MACHINE VISION FOR CAMERA-BASED HORTICULTURE CROP GROWTH MONITORING

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Abstract
Plant growth and fruiting development monitoring is required for horticulture crop and irrigation management. However, this monitoring is typically manual, labour-intensive and conducted in a limited number of locations in the field which may not represent the whole field. Rapid crop assessment throughout the season can be achieved using machine vision analysis of images captured with cameras. High spatial resolution plant growth and fruiting information can be used for yield estimation and to manage site-specific irrigation and fertiliser application.

Camera-based plant sensing systems have been developed for high spatial resolution data collection from top views of crops. The sensing systems have been installed on overhead irrigation machines. The cameras on the irrigation machine were smartphones with an App installed to capture and upload images and GPS location at a time interval. These cameras automatically captured and uploaded images during irrigation events as the machine traversed the field. Image analysis algorithms have been developed to estimate canopy cover for peas and carrots, and flower counts for peas.

These cameras have been evaluated at sites in Kalbar in South East Queensland, Australia, and Palmerston North, North Island, New Zealand. This paper compares the image analysis results with ground truthing measurements that were collected at approximately weekly intervals at the sites, and electrical conductivity, reflectance, yield and soil type maps.

Background
Inspection of horticulture growth rates and fruit load are required for management of irrigation, fertiliser, pesticide and fungicide application, and harvesting. This is typically conducted weekly by growers and/or agronomists manually inspecting crops in each field. However, there can be up to 200% variation in soil properties within a single field, leading to spatial variation in crop growth, crop water requirements and yield. Manual inspection of each non-homogeneous area of the field is required for site-specific management, but this data collection and processing is labour-intensive. Machine vision using infield cameras and automated image analysis algorithms have potential for rapid crop assessment at a high spatial and temporal resolution.

Existing machine vision systems often involve multi-spectral cameras on tractors or Unmanned Aerial Vehicles (UAVs). These cameras detect canopy cover and vegetation indices (e.g. NDVI) to identify areas of stress in the field. This camera system cannot detect individual plant components (e.g. leaves, flowers) that can help detect the cause of the stress in the field (e.g. pests). High resolution imagery can be collected using visible-spectrum cameras from ground or aerial vehicles. Image analysis algorithms can then be implemented to extract canopy cover and flower counts (for potential yield prediction). Canopy cover and flower counts are used to indicate crop growth stage. In particular, cover can be used to identify need for herbicide (if cover is low at start of season) and fungicide (before canopy is closed). These can also be compared with crop production models that track crop development in season for yield prediction and management optimisation.

A camera system and image analysis algorithms were developed to monitor pea and carrot crops using cameras on ground vehicles (i.e. irrigation machines). The irrigation machine was selected as the camera platform rather than UAVs because the irrigation machine enables unsupervised data collection. UAVs have a higher labour requirement as they require an operator within line of site following current Civil Aviation Safety Authority regulations. Low cost smartphone-based cameras were installed along irrigation machines for collecting imagery as the machine passed over the field.

Materials and methods
Field sites
The smartphone cameras were evaluated at a carrot centre pivot site in Kalbar, Queensland and at a pea centre pivot in Palmerston North, New Zealand. Each field was divided into two management zones according to electrical conductivity maps and soil sampling. The locations of these zones are

shown in Figure 1. For both sites, Zone 1 was sandier then Zone 2. The field was divided into management cells of grid size 10 m for the Palmerston North site and 20 m for the Kalbar site. Simple kriging was implemented to spatially interpolate the field measurements into each cell in the field. Table 2 shows the layout of the cells in each field site.

Data collection
Cameras were placed onto the machine to ensure that images of both zones were captured. Seven cameras were installed on the carrot site and two cameras were installed on the pea site. Table 1 shows the details for the trial sites. Figure 1 shows a solar-powered smartphone camera installed on an irrigation machine for on-the-go imagery collection. An App was developed and installed on the smartphone that captured and uploaded an image and corresponding GPS location every 15 minutes. The field of view of each camera was 3 x 2.25 m which is approximately 720 plants with 107 plants/m².

