Potential applications of Unmanned Aerial Vehicle multispectral imagery in vegetables

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Summary

A proof of concept project using UAV technology was conducted in conjunction with Rugby Farms, Gatton to assess the potential application of UAV crop sensing imagery in vegetable systems.   The work focused on 2 key areas: detection of Sclerotinia in green beans using NDVI as an indicator of crop stress; and the development of predictive capacity for yield and final plant parameters. Green beans, lettuce, sweet corn and broccoli were the key crops studied.

Sclerotinia was evident in field sampling of green bean crops but not in the initial crop sensing data. Higher resolution flights at key crop stages might have been more successful. UAV NDVI imagery successfully identified spatial variability in all crops. Small plot yield assessments in green beans identified a 20% reduction in yield in lower NDVI areas (approximately 27% of the field).

In additions to identifying spatial variability, UAV NDVI imagery was also utilised to determine what predictive capacity could be developed for yield and final plant parameters across the experimental sites. The small scale assessments reported here confirm that early season variability is maintained through to maturity suggesting that early season data measurements could be used to predict final yield and plant characteristics.

Classification and automated counting process were applied to corn data as a mechanism for potentially predicting final yield. The automated corn counts were 10% less than manual counts. Automated counts of lettuce were 98% accurate relative to manual counts. Field measurements of plant parameters (plant and head diameter and final weights) were highly correlated with predicted harvest data (R^2 0.608-0.915).

Given the project was a small scoping study, significant development would be required to further assess this application of technology in vegetable systems. This would include refinement of the algorithms and classification counting processes with significant larger datasets and rigorous validation and testing.

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Background

Precision agriculture (PA) technologies, such as crop biomass sensing, have until recently had limited adoption into Queensland vegetable production beyond GPS guidance systems. The Australian Government funded Department of Agriculture and Fisheries (DAF) project 'Adoption of variable rate technologies into Queensland's intensive vegetable production systems' has focused on implementing and optimising a range of PA technologies in vegetables over the last 2 years (Limpus *et al.* 2016).

Collaboration between DAF and Boeing Australia in 2014-15 as part of this project involved the use of UAV technology to monitor onions in south-east Queensland with the aim of developing specific analytical algorithms that could be used in a predictive capacity. The initial Agri-Science Queensland Innovation grant proposal aimed to build on this existing collaboration with Boeing Australia by groundtruthing the progression of white rot in red onions for the development of an algorithm with predictive capacity for disease incidence. However, after acceptance of this project proposal, Boeing Australia notified DAF that it would no longer be undertaking UAV flights in 2015 and the situation had still not been clarified for 2016. Given these circumstances the project leader was advised to redevelop the project into something with similar objectives that would be able to be sufficiently resourced. The work presented here reflects a redevelopment of the initial proposal as a scoping study to assess the potential applications of UAV imagery to vegetable systems.

Remote sensing has been successfully used in a range of crops, primarily broadacre (cotton and grains) for a range of purposes related to soil and crop variability (De Benedetto *et al.* 2013; Hatfield and Pinter Jr 1993; Schofield *et al.* 2016; Seelan *et al.* 2003). The Normalised Difference Vegetation Index (NDVI) has been the primary vegetation index used. NDVI is calculated from the visible and near-infrared light reflected by vegetation (**Figure 1**). Healthy vegetation absorbs most of the visible light it intercepts and exhibits higher reflectance of near-infrared light. Unhealthy or stressed vegetation reflects less near-infrared light and more visible light.

A range of imagery options can be deployed utilising UAV's, increasing the potential application of this technology in agriculture. Advances in technology now mean that UAV's can offer precise navigation. Reduced instrumentation weight and size improves their potential as a remote sensing alternative compared with previously available remote sensing options. With advances in drone technology, the number of operators in the marketplace is rapidly growing. However, much of this service delivery is focused on imagery capture and provision of photos or a multi-colour map with little interpretation or further analysis.

Figure 1 Reflectance of Red/ Green/ Blue and NIR light from a healthy and unhealthy leaf (left) and calculation of NDVI from a healthy and unhealthy plant (right). Source: Basics of crop sensing, Alabama Cooperative Extension System www.aces.edu
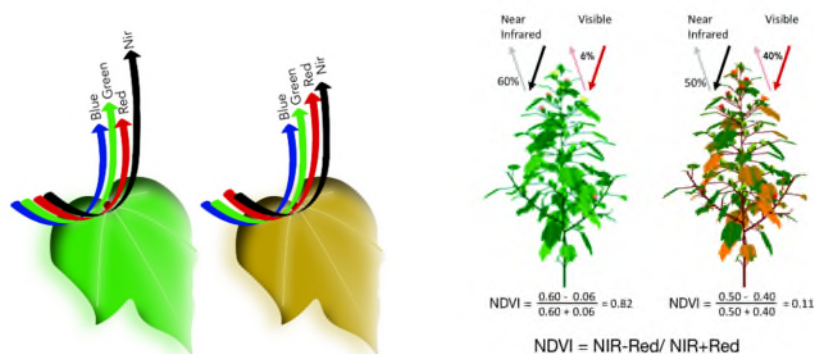
The application of these technologies to assess or predict plant parameters has been extremely limited in vegetable crops (Yang *et al.* 2008). This project aimed to scope on a small scale the

potential for UAV technologies to be used to assess and develop predictive capabilities for a range of crop parameters including: disease detection using remote sensing; accurate prediction of yield from early season automated counts and sizing; and forecast of market specification information.

