An innovative approach to estimate carbon status for improved crop load management in apple

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Abstract

Inconsistent cropping is a major issue in apple fruit production. Consequently, crop load management is critical for growers. Unbalanced crop loads can lead to the establishment of biennial bearing with subsequent high economic losses. An international collaborative project between Australia and Germany was set up to investigate the various aspects of crop load management utilising standard (physiological and molecular) and innovative (image analysis and thinning predictors through modelling) methods. The modelling aspect of the project will investigate a simplified MaluSim model to determine tree carbon status with the aim of providing advice for application of chemical thinners. The focus of the modelling effort will be on early season fruit development as chemical thinners are typically applied up to 80 days after green tip. The first step in evaluating a simplified model is the conversion of key parts of MaluSim into a more flexible format using the software program R. Another aspect of the project is to efficiently measure the physiology of the apple tree through state-of-the-art stereo image reconstruction and improve the accuracy in the carbon balance status. Stereo image reconstruction involves multi-view geometry to detect a number of different variables automatically (including spurs, shoots, flowers, fruit and leaf area) and will considerably reduce manual measurements. This paper will discuss the innovative methods being used and some of the results generated so far.

Keywords: Nicoter, 'Cripps Pink', biennial bearing, MaluSim, R, image analysis

INTRODUCTION

In apple (*Malus* × *domestica*) yield potential is closely related to flower induction and flower development. Unlike annual crops, the designation of buds as floral occurs in the year prior to anthesis, typically 11 months after floral induction. The precise time when meristems are committed to floral as opposed to vegetative is currently not clearly understood. These morphological changes depend on cultivar, bud type and climatic conditions and usually occur 4-6 weeks after full bloom of the current season's crop (Foster et al., 2003; Kotoda et al., 2000). Hence, the decision to commit resources to the next season's flowers occurs when the tree is using the bulk of its resources growing this season's fruit.

Climate conditions and crop management have been related to the number of meristems induced to become floral (Jonkers, 1979). There is good evidence that high crop loads reduce next season's flower density and fruit yield. This observation has been attributed to internal processes including signals from developing seeds in fruit and lack of carbohydrates from nearby apical bud meristem (floral versus vegetative) due to competition (Monselise and Goldschmidt, 1982). Note that characterisation and quantification of the role of hormones, including that of gibberellic acids, auxin and cytokinins remain to be demonstrated (Bangerth, 2006).

Results of microscopic studies (Hanke, 1981) and gene expression experiments (Hättasch et al., 2008) suggest floral induction occurs between the end of May and mid-June in Germany and that suppression of floral induction in meristems by nearby developing fruit (or seeds) must occur at the same time. This is supported in commercial orchards where chemical thinners are applied in the early season to reduce the number of fruit, and hence seeds, to improve fruit size of the current crop and to guarantee the induction of adequate flowers for the following season. Given this theory and the large variation between cultivars in responding to these strategies (Wünsche and Ferguson, 2005), genetic control of the overall process may be likely.

An international project between Germany and Australia is underway to advance knowledge on the key molecular and physiological processes involved in the major impediments to flower bud induction which establish biennial bearing patterns. As part of this project practical innovations are being tested to assist growers with chemical thinning decisions which are an ongoing, and sometimes difficult, management strategy in commercial orchards. Two approaches are being investigated. Firstly, use of the carbon balance model MaluSim (Lakso et al., 2006; Lakso and Johnson, 1990) is being investigated to assist with chemical thinner applications based on the carbon status of the tree following the service currently available in the USA. The initial results centre on the conversion of MaluSim from a Stella® platform into the programming language R (R Core Team, 2014). This process allows flexibility for batch analyses and provides scope for investigation of model simplification for the supply of thinning advice. To initialise MaluSim for this purpose key tree properties are required. These include time of green tip (to begin the model) and the number of vegetative and floral growing points (for carbon balance evaluation). These aspects motivated the second innovation being investigated, image analyses.

Hand measuring several different variables (including spurs, shoots and flowers) required to initialise MaluSim every year would be time-consuming and financially expensive for growers. However, if this could be achieved automatically via an innovative computer vision approach using a digital camera, this onus could be dramatically reduced and provide high accuracy of measurements.

