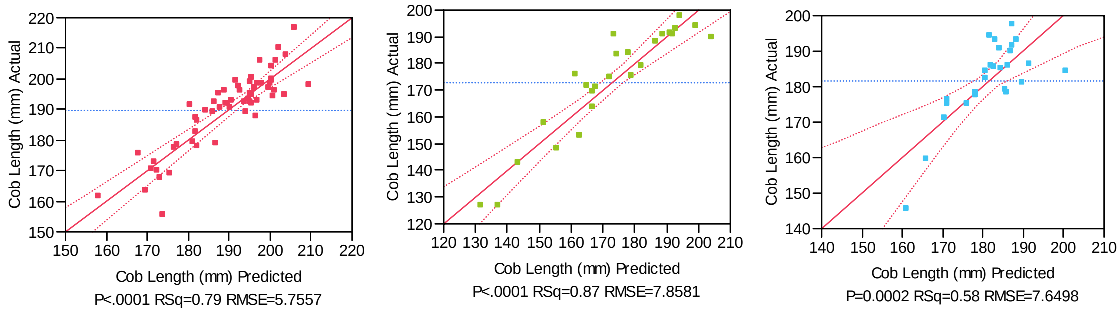


Figure H2: Plots of model fits and model parameters for prediction of cob length using yield, plant density and moisture content. Plots show left - Bidgeribbin (red), centre – Post Office (green) and right - Pivot 1 (blue)

Regression equations for prediction of yield for the three fields:

Bidgeribbin

Cob Length (mm) = 196.884 + -1.029*Plant Density + -0.160*Moisture % + 3.751*Yield (ton/ha)

Post Office

Cob Length (mm) = 167.133 + -0.742*Plant Density + -0.115*Moisture % + 3.890*Yield (ton/ha)

Pivot 1

Cob Length (mm) = 193.983514149634 + -0.882445577356955 * Plant Density + 0.111008737142057 * Moisture % + 3.70659393888917 * Yield (ton/ha)

APPENDIX I: Comments on harvest sensors.

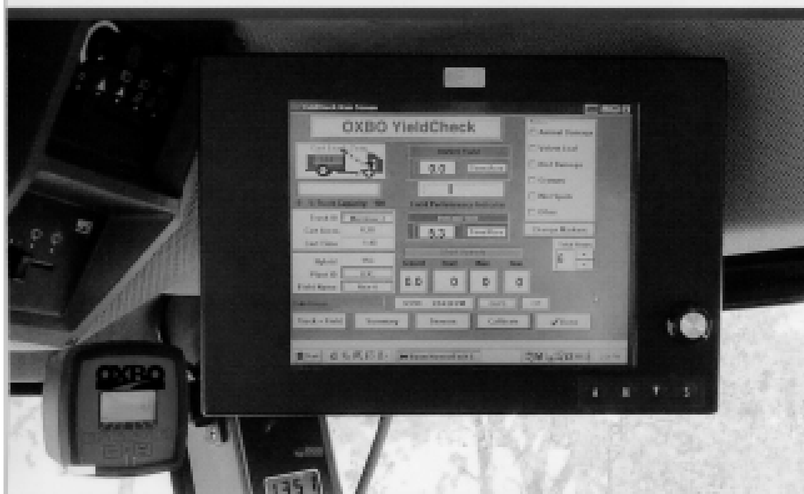
In the mid to late 1990s Byron Enterprises and Oxbo Corporation invested in the development of a yield monitor for sweet corn harvesters. These are the harvesters that are used by Simplot in Australia. Contact has been made with Mr Brian Maul (Oxbo Corp. Project Manager – Processed Veg. Equipment) regarding these sensors and options for leasing or purchase of a sensor if available. This avenue should be exhausted before moving onto other options.

Other potential options are adaptation of an existing system. Load cell-based yield sensors may be difficult due to the short horizontal platform on the discharge conveyor. A light sensor (similar to a cotton sensor) may be possible at the end of the discharge conveyer. A prototype system like this has been trialled at the end of the discharge conveyer in grapes with some success. An alternative is to use an imaging sensor. Rapid imaging of the corn on the sensor belt could be be calibrated for cob size (length and diameter) as well as yield. Any sensor not directly measuring mass will be subject to eror induced from variable moisture contents.

The reliable, low maintenance, accurate sensor is obviously the goal but an imperfect sensor will still be of enormous value since no other information is available. The sensor signal can always be recalibrated to field means or smoothed to remove noise.

HarvestTech System™

A highly advanced system for accurate yield monitoring, mapping capabilities, diagnostics and remote communication.



Yield monitor combines GPS tracking and precise data collection for accuracy of ± 3%.