Project Objectives

The objective of this small project was to assess the potential application of UAV crop sensing imagery in vegetable systems including:

- Detection of diseases in green beans
- Early season crop counting and sizing of lettuce and broccoli to predict maturity and yield from crop vegetation indices
- Optimal timing and resolution of imagery for different purposes without compromising data quality and cost effectiveness

Methodology

An initial meeting between DAF, Airborn Insight (UAV operator) and Rugby Farms (grower co-operator) identified green beans, sweet corn, lettuce and broccoli (data not shown) as key crops for image capture. Key crop stages for flights were identified to optimise the amount of information we could obtain from the minimal number of flights (**Table 1**). Rugby farms indicated that for their business, plant counts and sizing of crops for predicting harvest timing and potential yields would be key areas of interest.

Table 1 Crop and flight plan

	Flight 1	**Flight 2**	**Flight 3**	**Flight 4**	**Comments**
Green beans (x3)	√	√	√		Weekly flights x 3 from flowering
Sweet corn	√			√	Early crop and silking
Lettuce			√		Early crop before plants touching

Unmanned Aerial Vehicle

A Toowoomba based UAV business Airborn Insight was selected to perform UAV services relating to this project as the only commercial operator that could also support image processing, statistical analysis and the development of algorithms for automated image analysis. The UAV utilised for this work was multirotor aircraft (**Image 1**) fitted with a Red Edge 5 sensor multispectral camera with narrow band channels optimised for agricultural crops (**Table 2**). Also included on the UAV was a 20 megapixel RX 100 III Sony camera for the development of 3D crop models. Post processing of the images from this camera generates final images of 500-1000 megapixels. The two cameras were mounted on the UAV during each flight to collect both multispectral images and high resolution photos that could be post processed into 3D models for analysis. Flight heights were manipulated to achieve the desired ground resolution depending on the data analysis requirements. Depending on the site and project objectives the resolution of each pixel ranged from $0.7cm^2$ (25 m flights with Sony) – $8.2cm^2$ (120 m flights with Red Edge).

Image 1 UAV craft used in this scoping study

Table 2 Attributes of sensors used to collect aerial imagery for the project

Sensor	Attributes
Red Edge Multispectral Camera	8.2 cm resolution at 120 m above ground level (AGL) Reflectance bands: Blue (475 – 495 nm) Green (560 – 580nm) Red (668 – 678nm) Rededge (717 – 727 nm) Near-Infrared (840 - 880)
Sony RX100 III camera	20 megapixel / 3.3 cm resolution at 120 m AGL

The 5 sensor multispectral camera utilised in this work generated a range of vegetation indices:

- NDVI/NDVI2 – Normalised Difference Vegetation Index with values ranging from 0 to 1. The software used for post-processing this work only uses NDVI values greater than 0.5 in the NDVI mapping layer whereas NDVI2 visualises all NDVI values between 0 and 1.
- NDRE – Normalised Difference Red Edge Index, calculated similarly to NDVI but using the Red Edge reflectance band rather than the Red band.
- NRG – Near infra/Red/Green to visualise the amount of infrared light reflected.
- RGB – Red/ Green/ Blue, a true-colour representation of the crop
- DSM – Digital Surface Model, generated to visualise changes in topography

Field sampling

A range of field sampling activities were carried out to groundtruth the UAV imagery, **Table 3**.

Table 3 Field sampling plan

Crop	Field sampling
Green beans	Weekly crop scouting for disease post flower, manual yield assessment (4 x 1m rows)
Sweet corn	Hand harvested yield assessment (8 x 4m rows)
Lettuce	Plant parameter measurements early season (plant diameter) and end of season parameter measurements (plant and head diameter and weight) in marked plots

In crop disease inspections were carried out by the Project Leader with assistance from John Duff, Senior Plant Protectionist, DAF. Hand harvested yield assessments were replicated 4 times and involved removing and weighing all produce within a delineated length of row. This weight was then converted to a tonnes per hectare value.

Data Processing and Analysis

Imagery was available within 24 hours of capture and viewed through the Atlas MicaSense website e.g. https://atlas.micasense.com/data/map/public?token=rJVyFeH74C7pemhzoxKfAw

This website also has a geo-locator tool which facilitated tracking the location of personnel in the field for groundtruthing activities. Data analysis was completed by Airborn Insight staff. For the lettuce analysis, an automated process was used on jpeg imagery to separate NDVI signatures. The corn analysis used training software in ArcGIS.

Results

The following results summarises the key findings from this work.