This is a recently new field of research with computer vision algorithms only been deployed to aid in prediction of agricultural fruit yield estimation in the last decade (Payne et al., 2013; Nuske et al., 2011). Apple in particular has shown progress in image analyses applications through automatically segmenting the apple fruit using hue saturation and specular reflection from a digital camera with flash illumination during night-time (Wang et al., 2013). Other works involve utilising RGB-IR (red-green-blue-infrared) camera to detect the fruit and other variables of the apple trees during day time (Hung et al., 2013). These two approaches suggest that depth can be utilised to isolate the tree from the background whilst the automation of counting the variables required for MaluSim can be accurately achieved through recent methods in object detection (Hung et al., 2013). These approaches are explored in this study.

MATERIALS AND METHODS

MaluSim

Key components of the MaluSim model relevant to carbon balance estimation in early season fruit development were re-written into the software program R (R Core Team, 2014). The outputs specifically evaluated were carbon production, respiration and the resultant carbon balance. MaluSim was evaluated in Stella® and R for the sites and seasons in Table 1. Ithaca was included as it is close to the region where MaluSim was developed, Three Bridges is the site where the image analysis is being conducted, Coldstream is a nearby site for additional seasonal comparison and Tumbarumba is a secondary site included for trailing of MaluSim for thinning recommendations.

Comparison between results between the two software programmes for each of the datasets was conducted from day of green tip to 80 days after green tip. The two software program outputs were compared in relation to daily carbon balance (carbon assimilation minus respiration) in terms of maximum daily deviation and root mean square error (RMSE).

Table 1. Weather data used to test conversion of MaluSim.

Site	Latitude	Longitude	Year	Climate data source
Ithaca (USA)	42.45	-76.51	2015	Network for environment and weather applications (Ithaca Cornell Orchards)
Three Bridges (Australia)	-37.83	145.68	2016	Collected on site (data logger Campbell Scientific CR1000)
Coldstream (Australia)	-37.72	145.41	2014, 2015	Australian bureau of meteorology (086383)
Tumbarumba (Australia)	-35.78	148.00	2015, 2016	Australian bureau of meteorology (072043)

Image analysis

Investigation for use of image analysis to automate detection of tree properties will be considered through three major steps. Firstly, the tree needs to be isolated in the image. To do this, Structure-from-Motion, a state-of-the-art stereo reconstruction algorithm, was used to generate a depth map such that the tree and all its physiological variables can be isolated. This can be conducted during night time (Wang et al., 2013) or day time (Ha et al., 2016). This process requires a digital camera of a wide angle lens and flash to capture the full height of the tree and it is recommended to also have high resolution with a capability of taking videos. This step is explored in this study.

Secondly and subsequent to the tree being isolated, state-of-the-art object detection algorithms will be deployed to automatically count the variables of interest accurately. Examples of these include convolutional neural networks (CNN), random forests (RF), conditional random fields (CRF) and support vector machines (SVM). Finally, validation of the image analyses process will be conducted against measured values for each of the physiological variables. These measurements will be taken weekly from green tip, through flowering and into fruiting season.

Computer vision methods utilise both Matlab and C++ programming tools with, the mathematical theory behind the computer vision approaches available in Wang et al. (2013) and Ha et al. (2016).

RESULTS

MaluSim

Comparison of two software programs output indicate confidence that the re-coding of MaluSim in R is similar to that in Stella®. Across all tested datasets, RMSE was less than 0.20 g CO_2 m^{-2} day^{-1} and the maximum error was 1.38 g CO_2 m^{-2} day^{-1} (Table 2). This maximum divergence was a single occurrence (Figure 1) and occurred prior to the period for which thinning decisions will likely be made (before 20 days after green tip).

Table 2. Difference of R code from Stella® of daily carbon balance for maximum divergence and root mean square error (RMSE).

Site	Year	Daily maximum difference (g CO_2 m^{-2})	RMSE (g CO_2 m^{-2} day^{-1})
Ithaca	2015	0.47	0.07
Three Bridges	2016	1.38	0.16
Coldstream	2014	0.08	0.04
Coldstream	2015	0.08	0.04
Tumbarumba	2015	0.08	0.04
Tumbarumba	2016	1.13	0.16