Ground truthing measurements were collected at approximately weekly time intervals. This included canopy cover (%) and height for peas and carrots, and number of flowers and pods for peas. Thirty manual measurements were collected in each zone. Electrical conductivity maps were collected at each site to identify the variability in soil properties across the field using a DUALEM-1 sensor.

Table 1: Field site details for data collection

Location	Crop	Season	Cameras along machine (m)	Data collection days
Kalbar	Carrots	30 May 2015 - 26 Oct 2015	80, 106, 125, 165, 180, 210, 225	7/7, 20/7, 7/8, 14/8, 22/8, 5/9, 26/9, 2/10, 10/10
Palmerston North	Peas (Ashton, Massey)	18 Oct 2016 - 9 Jan 2017	52, 56	16/11, 23/11, 30/11, 7/12, 17/12, 21/12, 26/12, 4/1

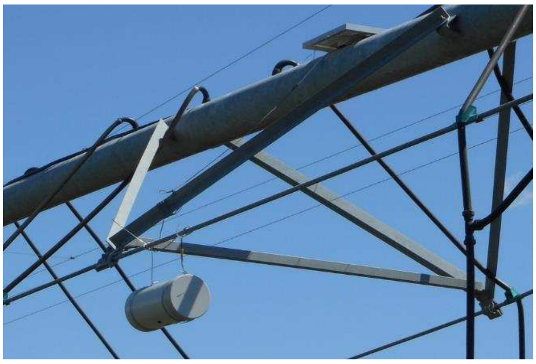


Figure 1: Smartphone on irrigation machine for on-the-go imagery collection

Image analysis
Image analysis algorithms were implemented on the server to extract canopy cover for carrots and peas, and flower counts for peas. Canopy cover was estimated from the proportion of green pixels in the image, whilst flower count was estimated using the number of detected white components in the image. Figure 2 shows sample image analysis for estimating flower counts of peas.

(a) (b)

Figure 2: Sample captured image at Palmerston North: (a) original visible image; and (b) image analysis results for flower detection on peas where red areas indicate detected flowers

The carrot canopy cover and pea flower count, detected using image analysis, were compared with infield measurements. The pea canopy cover from image analysis was compared with manually measured height rather than pea canopy width. This is because the measured pea canopy closed in November and measured width between rows did not indicate the growth of the pea crop.

Crop mapping
The image analysis algorithms were executed on images uploaded during irrigation events or dry runs of the machine. The Palmerston North centre pivot collected images using dry runs of the machine as there was high rainfall and no need for irrigation. The results were spatially interpolated to produce crop maps of canopy cover and flower counts. These measurements were compared with ground truthing measurements collected in each zone.

Results and discussion
Figure 3 compares the pea flower count and carrot canopy cover from the image analysis and field measurements. The standard error in flower count estimation using image analysis was 0.6 flower/plant (Figure 3a). This error in flower count estimation is likely caused by the manual measurements covering a smaller area than the smartphone images (i.e. manual measurements of 30 plants, whilst the camera images covered approximately 720 plants). Another source of error is that the cameras only detected flowers from the top surface of the plant and other flowers lower in the canopy may have been hidden by leaves.