Disease detection in green beans

Field sampling detected Sclerotinia in scattered individual plants in only one of the UAV mapped fields. Initial imagery was captured at a flying height of 90 metres. Though variability in plant vigour was clearly defined using the NDVI index at this height, the resolution was not sufficient to detect changes at an individual level due to Sclerotinia. At the resolution achieved it was possible to detect where 'pinching in' of the plant canopy occurred (**Image 2, left**) due to missing/lost plants or reduced plant growth. It is possible some of these areas were due to Sclerotinia.

Image 2 Green beans NDVI imagery at first flower at 90m AGL (left – circles highlight 'pinching in' of plant canopy), diseased plant (top right) and Sclerotinia in green beans (bottom right)
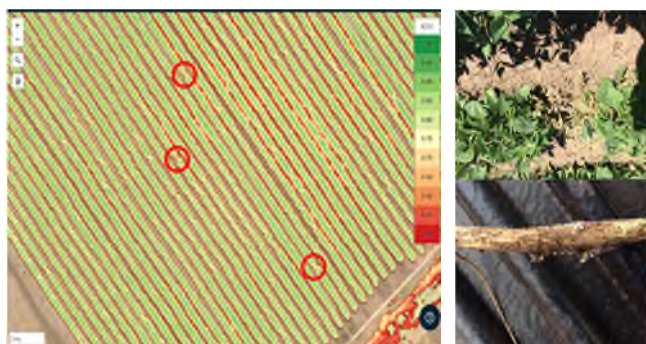
This crop was subsequently mapped at a flying height of 25 metres AGL. At this stage of the crop, the canopy growth was much greater and the NDVI index had saturated making it harder to discern variability in plant vigour. It is possible that if this higher resolution flight had have occurred earlier in the crop i.e. first flower then stress to individual plants may have been evident.

Detecting spatial variability

The NDVI imagery of this same bean field did successfully identify spatial variability (**Image 3**). The area of lower NDVI values accounted for approximately 27% of the field (**Appendix 1**). The discrepancy in NDVI values was further reflected in plant heights (10% shorter plants in lower NDVI areas) and final hand harvested yield assessments (**Image 3 and Image 4**), with a 20% reduction in yield between higher NDVI and lower NDVI small plots sampled (**Figure 2**). This discrepancy could be greater or less across the total area of the field but this is impossible to determine without spatial yield mapping or an accurate algorithm that could estimate yield from NDVI imagery. Further groundtruthing activities such as EM38 soil mapping or strategic soil and plant tissue testing would likely provide more information about soil characteristics and nutrient status that could be impacting on plant growth.

Image 3 NDVI imagery of green beans (centre) and zoomed in to each end of the field (left) and size of green bean plants from each of the areas indicated (right)
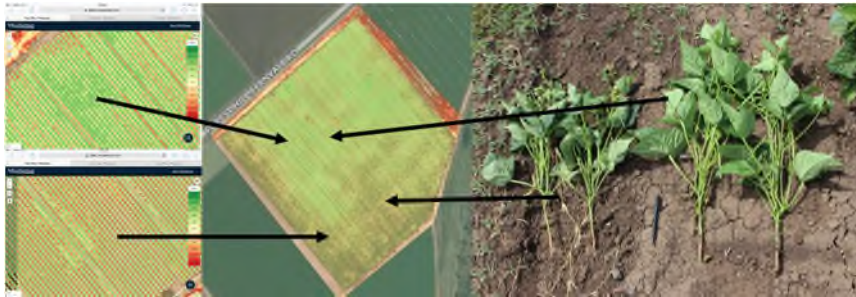
Image 4 Green beans harvested from 1 metre of plants from highest yielding plot and lowest yielding plot sampled from the areas indicated by the arrow tips in Image 2.

Figure 2 Yield from hand harvested small green bean plots compared with the NDVI value 3 weeks prior to harvest
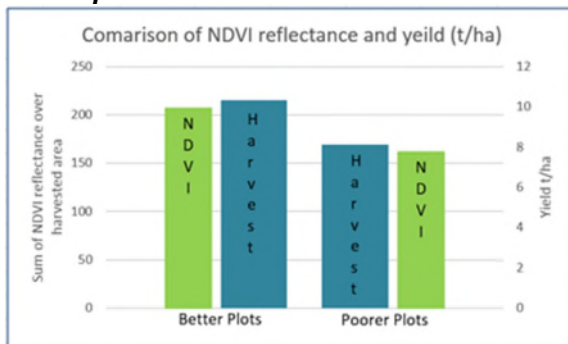
The UAV imagery for the pre-harvest bean crop (at 90m AGL 3 weeks before harvest) was used to calculate the NDVI reflectance values from each hand harvested plot to test its predictive capability. In total 369 pixels over 1m^2 were assessed from each plot and summed for the lower NDVI or higher NDVI plots to get a total NDVI score for each treatment. The NDVI score was closely correlated to the hand harvested yield data and had a 21% reduction in NDVI reflectance values from the poorer sites when compared to the better sites (**Figure 2**). This result suggests that with further development, early crop imagery could be used to assess yield potential in beans prior to harvest.