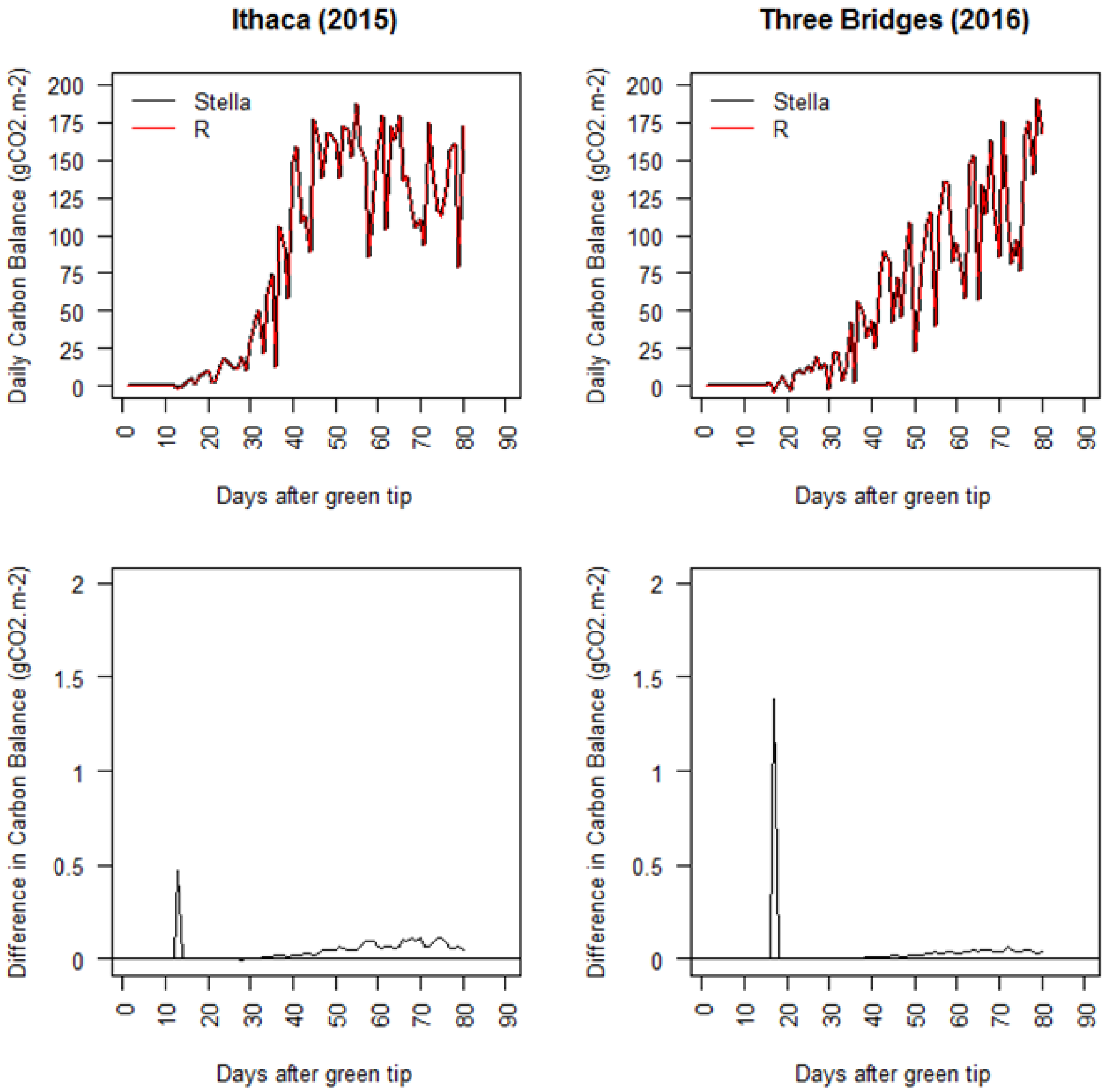

Figure 1. Comparison of Stella® and R output for MaluSim (top) and daily difference of R from Stella® (bottom) for Ithaca (USA) and Three Bridges (Australia).

Image analysis

Example images to demonstrate the two approaches to isolate the tree and all its parts displayed in Figures 2 and 3. Figure 2 shows a reference image of a three-second long video of a tree in sweep from left to right during day time. Figure 3 illustrates the night time segmentation of a different tree using digital camera with flash.

These preliminary results of image analyses show that the tree can be isolated either at night time or in the day time such that the physiological variables of the tree can be measured without background information, such as the sky, other trees and grass interfering with the results.