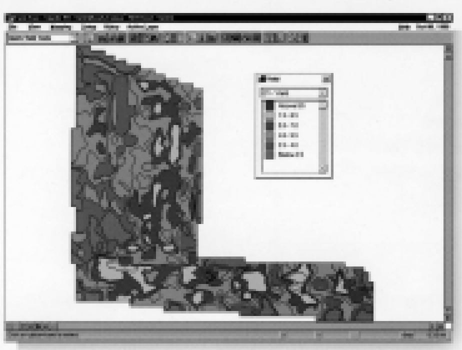
The OXBO *HarvestTech System (HTS)* is a harvest management tool combining four unique applications on your laptop with a sunlight readable, high bright monitor and a ruggedized mouse. PC based system is an industry first. The system includes:

- ***YieldCheck*™** ...a yield monitor for sweet corn and seed corn harvesting.
- ***TechBook*™** ...on-line operator, service and parts manuals.
- ***TechTools*™** ...for total machine monitoring with diagnostics.
- ***TechTalk*™** ...remote access for machine monitoring and data transfer.

Accurate Yield Mapping and Monitoring

The OXBO *YieldCheck* function monitors yield with a high degree of accuracy producing invaluable GPS tracking and mapping information. A database is initially loaded into the HTS software. During harvest, the operator selects a field, hybrid, processing plant and a truck to begin recording both yield for the field and truckload information. The operator knows when each truck has reached maximum load and changes trucks. Truckload monitoring aids fleet management in the field and provides a database for post season analysis.

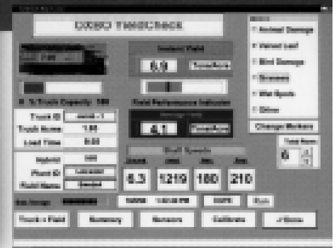
For mapping functions, data is stored in standard HarvestMaster™ format and can be used in many yield mapping and analysis programs. The yield maps can be viewed at any time on the HTS system using Farm Works™ software — Quick Yields™. The screen displays yield maps using the mapping software for instant feedback on any field.



The patented yield monitor uses a unique combination of load, angle and speed sensors to determine yield with speed adjusted DGPS location correction for mapping accuracy. In addition, up to six markers can be toggled on and off, which can later be mapped to identify factors affecting yield such as wet spots or weed infestations.

U.S. Patent No. 5,959,257
6,066,809

The OXBO HTS system uses a standard laptop computer, a screen readable in sunlight, and a rugged sealed mouse conveniently located at the operator's finger tips.



Sample HTS screen showing YieldCheck data recording features.

The PC based HTS System comes complete with angle sensors, load cell, *HarvestMaster* signal conditioner, laptop holder, console mounted mouse, AC/DC inverter, 10.5" High Bright cab monitor and mount.

Software included: *OXBO HTS* and *QuickYield* from *FarmWorks* for map generation.

On-Line Service Support

The OXBO *TechBook* function provides on-line operator, service and parts manuals. With a simple touch of a button, the operator can select any of the manuals needed for operation description, troubleshooting or parts description.

On-The-Spot Diagnostics*

TechTools on-board diagnostics displays all sensor output information. The system provides immediate interface and voice output warnings. Along with machine monitoring, this feature improves machine uptime with recorded performance changes, scheduled preventive maintenance and increased information availability.

Remote Access to Information*

TechTalk allows for remote access for data transfer of yield summary, truckload history, and diagnostics for complete management of operator and machine resources.

Chosen for the 1999 AE50 Award!

The OXBO *HarvestTech System* has been selected as an outstanding new product by *Resource* magazine, published by the American Society of Agricultural Engineers. The award is given to the best of the most innovative new products.

The HTS system provides the only available yield monitor for the sweet corn and seed corn processing industries, producing accurate information for precision farming. The combination of multiple systems in a standard laptop PC is the first of its kind in the industry.

OXBO International Corporation leads the field in research and development. The advanced technology of the HTS system is further indication of the company's resources along with its capabilities for introducing innovative concepts and providing practical technological application.

* *Currently under development.*

OXBO

OXBO International Corporation

Helping you harvest the future.

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APPENDIX J: Mean field results for yield and quality parameters from the factory (courtesy of Simplot Australia).

District	Grower	Variety	Paddock	Gross Load Wt (ton)	Grower Paid Tonnes	Mean of Moisture %	Mean Cob Length (mm)	Mean Cob Diameter (mm)	Area (ha)	Yield (ton/ha)
Bathurst	McSpedden	Punch	Bidgeribbin	551.78	485.13	69.49	192.33	51.33	24.5	19.8
Bathurst	McSpedden	Punch	Post office	161.92	144.33	68.01	208	50	9	16.04
Bathurst	McSpedden	Punch	Pivot 1	394.66	349.47	69.27	192.67	51	16.5	21.18