Counting and Sizing Lettuce

Image 4 depicts some of the spatial variability that can be evident in lettuce crops. Field based photo, UAV RGB and NDVI imagery (**Image 5**) indicates the same marked plot in all images. Image capture methods and algorithms were developed to count and size those plants highlighted within the marked plots (**Image 5 and Appendix 2**). Automated lettuce counts were conducted for 4705 m^2 (48 paired rows), with 37,879 plants counted, which was 98.3% of the manual count estimate of 38,520.

Image 5 Comparison of on ground photo (left), high resolution digital image (centre) and NDVI imagery (right) of a lettuce field 4 weeks after transplant (the same 2 metres of row are highlighted in each image)
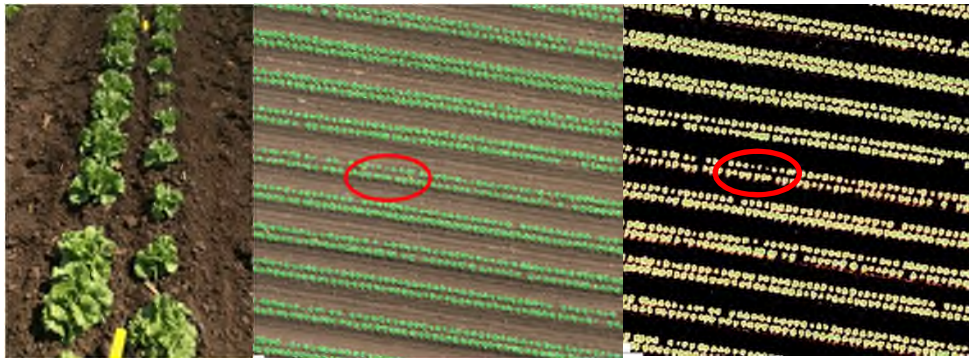
Figure 3 Lettuce harvest characteristics vs. automated sizing from UAV imagery
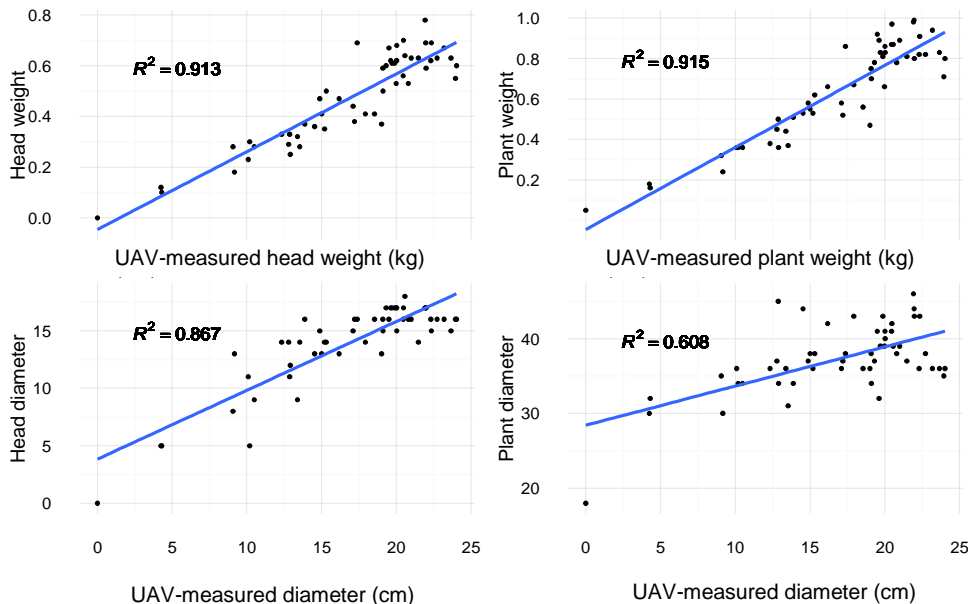
Measurements of plant characteristics (plant diameter) in crop and at harvest (plant diameter and weight, head diameter and weight) were used to develop algorithms for each parameter. These algorithms were then applied to the mid-crop UAV NDVI data to obtain predicted values based on the early crop imagery. The algorithms developed successfully counted and sized lettuce with a range of parameters correlating highly with harvest data (**Figure 3 and Appendix 3**). R^2 values ranged from 0.608 to 0.915. Clear protocols for consistency in diameter measurements that align with how the imagery is measured might improve the correlation between the manual and UAV measured plant and head diameter.

Automated Corn Counts

The process and results for three leaf sweet corn classification are depicted in **Image 6**. This involved processing the multispectral imagery to form a field image, converting this image to NDVI, and finally the image classification and extraction to capture individual sweet corn plants. During the plant classification stage, NDVI data is used to develop a simple algorithm which differentiates between

plants and soil based on differences in NDVI values and assigns a count based on the number of changes in these values. A comparison of plant counts done manually in the field and through classification of the NDVI imagery is presented in **Table 4**. This could be valuable for a range of crops where each plant represents one potential harvested unit.