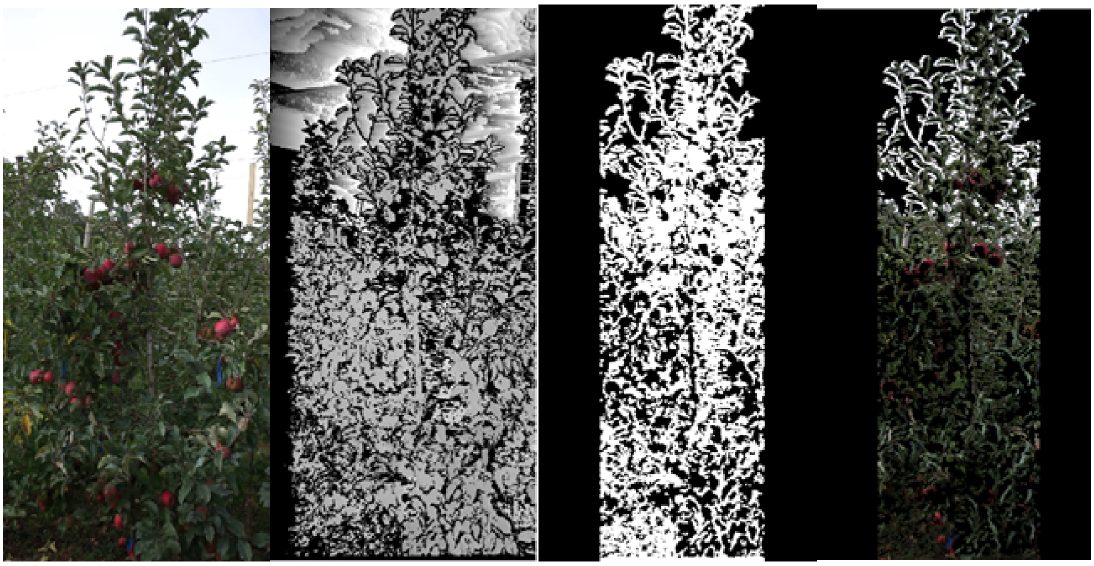

Figure 2. Day time segmentation using digital camera with 3-second video. From left to right: snapshot of one frame from video, depth map obtained from Structure-from-Motion, threshold mask based on grey-scale intensities within depth map, threshold mask overlayed with original photo to isolate the tree.

Figure 3. Night time segmentation using digital camera with flash. From left to right: original photo taken with a flash, threshold mask based on hue saturation, threshold mask overlaid with original photo to isolate the tree.

DISCUSSION

Results indicate the key components within MaluSim have been successfully re-coded from Stella® into R for the period up to 80 days after green tip. This is the first step required to conduct further analyses of MaluSim for chemical thinning application in Australia. As the program R provides a more flexible environment to conduct batch assessments of MaluSim, sensitivity analyses will be more easily conducted. For instance, monitoring of the input variables such as shoot and spur numbers for many years of data at many sites can assist to evaluate variability in seasonal responses and provide information regarding the accuracy of input data required. Furthermore, this conversion will more easily allow for investigations into the modification of parts of MaluSim to allow for direct input of measurable variables. Specifically, direct input of measured light interception from ceptometers, or from image analyses, rather than estimation via algorithms in MaluSim may be possible. In field trials are needed to evaluate if using the carbon balance evaluated by MaluSim is effective in making better thinning decisions.

To reduce the potential onus on growers to describe their trees to use MaluSim, image analysis techniques are underway to investigate the potential to automatically detect key tree attributes. Preliminary results of image analyses have shown that the tree can be isolated either at night time or during the day time. Although the night time flash shows promising results, it can be inconvenient for growers to collect data at night. As such, the novel approach of Structure-from-Motion was performed in the day time to eliminate this drawback. Based on the day time results from the structure-from-motion method, coupling with other state-of-the-art techniques may be required to further its precision in segmenting the physiological variables of the tree so that it reaches, at least, the same level of accuracy as the night time flash. The object classification algorithms, CNN, RF, CRF and SVM are currently being investigated to detect the physiological variables (including spurs, shoots, flowers, fruit and leaf area) to a high accuracy and to ensure robustness to tree structure variability. Once all image analysis stages are completed, the results will provide valuable knowledge for the agriculture community to assist with thinning practices. These results will likely provide a pathway for other innovative research outcomes and management strategies through the utilisation of automatic detection and characterisation of the various parts of apple trees at several growing stages.

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