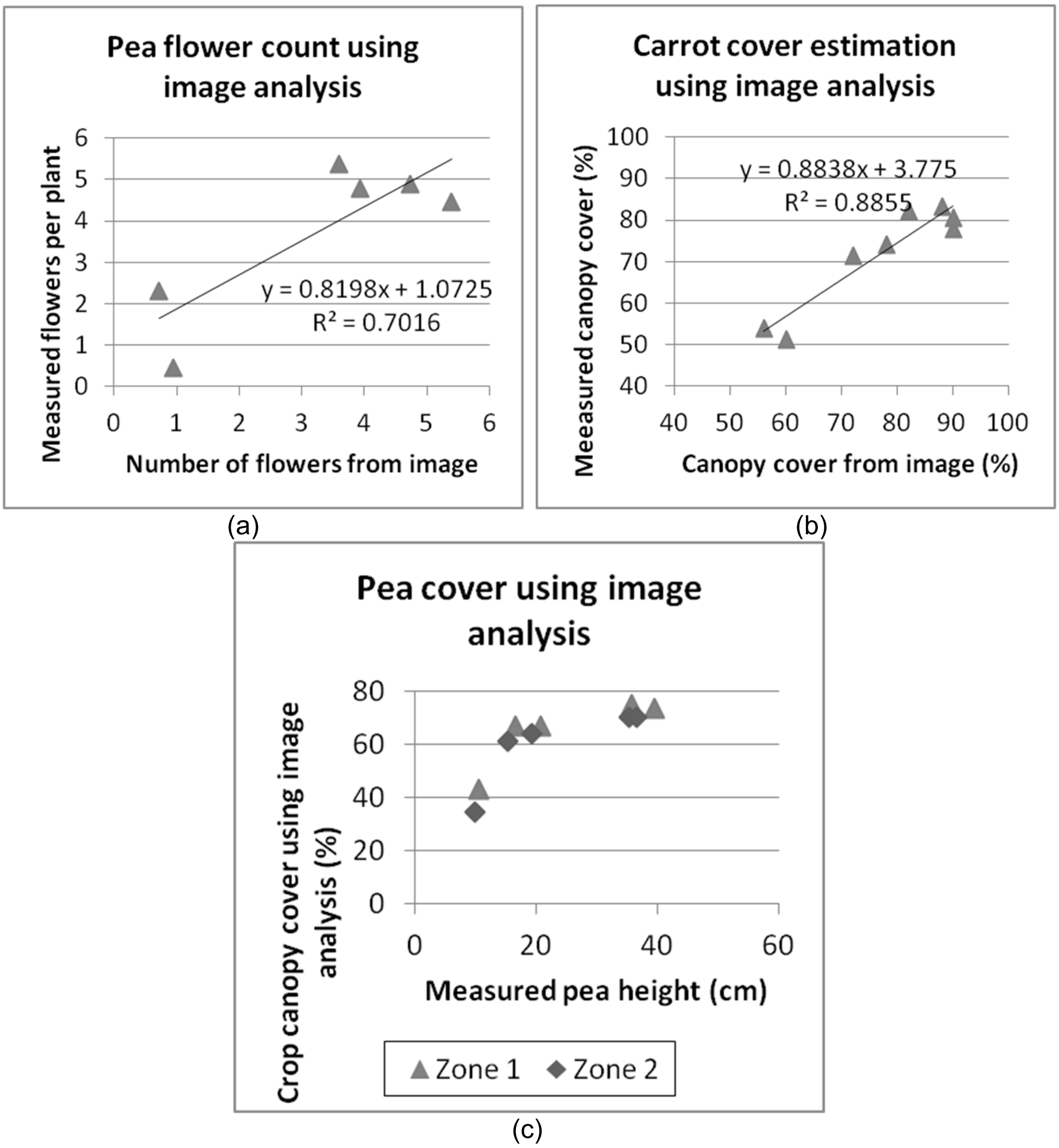
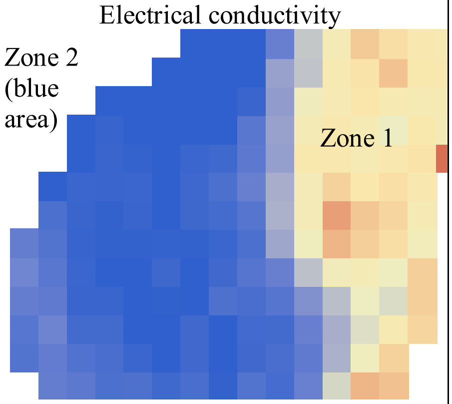
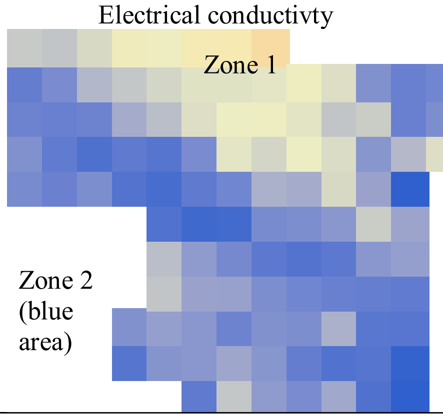
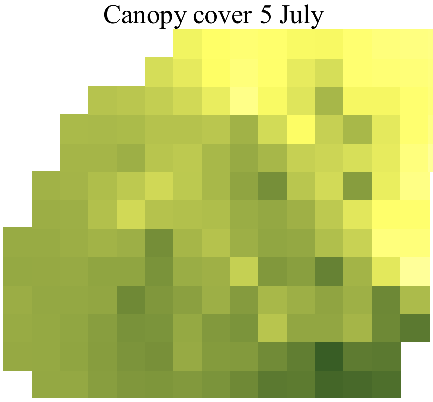
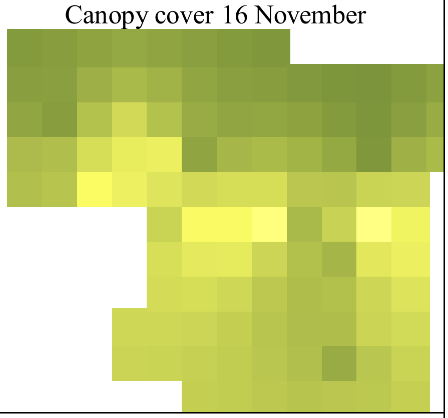
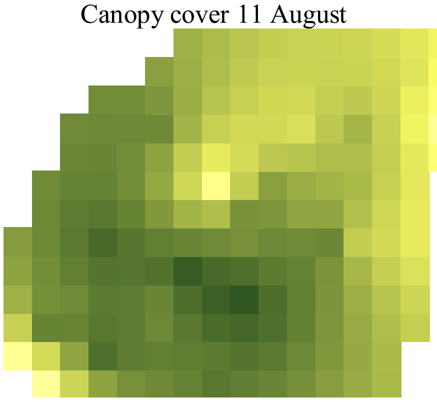
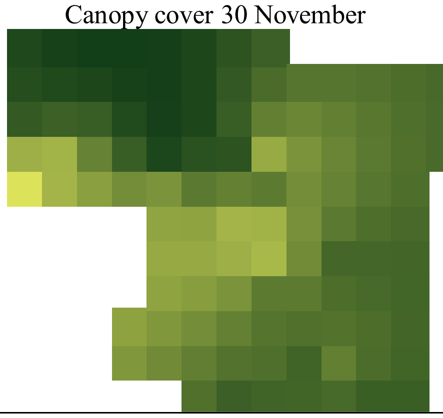