Image 6 Process to Extract Plant Count on corn
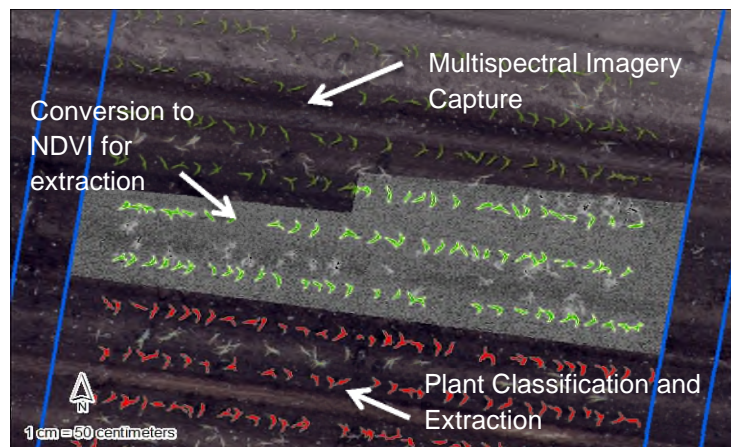
Table 4 Comparison of actual field plant counts and NDVI classification counts

Sample number	Weight of cobs (4 metres of row)	Number of plants/metre measured	NDVI classified plants/metre
1	3.91	4.5	4.6
2	4.09	5.5	3.7
3	1.67	5.3	5
4	2.68	3.5	4.8
5	3.72	3.5	3.6
6	3.49	5	3.8
7	4.08	5	3.4
8	2.60	2.8	2.6
Mean	3.65	4.4	4

Notes:
Both manual counts and NDVI counts were randomly selected across the paddock and not from the same location.

The automated count for corn was 10% less than the manual count. The main issue associated with this process was flight timing, as in the NDVI image most of the corn was touching and made auto counting difficult. With more development these algorithms can be refined and improved.

Use of different indices

Using a sophisticated multispectral camera for this research allowed for the comparison of a number of vegetation indices that can be derived from the reflectance bands it uses. Typically, NDVI is significantly influenced by shadows and clouds (Laliberte *et al.* 2011). This also means that there are limited windows for capturing imagery each day. Best results are in the middle of the day as shadowing of adjacent plant rows can occur early and late in the day. Also as the crop matures and canopy cover increases to 80-90% of the field area, NDVI values plateau and differences in crop

variability are not very clear. However, it was found that Normalised Difference Red Edge Index (NDRE) was effective at indicating crop variation in these later crop stages (**Image 7**). A week before harvest the RGB green bean image showed clearly defined irrigation footprints radiating from each sprinkler.

Image 7 NDVI (left), NDRE (centre) and RGB (right) imagery in green beans
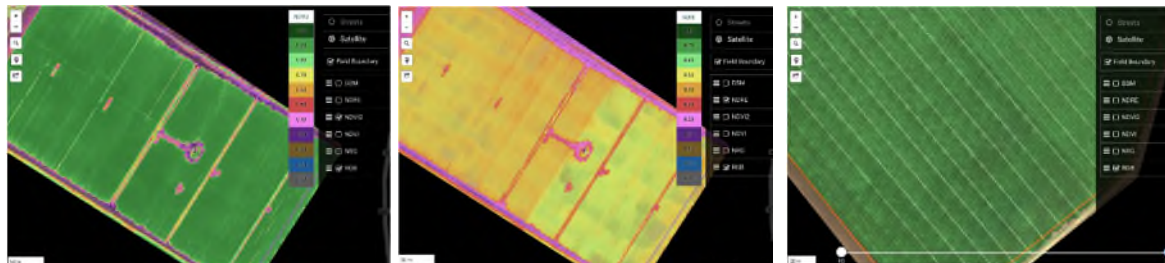
Significance

White mould, caused by *Sclerotinia sclerotiorum*, is a significant disease of green beans. Yield loss occurs through premature plant death from stem infection and/or infection of pods. The ability to detect disease incidence using remote sensing could change the way scouting for disease is carried out and prelude the development of predictive algorithms for disease occurrence. While Sclerotinia was confirmed in field sampling of a green bean crop, it could not be proven that the remote sensing could detect Sclerotinia from the imagery collected. However, earlier flights with higher (<1cm) image resolution may have detected diseased plants.

Spatial variability was evident in the green bean NDVI imagery, with groundtruthing activities confirming visible differences in plant height and pod production. Small plot measurements indicated 10% shorter plants and 20% yield reduction in plots from lower NDVI areas. These results are similar to case studies reported in Limpus *et al.* 2016. Further groundtruthing activities would be required to ascertain what could be causing this variability e.g. EM38 soil mapping, strategic soil sampling. Results from groundtruthing activities could identify opportunities for variable rate soil amendment or nutrient applications.

Image processing and classification processes were used to successfully derive datasets that matched closely with yield data. Lettuce could be counted with 98% accuracy in comparison with in field manual counts. Algorithms for automated sizing of plants were developed and were highly correlated with harvest data from experimental plots (R^2 ranging from 0.608 – 0.915. It would appear from this small scale study that unevenness in the establishment of plants (for whatever reason) is maintained through to maturity. With further development, methods and algorithms to assess variability in establishment, count plant numbers, predict yield and product characteristics could provide valuable data to producers.

- Spatial yield mapping of vegetable crops, in Queensland and Australia wide, is still in its infancy with some limited adoption of load cell based monitors on mechanical harvesters (sweet potato, potato and carrots) (Limpus *et al.* 2016). Yield monitoring of hand harvested crops is complicated as these crops tend not to refer to absolute tonnages for yield rather than boxes of known units e.g. lettuce or broccoli heads within tight sizing specifications. The ability to predict yield using vegetation indices derived from early season crop sensing data could be an alternative to spatial yield mapping for hand harvested crops.

- For the majority of vegetable crops, profitability is more closely linked to quality parameters

(market specifications) rather than absolute product tonnages. The ability to assess potential variability in these parameters prior to harvest could be used to inform packing shed requirements and marketing decisions. This could also provide a mechanism for assessing potential product quality spatially

- The bulk of vegetable crops are still reliant on hand harvesting. As labour is the highest cost in horticultural production, representing up to 27% of costs depending on the crop type, any efficiencies in the use of this labour is desirable. Understanding the extent of field variability in maturity could inform harvest decisions for more efficient use of labour.

Flight timing and height is crucial for appropriate imagery and data collection.   For lettuce and corn, classification (counting and/or sizing) was possible and accurate for the crop stages assessed. It was expected that where plants were physically touching, automated counts and sizing using the tools developed was difficult and prone to undercounting and oversizing plants. However, methods to reduce errors were developed to limit these issues. Timing of UAV flights at the correct crop development stage is critical for accurate crop counting and sizing and further development would continue to improve count accuracy, particularly in corn.

At lower flying heights there is a trade-off between resolution and the area captured or flying time as travel speed needs to be reduce to compensate for being closer to the ground and the requirement for more frequent image captures. For example for the bean field, at 100 metres AGL, the UAV travelled at 12 metres/second, capturing an image every 1.5 seconds and taking 30 seconds to map 1 hectare. In contrast, at 20 metres AGL, the aircraft travels at 7 metres/second, capturing an image every 0.5 second (limit of existing cameras) and takes 4 minutes to map 1 hectare.

The multispectral camera employed for this work generated several vegetation indices. NDVI was the most appropriate during the early to mid-growth stage of the crop. In later crop stages NDRE is an option for assessing crop biomass, where NDVI values have plateaued due to saturation of the index, and no longer depicts spatial variability clearly. Though NDVI and other vegetation indices can demark variability by capturing areas of low and high plant vigour, they do not provide any information on the underlying cause of any identified variation. In-crop groundtruthing is the only way of discerning or eliminating potential causes of variation in crop growth and these activities can be time consuming and costly.

Key Messages

- UAV captured NDVI data successfully identified spatial variability in green beans.

- While scattered Sclerotinia was detected in the crop, these plants were not evident at the resolution the imagery was initially carried out at. It is possible that infected plants would be evident at a higher resolution (or lower flying height).

- The small scale assessments here confirm variability in maturity early season is maintained through to maturity.

- In addition to identifying spatial variability for the purpose of improving uniformity using UAV imagery, there is potential to develop predictive tools to inform harvest and marketing of horticultural crops. This study suggests that classification and sizing algorithms could be developed from vegetation indices data to predict yield for vegetable crops such as lettuce and sweet corn.

- Flight timing and height are crucial to obtain valuable imagery for accurate classification and analytics.

- While NDVI is the most commonly used vegetative index, others can also provide valuable information in different crops and at different crop stages.

- Field sampling to groundtruth NDVI or other vegetative index imagery is critical. Though UAV imagery will indicate and calculate the areas of crop variability within a field, some level of crop and/or field inspection will be required to identify or confirm the cause.

Where to next

- Expanding on the results presented in this report would include higher resolution imagery specifically targeting disease detection at an individual plant level.

- NDVI and other vegetation indices were used to calculate and clearly delineate crop variability across paddocks. This information can be readily supplied to variable rate technologies, which could support reducing inputs (nutrient or chemical) and provide farm businesses with significant cost savings or increased profitability from improved uniformity into the future.

- The development of algorithms and tools for early season counts and assessment of vegetable crop characteristics requires further refining and validation. This work involved only small scale assessments and the biometric capacity developed through this project could be significantly expanded. Development and testing of accurate algorithms and tools for different crops and crop stages would require significantly larger data sets and resourcing.

- The optimum flight parameters to reduce UAV flight times and costs and still gain effective accurate counts also needs further assessment.

Budget Summary

The budget for this work was initially requested for field sampling assistance to groundtruth disease in crop. However, as the contribution of UAV services by Boeing ceased, the budget had to be reallocated to purchase UAV imagery. The full amount of $6000.00 was expended in the purchase of UAV imagery, processing and analysis. Groundtruthing activities were completed by the project leader with assistance from John Duff, Senior Plant Protectionist.

Airborn Insight staff provided significant in-kind contribution ($6,000) for the counting and sizing classification algorithm development.