Figure 3: Image analysis results for: (a) flower counts for peas; (b) canopy cover for carrots; and (c) height estimation for carrots from canopy cover

The standard error in carrot canopy cover was 3.7% (Figure 3b). Similar to the pea flower counts, this error may be caused by the manual measurements covering a smaller area than the smartphone images. The pea height was compared for the two soil types where the lighter soil is Zone 1 (Figure 3c). The detected canopy cover increased as the measured height increased. Figure 3c indicates a non-linear relationship between pea height and canopy cover. Further data collection and analysis is required to ensure robustness in different varieties and climates.

Table 2 shows the spatially interpolated maps for electrical conductivity and canopy cover collected using the smartphone cameras on the irrigation machines. These show that the canopy cover was generally higher in the sandier zone at Palmerston North (Zone 1) and lower in the sandier zone at Kalbar (Zone 1). This may be because there was high rainfall at the Palmerston North site which led to the heavier soil zone being overwatered and having a smaller canopy and yield, whilst there was average rainfall at the Kalbar site which led to the lighter soil zone being under-watered and having a smaller canopy and yield.

Table 2: Spatial variability at Kalbar and Palmerston North sites

Carrots at Kalbar	**Peas at Palmerston North**	**Legend**
Electrical conductivity  	Electrical conductivty  	
Canopy cover 5 July 	Canopy cover 16 November 	
Canopy cover 11 August 	Canopy cover 30 November 	

Conclusion

A low-cost camera was used to automatically detect spatially variable canopy cover and flower counts for peas and carrots in Kalbar, Queensland and Palmerston North, New Zealand. The standard error in flower count estimation using image analysis was 0.6 flower/plant and in carrot canopy cover was 3.7%. There is potential to use this low-cost machine vision system for unsupervised crop development measurements for herbicide and fungicide management, and incorporation into decision-making framework to predict irrigation requirements, harvest date and yield.

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