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Acknowledgements

Appendix 1 Quantification of field area characterised by lower and higher NDVI values as an indicator of plant vigour.
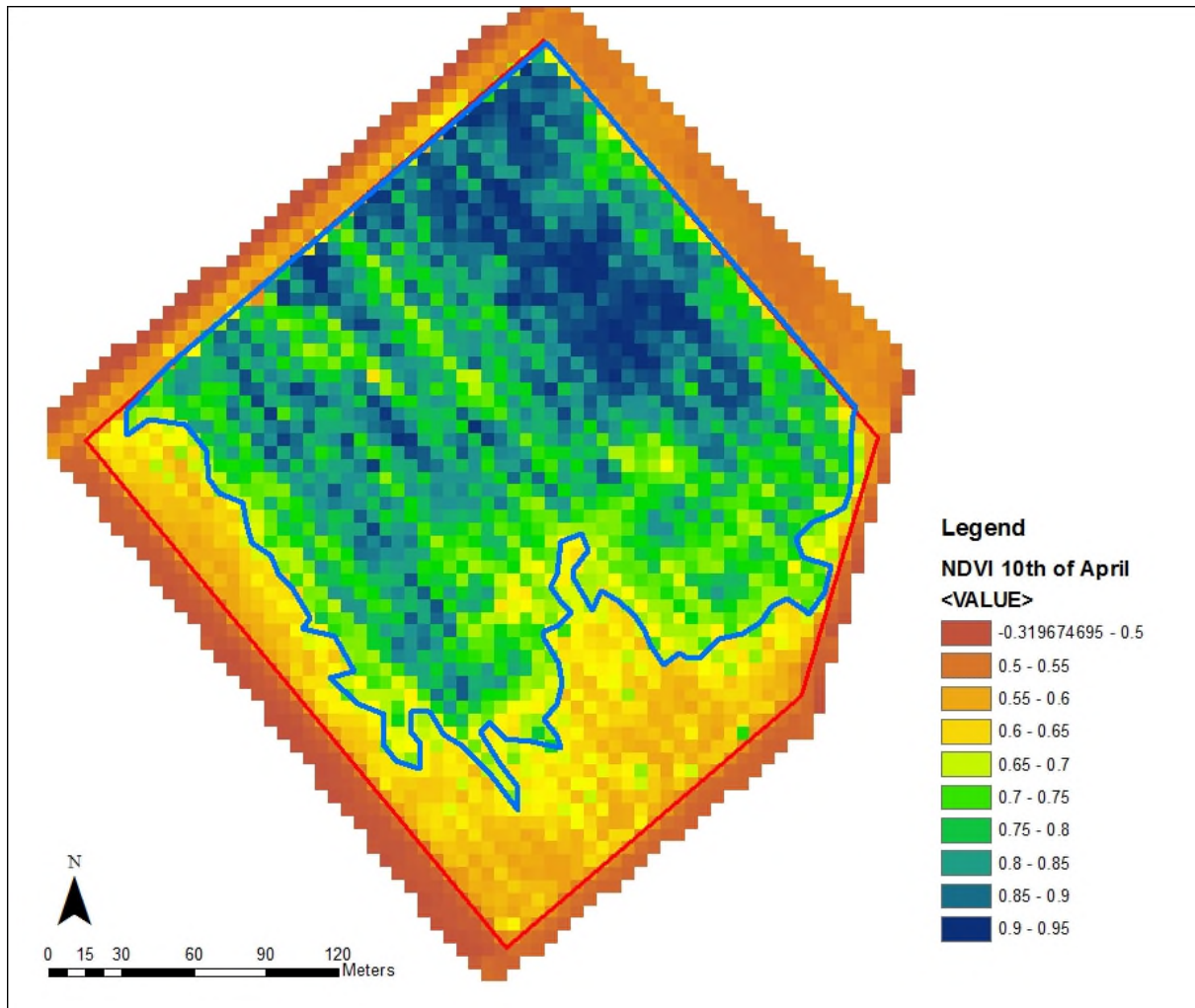
Total Paddock Area	Lower NDVI Area	Higher NDVI Area
6.7 ha	1.8 ha	4.9 ha

Appendix 2 Lettuce measured parameters and UAV derived parameters

| Plot	Plant diameter (cm) 26/4/16	Plant diameter (cm)13/5/16	Head diameter (cm) 13/5/16	Plant weight (kg) 13/5/16	Head weight (kg) 13/5/16	Row (north or south)	UAV-head Diameter (cm)
1	22	41	16	0.87	0.56	N	20.5
1	28	36	16	0.94	0.67	N	23.2
1	23	36	15	0.58	0.44	N	17.1
1	31	39	16	0.89	0.63	N	21.0
1	25	32	17	0.89	0.62	N	19.6
1	28	39	18	0.87	0.64	N	20.6
1	15	34	5	0.36	0.3	N	10.2
1	25	41	17	0.86	0.62	S	20.0
1	27	36	16	0.82	0.62	S	22.3
1	28	43	17	0.8	0.59	S	22.0
1	23	37	14	0.81	0.63	S	21.5
1	26	44	17	0.99	0.69	S	22.0
1	21	31	14	0.37	0.28	S	13.5
1	28	46	17	0.98	0.78	S	21.9
2	15	30	13	0.24	0.18	N	9.2
2	19	45	11	0.5	0.33	N	12.9
2	12	18	0	0.05	0	N	0.0
2	22	36	14	0.53	0.35	N	15.2
2	22	37	14	0.45	0.29	N	12.8
2	24	37	16	0.52	0.38	N	17.2
2	23	36	13	0.47	0.37	N	19.0
2	26	38	16	0.75	0.59	S	19.1
2	27	40	15	0.83	0.68	S	20.0
2	26	38	16	0.82	0.63	S	22.7
2	24	37	15	0.58	0.47	S	14.9
2	24	38	14	0.62	0.5	S	15.3
2	27	38	16	0.78	0.53	S	20.8
2	26	39	17	0.66	0.53	S	20.0
3	17	36	14	0.38	0.33	N	12.3
3	12	30	5	0.18	0.12	N	4.3
3	18	35	8	0.32	0.28	N	9.1
3	21	36	9	0.44	0.32	N	13.4
3	19	36	11	0.36	0.23	N	10.1
3	20	34	12	0.36	0.25	N	12.9
3	27	34	15	0.7	0.5	N	19.1
3	28	41	16	0.92	0.67	S	19.5
3	30	36	15	0.83	0.63	S	23.6
3	29	37	17	0.78	0.6	S	19.3
3	32	42	17	0.97	0.7	S	20.5
3	31	38	16	0.86	0.69	S	17.4
3	26	35	16	0.71	0.55	S	23.9
3	28	36	16	0.8	0.6	S	24.0
4	28	43	15	0.91	0.69	N	22.3
4	28	43	17	0.81	0.61	N	19.9
4	25	36	16	0.56	0.41	N	18.5
4	24	39	17	0.83	0.61	N	19.7
4	22	34	16	0.51	0.37	N	13.9
4	24	38	13	0.55	0.41	N	15.0
4	23	43	14	0.67	0.41	S	17.9
4	16	34	9	0.36	0.28	S	10.5
4	11	32	5	0.16	0.1	S	4.3
4	21	44	13	0.53	0.36	S	14.5
4	26	42	13	0.66	0.47	S	16.2

Appendix 3 Lettuce automated counting
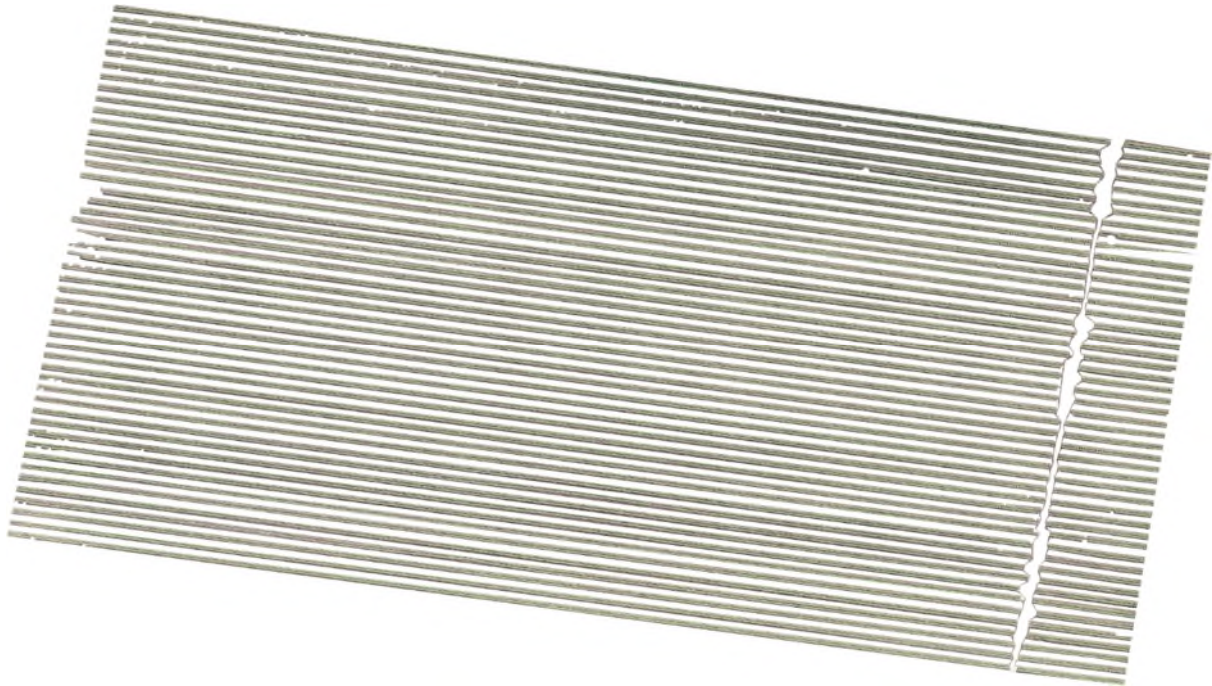
Manual plant count	Automated plant count	Difference between counts
38,520	37,879	3,852 (1.7%)

Notes:
Image captured 4 weeks after transplant. Lettuce harvested 8 weeks after transplant.